Chapter 1

Introduction

1.1. Introduction

The words fabric and textile are mostly used in correlated and interchangeable forms. Textile is a word derived from *textilis* in Latin, meaning *woven*. The word '*fabric*' also derives from Latin, *fabrica* meaning ‘workshop; an art, trade; a skilful production of structure’. In later days, fabric seems to be a derivation from the French *fabrique*, or 'building, thing made' or 'to fit together'.

During the 15th century, textile was the largest single industry. Fabrics can be made from natural and synthetic fibres. Sources of natural fibres can be animal based (wool, silk), plant based (cotton, jute) or mineral based (asbestos, glass fibre). In the 20th century, natural fibres were supplemented by synthetic fibres made from petroleum.

Weaving is a textile production method which involves interlacing a set of longer threads (called the warp) with a set of crossing threads (called the weft). This is done on a frame or machine known as a loom. Though the vast majority of weaving is mechanised, some weaving is still done by hand. Fabrics can be made in various strengths and degrees of durability, from the finest gossamer to the sturdiest canvas.

Although weaving sprang up independently in different parts of the world and was early known in Europe, its high development there in the middle ages was brought about by eastern influences operating through muslim and byzantine channels of culture. In the 9th century, Greece, Italy, and Spain became proficient in weaving techniques. In Flanders a high degree of skill was attained by the 10th century, especially in the weaving of wool. Flemish weavers were brought to England and Lancashire became an important centre. The 18th-century weaving and spinning inventions marked the transition from the old era of domestic craftsmanship to the organized industry of today. The factory system of machine weaving produces quantities of standardized material for mass consumption, though some of the finest silks, velvets, table linens, and carpets are still woven on handlooms [1, 2].

Woven fabrics are classified as to weave or structure according to the manner in which warp and weft cross each other. The three fundamental weaves, of which others are variations, are the plain, twill, and satin. In plain weave, also known as calico, tabby, taffeta, or homespun weaves, the weft passes over alternate warp threads, requiring two harnesses only. The relatively simple construction suits it to cheap fabrics, heavy yarns, and printed designs. Variations are produced by alternating fine and coarse yarns to make ribbed and corded fabrics. The second primary weave, known as twill, shows a diagonal design made by causing weft threads to interlace two to four warp threads, moving a step to right or left on each pick. Noted for their firmness and close weave, twill fabrics include gabardine, serge, drill, and denim. Satin weave has floating or overshot warp threads on the surface which reflect light, giving a characteristic lustre. Pile fabrics have an additional set of yarns drawn over wires to form loops. Warp-pile fabrics include terry and plush; weft-pile, velveteen and corduroy.

In double-cloth weave, two cloths are woven at once, each with its warp and filling threads, and combined by interlacing some yarns or by adding a fifth set. The cloth is made for extra warmth or strength. Velvet is commonly woven as a double cloth. In swivel weaving, extra shuttles with a circular motion insert filling yarns to form simple decorations, such as the dots on Swiss muslin. Figure weaves are made by causing warp and weft to intersect in varied groups. Simple geometric designs may be woven on machine looms by using a cam or a dobby attachment to operate the harnesses. The Jacquard loom attachment permits machine weaving of the most complicated designs [3,4].

1.2. Defects in fabric

The fabric defect can be simply defined as a change in or on the fabric construction. The perception of fabric defect varies from individual to individual and often one individual may have different sensitivity from time to time. The characterization of defects in textured materials is generally not clearly defined. American Society of Testing and Materials (ASTM), an international voluntary organization engaged in standardization of several products, has published a document on terminology related to fabric defects (ASTM D3990-12e1). However, categorization into major and minor defects is central to fabric inspection.

***(a) Major Defects* –** Defects, those if conspicuous on the finished product, would cause the item to be a second. A "second" is a fabric with a conspicuous defect that affects the saleability or service ability of the item.

***(b) Minor Defects* –** Defects, those would not cause the product to be termed a second either because of severity or location.

However, from technical point of view the fabric defects may broadly be classified into three major categories, namely, (i) weft way defect, (ii) warp way defect and (iii) defects with no directional dependence [5]. The weaving process may create a huge number of defects named as weaving defects. Most of these defects appear in the longitudinal direction of the fabric (the warp direction) or in the width-wise direction (the weft direction). The yarn represents the most important reason of these defects, where presence or absence of the yarn causes some defects such as miss-ends or picks, end outs, and broken end or picks. Other defects are due to yarn defects such as slubs, contaminations or waste, becoming trapped in the fabric structure during weaving process. Additional defects are mostly machine related, and appear as structural failures (tears or holes) or machine residue (oil spots or dirt). Over and above the quality of yarns the weaving irregularities generated in the weaving machines due to the change in operating conditions (temperature, humidity, etc.) also result in various fabric defects [6]. Some of the major defects are shown in Figure 1.1. Some of the defects in fabric along with their definition are indicated in Table 1.1.

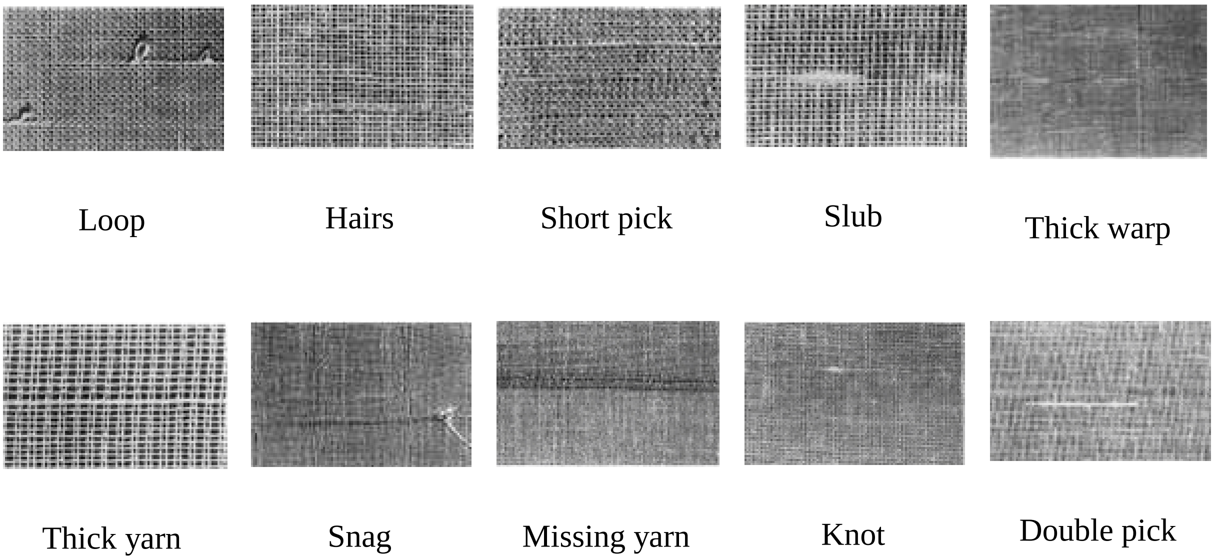

Figure 1.1: Some of the major defects in fabric

1.3. Defect inspection and detection

It has been estimated [7] that the price of fabrics is reduced by 45%-65% due to the presence of defects. Therefore it is necessary to introduce and use some form of defect detection mechanism. Fabric defect detection can be done in two distinct ways [8]. The first one is the process inspection in which the weaving process (or its parameters) can be constantly monitored for the occurrence of defects.

The process inspection is a preventive inspection, and is generally not performed in the textile industries due to the complexity of the weaving process. The second one, normally used in the textile industry, is the product (end) inspection in which the manufactured fabric is inspected for the defects by human or machines [9].

Table- 1.1: Some of the defects in fabric along with their definition

Defect type	Definition and cause
Slubs	Local variation in fabric thickness, caused by extra piece of yarn that is woven into fabric
Floats	An extended portion of yarn in the fabric caused by missing of interlacement of two threads
Knots	A type of defect where two ends of yarns are tied together caused by tying spools
Snag	A group of fibers pulled from normal pattern, created due to friction fabric and sharp machine parts.
Gouts	A local uneven lump in fabric where thickness differs caused by accumulated short fiber (fly)
Snarls	A short length of three fold twisted weft yarn caused due to insufficient twist setting
Pin marks	Marks along fabric selvage caused by the pins which hold the fabric
Holes	A fabric area free from both warp and weft threads, caused due to mechanical mishandling
Miss-end	A warp thread is absent for short length, caused by broken warp thread
Curling	A twisted weft thread appears on the surface of the fabric, caused by insertion of highly twisted weft thread
Double ends	Two ends threaded at the same place caused by incorrect wrapping
Smash	Many ends of warp threads are broken caused by wrong timing of shedding and damaged picking machine parts
Open reed	Usually occurs in coloured fabrics, where warp thread is held apart exposing the filling, caused by bend reed wires
Miss pick	A weft thread is absent caused by incorrect picking
Double pick	Two weft thread takes the same place in the fabric, caused by incorrect picking
Irregular pick density	A jammed or open area formed in the fabric due to uneven pick density caused by mechanical fault
Skew	Where weft and warp threads are not perpendicular, caused by different machine force
Moire	Wavy areas of periodic sequence, caused by different compression of weft or warp threads

The utmost priority of all weaving mills is to reduce the presence of weaving defects in the final product at early stages of the production process to ensure an optimized economical viability [10]. For manufacturers, some false positives (rejecting good products) are more acceptable than false negative (missing defective products) [11]. The concept of fabric inspection consists of grading the materials based on their overall texture characteristics such as material isotropy, homogeneity and coarseness or the severity of its defects [12].

It is, however, worthwhile to mention that fabric defects are loosely separated into two types [6, 13]; one is global deviation of color (shade). The other is local textural irregularities which is the main concern for our study.

1.3.1. Visual (Traditional) fabric inspection

Fabric like many intermediate products is available in a web form (continuous rolls), where a typical fabric web is 1.5-2 meter wide and rolls out at the speed of 0.3-0.5 meters per minute. In addition, defects to be detected by inspection are numerous and present complex appearance [14,15,16]. Traditionally, the inspection procedure must be performed by well-trained (expert) human inspectors in power driven inspection machines where the manufactured fabric rolls are removed from the weaving machines and unrolled on an inspection table (under adequate light) at a relatively higher speed of 8-20 meters per minute [17,18].

Typically, the inspection process relies strictly on the human eye and is done after the fabric formation process. Even with the best-designed man-machine interface, the probability of human error cannot in practice be reduced to zero. In addition, the visual inspection has worked well for many years in part because the amount of data has been small and manageable [19]. Lastly, with the modern weaving machines, the production speeds and consequently productivity are faster than ever. The experiments show that the error rate begins to rise rapidly as information output approaches about 8 bits/s [20]. Therefore, the traditional visual inspection method has no ability to cope with today requirements. Moreover, the human inspectors are prone to fatigue over time and inevitably miss small defects and sometimes even large ones. Therefore even in a well-run operation, the reproducibility of a visual inspection will rarely be over 50% while the maximum detection efficiency is about 70%-80%. Also, the relatively hostile working environment near the weaving machines is not suitable for human inspection [21].

1.3.2. Automated machine inspection systems

Because of these vast drawbacks of human inspection of defects in fabrics, and in order to increase accuracy, attempts are being made to replace manual visual inspection by automated one that employs a camera and imaging routines to insure the best possibility of objective and consistent evaluation for fabric quality [22]. These systems are collectively known as *fabric automatic visual inspection* (FAVI) systems [23]. The wider application of automated fabric inspection would seem to offer a number of potential advantages, including improved safety, reduced labour costs, the elimination of human error and/or subjective judgment, and the creation of timely statistical product data. Therefore, automated visual inspection is gaining increasing importance in weaving industry. Negative points for the automated fabric inspection may be attributed to the methodologies, which are often unable to cope with a wide variety of fabrics and defects. Moreover, the lag time that exists between actual production and inspection translates into more defective fabric produced on the machine that is causing these defects, must be taken into account.

An automated inspection system usually consists of a computer-based vision system. The basic components of a FAVI system are shown in Figure 1.2. After image acquisition, feature selection and image processing techniques are central to any FAVI system. Depending upon the algorithms used, the defect detection capability of the FAVI system is decided. The performance of the FAVI system also largely depends on grading of the materials based on the overall texture characteristics such as material isotropy, homogeneity and coarseness [24].

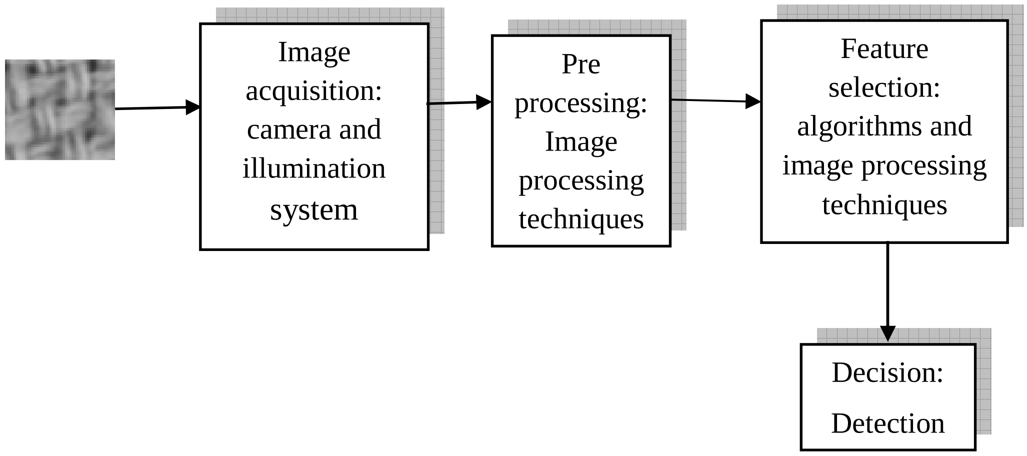

Figure 1.2: Block diagram of fabric automated visual inspection (FAVI) system

Further, for the implementation of FAVI systems, it is necessary to consider factors such as (1) contrast between defects and texture surface; otherwise a low contrast image may easily lead to a misclassification [19] ; (2) consistency of texture background related to colour difference and distortion along a texture which affect image acquisition; (3) resolution of input image where a low resolution image may not show fine defects in fabric; (4) alignment of input image during image acquisition [11] which may induce false defect detection in template matching approach; (5) size and shape of defects, particularly for defect of small size or defect similar to a pattern shape may increase the difficulties in recognition; (6) speed or computation complexity of defect detection system and (7) lighting condition, when improper illumination yields poor resolution and contrast.

The application of digital image-processing is useful in textile manufacturing and inspection. In last two decades, it has proven to be the most promising, rapid and reliable solution for the future development of an online automatic fabric defect detection. Considerable efforts have been given to develop and/or improve the task of online automatic fabric defect detection. However, fabric Inspection still presents a considerable challenge, on account of the variable nature of the weave [25, 26].

1.4. Review of past works in automatic detection of defects in fabric

Before 2008, few surveys of the automated visual inspection (AVI) system are available [5, 27, 28, 29]. But none covered the automatic visual inspection of fabric defect, probably due to their wide coverage on inspection problem. Though, the area of defect detection has been a popular research topic for many years [13] yet major techniques for defect detection in fabric are reviewed in recent papers with more or less complete lists of references [17, 30]. We restrict ourselves in this work on digital processing of fabric images, yet attempts are also made to detect fabric defect by using ultrasonic imaging [31] and reflected infrared frequencies [23].

At the microscopic level, the defect detection problem can be identified into three major classical categories: statistical (geometrical / structural) approach, frequency domain approach and model-based approach. Relatively new detection methods which include learning approaches showed promising results and are worth considering [32,33]. Some other techniques are also available which use several combinations of the classical and newer techniques and can be clubbed into the category of mixed approaches.

The research work relevant to the automation of fabric defect detection is very vast and diverse. It is reasonable to believe that, the results of an automated inspection system rely on its implementation where, the better approach for defect detection is related to the expected defect types. Mainly, all researchers consider this task as texture segmentation and identification problem.

In this thesis, the texture analysis problem is categorized into six approaches according to the used algorithm; (a) statistical, (b) structural, (c) filter based (d) spectral, (e) model-based approaches, and (f) learning. Finally, any combinations of these approaches are also used. Different approaches used by FAVI systems are shown in Table- 1.2.

Table-1.2: In-exhaustive list of textural defect detection method.

Approaches	Methods
Statistical approach	1. Bi level and gray level thresholding [12,14,18,19,29,30,36] 2. Auto and cross correlation [34] 3. Co-occurrence matrix [35,37,38] 4. Local linear transform [39,41] 5. Histogram properties and rank order functions [24,40,42,43,44] 6. Fractal dimension [45]
Structural approach	1. Primitive measurement [47,48] 2. Edge features [49,50] 3. Skeleton representation [51] 4. Morphological operations [17, 52,53,54]
Filter based approach in spatial and in frequency domain	1. Spatial domain filtering a. Optimized FIR filter [55,56] b. Eigenfilters [57,58,59,60] 2. Frequency domain filtering a. Discrete Fourier transform [61,62,63,64] b. Optical Fourier transform [65,66,67,68,69,70,71,72,73] 3. Joint spatial/ spatial- frequency domain filtering a. Gabor wavelet filter [74,75,76,77,78,79,80,81,82] b. Wavelet transform [83,84,85,86,87,88,89,90,91,92,93]
Model based	1. Gauss Markov Random Field model [95,96,97,98] 2. Texem model [99,100,101] 3. Model based clustering [102,103]
Learning approach	1. Artificial neural networks [5,104,105,106,107,108,109,26,110,111]

In the following section, brief overviews of the above mentioned approaches are given.

1.4.1. Statistical approaches

Statistical texture analysis methods measure the spatial distribution of pixel values. The objective of the statistical feature extraction is to separate the inspection fabric image into regions having different statistical behavior. The uniform textured images are developed by the repetition of the basic texture primitives and any deviation from the primitive indicates the presence of a defect. A large number of statistical texture features have been proposed, ranging from first order statistics to higher order statistics. Some important contributions using statistical approaches for defect detection in fabric are discussed below.

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1.4.1.1. Bi level and gray level thresholding technique

One of the simplest methods to detect high contrast fabric defects is to use gray level thresholding directly. Due to the high contrast defect the received signal rises or falls momentarily, which make the threshold selection task possible [29,30]. Bradshaw [14] and Cho et al. [12] have used this idea to detect fabric defects on the textile web by using bi-level thresholding. Stojanovic [19] et al. have developed a fabric inspection system that uses bi level thresholding for noise removal followed by local averaging to identify eight categories of defects with 86.2% accuracy.

The technique of bi-level thresholding does the independent classifications of individual image pixels and therefore it performs poorly for the low contrast fabric defects, where the effects of the neighboring pixels are also required. For the detection of low contrast defect, most defect detection algorithms operate some form of smoothness either implicitly or explicitly before the thresholding. Gray level statistics are used by dividing the fabric images into arbitrary blocks and classifying these blocks into defect or defect-free classes [18]. The optimum block size has been chosen by autocorrelation function. A threefold strategy to detect fabric defects is used in the weft and warp-directions to calculate separately statistical data using 1-D pixel values from the line-scan camera [36]. The defect detection from each of the two separate 1-D signals is achieved by thresholding. The main advantage of approaches in [18, 36] is related to their computational simplicity.

1.4.1.2. Defect detection using auto and cross correlation

Auto correlation function calculates maximum spatial frequencies at multiple locations corresponding to repetitive interlaced structures. The maximum peak remains constant for defect free fabric but changes dramatically for defective fabric, which can be a measure for defects present. The cross-correlation function provides a direct and accurate measure of similarity between the two images. Any significant variation in the value of this measure, while correlating a defective and non- defective fabric sample indicates the presence of a defect. Bodnarova et al. [34] have used the correlation coefficient from multiple templates to generate a correlation map for defect detection. But one of the major problems with this method is its ad-hoc selection of template and window sizes. The experimental results presented in [34] are few and do not show any advantage over those based on first order statistics in [18, 36].

1.4.1.3. Defect detection using features of co-occurrence matrix

The gray level co-occurrence matrix (GLCM) determines the spatial interactions of the image pixels, from where textural features using high order statistics like, energy, entropy, correlation, contrast, homogeneity etc are extracted for detection of fabric defects [37, 38]. Davis et al [35] have showed that the GLCM is one of the best descriptor among the types which gives the relationship between the neighboring pixels. The GLCM can also be made rotation invariant.

1.4.1.4. Defect detection using local linear transform

Several popular bi-dimensional transforms such as discrete cosine transform (DCT), discrete sine transform (DST) or discrete Hadamard transform (DHT) can be used for the extraction of local texture properties and defects [41]. The results of the experiments have been compared with the set of empirical filters. However their dataset is limited to only two types of fabric defects and therefore their results are subjective and lacking in generality. A novel scheme of characterizing and classifying defects in woven textile fabrics has been attempted in [39] by using back propagation based neural network coupled with the DCT technique.

1.4.1.5. Defect detection using histogram properties and rank order function

Commonly used histogram statistics like range, mean, geometric mean, harmonic mean, standard deviation, variance, median are used to identify defects. Moreover, histogram comparison statistics, such as L1 norm, L2 norm, Bhattacharyya distance, Matusita distance, divergence, histogram intersection, Chi-square and normalized correlation coefficient are also as texture features to detect fabric defect. Despite of their simplicity, histogram techniques have proved their worth as a low cost, low level approach [40]. They are invariant to translation and rotation.

Three (5 × 5) masks corresponding to ripple, edge, and weave features [42] are used to extract histogram features from every window of the test image. These features are then used for the classification of corresponding window into defect-free and defect class [43]. Recently in [24], by thresholding on histogram equalized image, pills in cotton fabric surface has been detected.

The rank-function of a given image is derived from its histogram, and is given by the sequence of gray levels in the histogram when the sequence is sorted in the ascending order. The advantage of using rank functions instead of histograms lies in the fact that the rank distances can be computed efficiently. Natale [44] has used rank order functions for the detection of artificially introduced defects in a typical texture. An appropriate rank-distance function was introduced, which proved to have substantial advantage over the classical histogram based approaches for the defect detection.

1.4.1.6. Fractal dimension as a tool for defect detection

The fractal dimension is the statistical index of complexity, which shows how detail a pattern changes with the scale at which it is measured. This is used to model the statistical qualities like, roughness and self similarity on many natural surfaces. Conci and Proença [45] have used the estimate of fractal dimension (FD) on inspection images to detect fabric defects. This defect detection approach is computationally simple but presents very limited experimental results. However in [45], 96% success rate is obtained while tested on eight types of defects.

1.4.2 Structural approaches

In structural approaches, texture is characterized by texture primitives or texture elements, and the spatial arrangement of these primitives [46]. Thus, the primary goals of structural approaches are firstly to extract texture primitives, and secondly to generate the spatial placement rules for detection of variations or deviations. Apart from morphological processing, structural approaches are not very successful in defect detection in fabric. Therefore these approaches are used in conjunction with other approaches during post or preprocessing.

1.4.2.1. Use of primitive measurement for defect detection

By this category of techniques, mainly blob analysis is performed to measure the primitives, followed by clustering detection by any method. K-means clustering has been used to split randomly textured images into binary stacks [47, 48]. The measurements include size, perimeter, and spatial distribution of fabric images.

1.4.2.2. Defect detection using edge features

The distribution of the amount of edge per unit area is an important feature in the textured images to detect defects. The gray level transitions can represent lines, edges, point defects and other spatial discontinuities. These features have been used to detect fabric defects [49, 50]. However, grating structures in the fabric may produce many edges and therefore defect detection tasks become too complicated.

1.4.2.3. Skeleton representation for defect detection

Another structural approach to identify defects in fabric images is proposed using skeletal structure [51]. The image is first thresholded using histogram analysis and then mapped into a data structure which represents the skeleton structure of the fabric. Statistical measurements are then taken from both location and length histograms of the skeleton. These measurements are compared with a pre-defined acceptance range which is learnt from defect-free samples to detect defects.

1.4.2.4. Defect detection using Morphological operations

Morphological operations like, dilation, erosion, opening and closing by suitable structuring element is capable of detecting fabric defects. Lane [52] has detailed a systematic approach to detect fabric defect using morphological operations in a U.S. patent. The image under inspection is transformed into a gradient image using a set of masks from where possible defect pixels are selected by suitable thresholding followed by the dilation with the structuring element. One of the successful morphological method, as reported in [17] uses optimal morphological filter [53], for plain and twill fabric defect detection. The method gives an accuracy of 94.87% (offline detection) for different defects, resolutions and textural backgrounds. Mallik-Goswami and Datta [54] have detected fabric defects using laser-based morphological operations. This approach filters out the periodic structure of fabric in the optical domain by inserting Fourier lens after proper spatial filtering. However, all morphological operations used for defect detection of fabric, are highly sensitive to the selection of size of structuring element and threshold value.

1.4.3. Filter based approach

Development of filter based approach for defect detection in fabric started initially for the elimination of interlaced grating structures in fabric. However, the progress of this technique has now become so successful that it may be identified as a separate category. Basically, this approach involves the application of filter banks on the image and computation of the energy of the filter responses to detect the fabric defects. Instead of energy, frequency of repetition is also a parameter on which the filter banks are designed. Filtering may also be done in frequency domain.

1.4.3.1. Defect detection using spatial domain filtering

In the spatial domain, the images are usually filtered by gradient filters to extract edges, lines, isolated dots. The operators like Sobel, Robert, Canny, Laplacian, Deriche are all used. These filtering operations help in the detection of fabric defects. Optimal finite impulse response (FIR) filters are also used since fabric defects reflect very subtle intensity transitions. The optimization offers the potential of large feature separation between the defect-free and the defective regions of the filtered image. The optimal FIR filters used for fabric defect detection show high detection accuracy of very subtle defects and unsupervised inspection using a bank of these filters [55,56].

In many defect detection applications eigenfilters are used. The distribution of data of defect free and defective fabric samples can be understood by constructing the eigenfilters, using an ensemble of micro windows containing defect free and defective fabric information. Attempts have been made to design the most suitable eigenfilters by rotating, negating and mirroring the fabric images [57,58] and taking the KL transform of local image patches [59]. However, the eigenfilters suffer from the inconvenience of calculating the covariance matrix for large numbers of training fabric images. A solution is proposed by using principal component analysis and utilizing fuzzy C-mean clustering based particle swarm optimization method [60]. 98% recognition rate has been achieved while tested on 250 images from 4 classes of plain fabric samples.

1.4.3.2. Defect detection using frequency domain filtering

When no straight forward kernel of filter in the spatial domain is available, the image is converted in the frequency domain. The periodic interlaced grating structure of the fabric image also promotes the frequency domain processing. The scope of using Fourier transform opens up the possibility of using frequency domain operations.

The Fourier transform has the desirable properties of noise immunity, translation invariance, optimal characterization of periodic features and hence has enough scope for use in fabric defect detection. In [61], the authors have used the Fourier transform to reconstruct textile images for defect detection. The line patterns in a textile image, are taken out by removing high energy frequency components in the Fourier domain using a one-dimensional Hough transform. The differences between the restored image and the original image are considered as potential defects. A similar idea is explored in [62], but low pass filtering is used to remove the periodic information. Harmonic peaks from horizontal and vertical power spectrum slices are extracted in [63], based on the assumption that defects usually occur in horizontal and vertical directions. Later, in [64], a Fourier transform based approach has been proposed to detect fabric defects, where the central spatial frequency spectrum is used. Seven significant characteristic parameters are extracted for detecting two types of fabric defects (double yarn and missing yarn). The result is found to be consistent for a number of samples. But the DFT based methods are not suitable for defect detection in random textures.

Major advantage of using Fourier transform for analysis in fabrics is related to the hardware implementation in optical domain, where a lens can perform Fourier transform operation. It is then possible to use spatial filters for filtering out the interlaced structure of fabric. The detection of fabric defects using such an optical Fourier transform (OFT) is relatively easy and fast [65]. As the luminous intensities of the zero and the first-order diffraction patterns are modulated by the existence of fabric defects, by measuring their intensities, the defects can be detected [66,67,68,69,70]. Spatial filter of pinhole type or universal type has been used by Kim et al. for detecting defects [71]. Hoffer et al. [72] have used a small subset of pixels from the optically Fourier transformed images to classify fabric defects into four categories using a three-layer back-propagation neural network. Joint Fourier correlation technique has also been applied for defect detection in fabric [73].

1.4.3.3. Defect detection using Joint spatial / spatial frequency domain filtering

The psychophysical research has indicated that human visual system analyzes the textured images in spatial-frequency domain, which inspires the researchers to work in this domain. The discrete Fourier transform and optical Fourier transform based techniques are suitable for detecting global defects rather than local defects, as detection of local defects requires the techniques of localizing and analyzing the features in spatial as well as frequency domain. Thus for determining the small fabric defects space-dependent Fourier transform or running-window Fourier transform or windowed Fourier transform is used, where a small window is considered to extract the features of fabric defect.

(a) Use of Gabor wavelet filter

In the windowed Fourier transform if the window function is Gaussian, it becomes the well-known Gabor transform. This transform can perform optimal localization of anomaly in textured surfaces in the spatial and frequency domains. The 2-D Gabor filters which have tunable angular and axial frequency bandwidths, tunable center frequencies, and optimal joint resolution in spatial and frequency domain are appropriate for the spatial filtering [74]. The parameters of a Gabor filter can be selectively optimized to discriminate a known category of defects. Such segmentation of fabric defects using optimal Gabor filter has been demonstrated in [75,76,77,78,79]. Kumar [80] has demonstrated that the dominant spectral component in defect-free fabric can be computed from the FFT decomposition and used to automatically select the center frequencies of Gabor filters. In [81], Gabor filters are designed on the basis of the texture features extracted optimally from a non-defective fabric image. The result exhibits good defect detection, showing the effectiveness and robustness of the scheme. Recently, Li et al. [82] integrated Gabor transform with a Gaussian mixture model for defect detection on plain fabric. In [82] classification success rate of 87% is reported while detecting 9 defect classes.

(b) Defect detection using wavelet transform

Multi-resolution decomposition using a bank of Gabor filters results in redundant features at different scales for which it is often criticized. The spatial resolution of wavelet transform is adapted to its frequency content, unlike that in Gabor transform, where the spatial resolution is constant. Sari-Sarraf and Goddard [83] have performed discrete wavelet transforms on fabric images, where the detailed images are fused together to produce a feature map in which the normal texture regions, assumed to be homogeneous, have small values. The defects are segmented by thresholds learnt from training templates. Discrete wavelet transform is used to classify stochastic textile textures [84] and a learning process is employed to select the wavelet scales for maximizing the detectability of fabric defects [85]. Co-occurrence and MRF-based features are extracted from wavelet transform coefficients for fabric defect detection [86]. Multiscale representation of fabric image using B-spline transform is also proposed for defect detection [87].

The design of a texture specific wavelet basis filter is proposed in [88,89,90,91]. The detection of fabric defects using wavelet packet decomposition and independent component analysis has been investigated in [92]. A defect detection method is described, where signal feature after wavelet decomposition of fabric image is extracted and compared with the signal feature of defect-free fabric image [93].

1.4.4. Model based approaches for defect detection

Defects in fabric with stochastic components are difficult to detect by statistical, structural and filter based approaches. Fabric images containing stochastic components (possibly due to fiber heap, noise, hairs etc.) can be observed as samples of parametric probability distributions on the image space. Here lies the advantage of the model based approach, which can produce textures of fabric that can match the textures of the test sample. The defect detection problem therefore, can be treated as a statistical hypothesis-testing problem on the statistics derived from this model. Several probabilistic models of the textures have been proposed and used for the defect detection. In [94], the authors have found MRF based methods is competitive with other statistical, structural and filter based methods in fabric defect detection. Some of these model-based methods for defect detection are discussed below briefly.

1.4.4.1. Defect detection using Gauss Markov Random Field model

Markov random fields (MRFs) are a two-dimensional generalization of Markov chains which are defined in terms of conditional probabilities. The assumption made is that the conditional probabilities are the same throughout the chain (or field) and are dependent only on a variable’s neighborhood. The size and form of the neighborhoods are defined by the order of the model [95, 96]. In [97], Gaussian Markov random fields (GMRF) are used to model defect free textile web. The statistical measurements of defect free texture are taken from the GMRF model and then compared with the test fabric by partitioning it into numbers of blocks. The stochastic modeling of fabric images can be done more efficiently by using Markov random field (MRF) than fractal models. In [98] fifth order MRF method is applied in fabric defect detection with a dedicated signal processing electronics, where significant speed of defect detection is achieved.

1.4.4.2. Defect detection using Texem model

Xie and Mirmehdi [99,100,101] have proposed a novel statistical model, called texture exemplars or texems, to represent and analyze random textures. In a two-layer structure, a texture image, as the first layer, is considered to be a superposition of a number of texture exemplars, possibly overlapped, from the second layer. Each texture exemplar, or simply Texem, is characterized by mean values and corresponding co-variances. Each set of these Texems may comprise various sizes of exemplars from different image scales. The model is applied to localize defects on random textured surfaces and show significant improvements when compared against Gabor filtering based methods. However its usefulness in defect detection in regular fabric is yet to be established

1.4.4.3. Defect detection using model based clustering

Campbell et al. [102] have used model-based clustering to detect fine defects in the denim fabrics. They have used Bayesian information criterion (BIC) [103] to indicate the presence of defect. A chain of pre-processing operations, like thresholding, opening and labeling are used before the estimation of BIC from the inspection images. The results suggest that the BIC value is a reliable indicator to detect the presence of defects.

1.4.5. Defect detection using learning technique: use of artificial neural networks

Neural networks are one of the best classifiers used for detection of defects in fabric due to their non-parametric nature and ability to describe complex decision regions. The problem of fabric defect segmentation using feed-forward and back propagation neural networks (FFN) has been investigated in [5,104,105]. Hung and Chen [106] have used the back-propagation neural network, with the fuzzification technique to achieve the classification of eight different kinds of fabric defects along with the defect-free fabric. The support vector machines (SVM) offer attractive alternative to FFN as they do not suffer from the problem of local minimum and are computationally simpler to train. Therefore fabric defect detection using SVM has been proposed in [107]. FFN and SVM require training from the known classes of fabric defects, for which the features representing fabric defects are to be extracted. Fabric defect detection using a cellular neural network [108] and an adaptive image segmentation method based on a simplified pulse coupled neural network (PCNN) [109] are also proposed. A new parameter called the deviation of the contrast (DOC) is introduced to describe the contrast difference in row and column between the test image and a defect-free image of the same fabric. The simplification of PCNN has reduced the number of the network parameters by utilizing the local and global DOC information for the parameter selections.

A real-time fabric defect detection based intelligent techniques using neural networks and fuzzy modeling is presented in [26]. The authors claim that the online implementation of the algorithms is easy and may be adapted to industrial applications without great efforts. Recently, another method of textile defect detection and classification based on wavelet reconstruction and back propagation neural network is detailed in [110], where two types of defects are detected. Lastly, a recent radial basis function method [111] has achieved 83.4% defect classification for 270 images, although it is not promising compared to other neural network techniques.

1.5. Performance metrics

Accuracy of detection can be measured in two ways depending on the task involved. The detection success rate can be taken as a measure of performance when only defect detection task is attempted. When over and above detection, classification of defects is attempted sensitivity and specificity may also be tested [112].

In general, detection success rate, also known as detection accuracy, is defined as,

$$\text{Detection Success rate} = \frac{\text{Number of samples correctly detected}}{\text{Total number of samples}}$$

where, total number of samples include defective and defect-free fabrics.

Performance metric can also be related to detection rate and false alarm rate. The definitions are,

$$\text{Detection rate} = \frac{\text{Number of defective samples correctly detected}}{\text{Total number of defective samples}}$$

$$\text{False Alarm rate} = \frac{\text{Number of defect free samples detected as defective}}{\text{Total number of defect-free samples}}$$

For defect classification tasks , the performance of FAVI system can further be defined in terms of true positive (TP), false positive (FP), true negative (TN) and false negative (FN) in defect detection. Table 1.3 indicates the situations where TP, FP, TN and FN may occur.

Table 1.3 Situations of occurrence of different results for a particular test

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

Accordingly, detection success rate can be defined as,

$$\text{Detection Success rate} = \frac{TP + TN}{TP + FN + TN + FP}$$

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,

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

$$\text{Specificity} = \frac{TN}{TN + FP}$$

1.6. Comparative studies of different defect detection techniques

The different methods available for fabric defect detection are shown in Table-1.2 and discussed under 1.4. There are some other methods also which strictly do not belong to the mentioned categories. These methods may be the combination of a numbers of methods described above and show promising results in fabric defect detection.

Though this section is dedicated for the comparative studies of the different available methods of fabric defect detection, yet from the obtained literature it is difficult to do so due to the following reasons.

a. The methods have been tested on different data sets and possibly for different parameter settings.

b. The method to be employed for defect detection depends on the resolution of the image.

c. Many of the defect detection techniques showing satisfactory results are computationally complex, resulting in appreciable consumption of time and thus not suitable for fabric defect detection in real-time.

However it has been reported [113] that the low-resolution images are prone to distortion due to the geometry of the imaging lens and/or non-uniform illumination. In such cases, approaches using Gabor filters, FFN, wavelet packets may not be suitable. Instead, inspection methods using imaginary Gabor functions (IGFs) [79] and linear neural networks [104] may show promising results.

Images with medium resolution have also shown some distortions. Proper pre processing of the acquired image may correct the distortions. Unsupervised web inspection is suggested for online inspection of the medium resolution fabric images. Six texture algorithms for fabric defect detection used are: MRF, KLT, 2D lattice filters, Laws filters, Co-occurrence matrices, and FFT. It has been concluded that the MRF (9th order with 25 sufficient statistics) performs better than filter based approaches [14, 98]. FFT based approaches on images of about medium resolution seems to be effective in detecting defects and its optical implementation demands less online computations even for high resolution images. However, very fine fabric defects may escape detection when such techniques are used.

The high-resolution images are more suitable for detecting defects, though their use require high volume of online computations for unsupervised defect detection. Thus the supervised defect detection methods like optimized FIR, optimized Gabor filter, FFN etc. are suggested for the high resolution images. Since the FIR filters have more free parameters than a Gabor filter, the size of optimized FIR filter masks are expected to be smaller than those for optimal Gabor filters. Therefore, optimized FIR filters may be a preferred choice over the optimal Gabor filters for supervised defect detection. The authors in [75] have concluded that the optimal Gabor filters perform better than gray level co-occurrence matrix, correlation and FFT based approaches.

The two-point correlation function was proposed as performance measure. This function is a useful tool appropriate for both the visualization of the presence (or lack of) structure in any feature space of high dimensionality. Further, the two-point correlation function can be used as a tool for choosing the best features to be used in the detection process.

In [18] two software approaches were studied for detecting and classifying knot and slubs in solid-shade, un-patterned woven fabrics. The approaches were based on either gray level statistics or morphological operations. The autocorrelation function was used for both methods to identify fabric structural repeat units, and statistical or morphological computations were based on these units. It was found that, both methods exhibited similar performance. While due to the gray level approach was more noise tolerant, fewer defect-free specimens were falsely determined as defective.

A comparative study to examine the suitability of four different detecting algorithms was presented in [25]. Gray level co-occurrence, normalized cross-correlation, texture-blob detection and spectral approaches were applied in this study. The correlation approach appeared to be the most promising method for a real time, high accuracy defect detection algorithm. While comparing Sobel edge detection with thresholding and fractal dimension it has been found that the use of fractal dimension method gives the reliable results because it correctly detects all defect types with only 2% false alarms [114, 50, 53].

Cuenca and Cámara [115] evaluated their method of using a texture descriptor, by comparing it with co-occurrence matrix, histogram, Gabor filters, wavelets transforms and fractal dimension algorithms. The results showed a similar or superior performance to more complex approaches but with greatly saving computational cost. [116, 117] detailed the description of the state of the art techniques for texture segmentation as well as an evaluation on the basis of selected algorithms suitable for real-time applications. They concluded that the efficiency of the various methods is strongly related to the nature of the inspected image while an algorithm for real-time applications should be specially designed on the basis of fast computational approaches.

1.7. Motivation of the present work

From our survey, it is concluded that the need for a comprehensive, consistent way to produce first quality or defect-free fabrics has utmost priority than ever. To ensure the quality level, full proof automated inspection is needed. Therefore, automated fabric inspection is required as a robust alternative to the existing traditional visual offline systems. Consequently, such system must operate preferably in real-time, must produce low false alarm, and also flexible enough to accommodate changes in the manufacturing process. Over and above the hardware constrains, the used algorithm must be the central to all approaches. It should be fast and designed on a basis to process the data in such a way so as to minimize computational complexity with enhanced detection capabilities.

Surprisingly, it is observed that a perfect approach that detects all types of defects in all types of fabric does not exist yet. It may not be technically possible to evolve such an ideal system.

In fact, the ability of structural approaches to detect fabric defects is very restricted mainly due to the stochastic variations in the fabric structure. Besides, despite they are very popular, simple-order statistics based approaches (e.g. classical histogram, morphological operations, gray level statistics, and gray level thresholding) often yield inadequate results and relatively invariant with respect to changes in illumination and image rotation. On the other hand, methods based on higher-order statistics, (e.g. co-occurrence matrices or artificial neural networks) are extremely time consuming or do not scale well to massive datasets. In addition, Model-based approaches are very difficult and computationally intensive especially where a large number of models must be considered. It is also notable that, spectral approaches simulate the human vision system and render heralded methods for automated fabric defect detection. But as a result of the non-orthogonality of Gabor functions, when applying Gabor filters there are many correlations of features between the scales. Wigner distributions suffer from the presence of interference terms between the different components of an image. Moreover, wavelets cannot solve all problems and there are still a lot of limitations inherent to wavelet transform. Also, wavelet transform-based techniques suffer from either image components interference or features correlations between the scales.

Therefore, it is reasonable to find an approach that combines most advantages with lower drawbacks to be implemented as the base of constructing an effective and accurate method to detect automatically fabric defects during the manufacturing (weaving) process.

These statements are the driving force to further study the problem of defect detection in fabric using available techniques and combinations thereof to evolve better solutions. Simplicity, ease in deployment and reduced complexity is the key of the development of evolved techniques.

1.8. Organization of the work

The thesis is divided into seven chapters. The first and seventh chapters are dedicated for literature review and conclusion respectively. The contributions of the chapters are given below briefly.

a. In Chapter 1, a review of literatures in the area of detection of defects in fabric is presented along with definition of defects. Also in this chapter the motivation of undertaking the present work is included.

b. In Chapter 2, a proposal for defect detection using sub image based singular value decomposition (SVD) is presented. The method is straight forward and reduces the computational complexity to a great extent. Computational complexity is further reduced by applying the concept of novel adaptive partitioning of fabric image to identify the region of interest.

c. Chapter 3 proposes a fabric defect detection technique by using reduced dimensional, reduced coefficient fabric space evolved by a modified SVD technique. This technique offers some more additional advantages than the method proposed in Chapter 2. The reduced fabric space is further optimized by using particle swarm optimization (PSO) technique.

d. It is evident that a few fabric defects are defined relative to the fabric class. Therefore in Chapter 4 a technique is evolved to identify fabric class. A set of optimized Haralick parameters for identifying fabric classes is evolved by using the rough set theory. These optimized fabric parameters are used for training the system evolved in chapter 5.

e. Chapter 5 proposes a fabric defect detection method by training an artificial neural network (ANN) in conjunction with morphological processing. Morphological operations like, opening, closing, opening by reconstruction are used, for which the required sizes of structuring elements and threshold values are obtained from ANN trained by optimized fabric parameters obtained in Chapter 4 and parameters representing fabric defects.

f. Chapter 6 proposes a technique of fabric defect detection by using 3D Fourier transform. The method uses a cylindrical filter to eliminate the interlaced grating structure of fabric. The radius of cylindrical filter and energy threshold value required for fabric defect detection are estimated by using particle swarm optimization (PSO) technique.

g. Chapter 7 gives a summary of the work done highlighting the finding and also indicates some direction for the future scope of work in the area of defect detection in fabric.

1.9. Dataset used

During the testing of different algorithms developed in the present work, TILDA [118] dataset are used extensively. TILDA is a Textile Texture Database (ver 1.0) which was developed within the framework of the working group Texture Analysis of the DFG`s (Deutsche Forschungsgemeinschaft) major research program "Automatic Visual Inspection of Technical Objects".

A total of eight representative images of textile classes are included in the database. Based on the analysis of textile classes, seven defect classes are defined. Fabric images without defects for each class are also available. Eight different fabric classes are given in the dataset.

For each of the above classes 50 TIF 8 bit gray images of size (768×512) are acquired through relocation and rotation of the textile sample. The entire texture textile database consists of 3200 TIF images with a total size of 1.2 Gb.