CHAPTER 2

LITERATURE REVIEW AND MOTIVATION

2.1 INTRODUCTION

Generally, fabric defect detection is done in two ways. The first way is the (offline) inspection in which the manufactured fabric has to be inspected by fabric inspection machines. The second way is the process inspection (online) in which the weaving process can be constantly monitored for the clearance of defects. In this method, manually defect detection is done by the inspectors. Once the fault is identified on the moving fabric, the inspector stops the machine, records the defect and its location. Then clears the defect and starts the motor again. For each inspected fabric roll, the number of defects per meter length is calculated and the fabric is classified. Bowling et al (2004) proposed the use of two inspectors on the same machine when inspecting the fabric as another procedure to decrease this rate.

2.1.1 Issues Related to fabric quality

In Textile Industries fabric Quality stands as a priority issue. Hence all industries compete to satisfy the customers in that issue. Manufacturers will also concentrate to achieve the standards and design on fabrics. These issues can be controlled by applying fabric inspection method. This Inspection may be done either manually or by automated fabric inspection methods.
2.1.2 Issues in Visual Inspection Method

Visual inspection process strictly depends on the human eye and is done after the fabric formation process. By Visual Inspection, even with the best-designed man-machine interface, the probability of human error cannot in practice be reduced to zero given by Sylla et al (1995). Finally, with the modern weaving machines, the production speeds and consequently productivity are faster than ever. Previous experiments ensure that the error rate begins to rise rapidly as information output approaches about 8 bits/s explained by Sylla et al (1995) and Ayres et al (1987). Thus, the traditional visual inspection method has no ability to cope with today requirements.

The major issues due to this method are discussed below

i) Human experts are difficult to find or maintain standards in an industry.

ii) Human requires training and their skills requires time to enrich their technical knowledge.

iii) In some cases visual inspection tends to be tedious or difficult, even for strained experts.

iv) Manual inspection is slower than the machines which mean that inspection is a time consuming task.

v) Human inspectors become fatigue over time. Therefore, visual fabric inspection is extremely tiring task, after a while, the sight cannot be focused (the maximum period of concentration is 20-30 min). However, the operator inevitably misses small defects and sometimes even large ones with the number of meters of the inspected fabric.
vi) Human inspectors have to deal with an extensive variety of defects.

vii) Human inspectors make mistakes because inspection is unreliable when the fabric of 1.6-2 meters width is unfolded at a speed of 20 m/min. It is difficult for humans to keep up with these hard conditions. Because their efficiency is based on experience and 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%.

viii) The inspector can hardly determine the level of faults that is acceptable, while comparing such a level between several inspectors is almost impossible.

ix) It is a subjective method that is difficult to reproduce result.

x) The grading process is slow and varies from industry to industry.

xi) Usually, there is an absence of feedback to support processes for corrective measures.

xii) The low quality control speed when compared to the production speed offers a major bottleneck in the high-speed production lines.

xiii) It is extremely difficult to achieve 100% fabric inspection with this traditional method.

xiv) Labour-intensive and more floor space required. That is, there is an expense of manual inspection, which is essentially a non-value added activity.
xv) Traditional visual fabric inspection is cost-intensive. Even, through the incidence of serious weaving faults can be reduced by the use of modern weaving technology, fault detection in many plants still continues to create considerable extra cost.

xvi) Moreover, the problem of the visual inspection does not correspond only to the undetected defects but also, it changes the mechanical properties of the fabric under inspection. For instance, the fabric dimensions usually changed due to the applied tension on fabric roll during the inspection process. They are not good for the customers because they have to pay for false materials.

Figure 2.1 Visual Inspection

Figure 2.1 shows traditional inspection type. This procedure must be performed by well-trained (expert) human inspectors. The existing methods of fabric inspection vary from mill to mill. In few mills, trained labours pull the fabric over a table by hand. Most mills have 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.
When the inspector notices a defect on the moving fabric, he stops the machine, records the defect and its location, and starts the motor again. For each inspected fabric roll, the number of defects per meter length is calculated and the fabric is classified. The early detection of repetitive defects and extraordinary defect rate is left to the operators or so called (roving inspectors). During the control, if the operator notices an extraordinary defect rate or repeating defects, these roving inspectors warns the production department so that appropriate measures can be taken to decrease the defect rate.

Moreover, the shrinkage takes place after the spreading of the fabric in cutting departments increases the probability of producing second quality garment either due to poor assembling (sewing) quality or incorrect size. This is either due to mechanical malfunction of the loom, or due to low-quality fibres and spreads. Due to these major issues this visual inspection method is not preferred in textile industries.

Thus by applying the proposed automated defect detection system reduces time consumption comparatively and reduces these manpower defects.

2.2 AUTOMATED FABRIC INSPECTION

Automatic inspection systems are designed to increase the accuracy, consistency and speed of defect detection in fabric manufacturing process to reduce labour costs, improve product quality and increase manufacturing efficiency given by Chan et al (1998). In the last two decades, there have been several key developments in automated visual inspection technique for fabric defects where new approaches such as an ultrasonic imaging system explained by Chien et al (1999) and laser-optical systems have been proposed by Allgood et al (2000) and Shao et al (1990).
But, the main common alternative to human visual defect detection is the use of a computer vision system to detect differences between images acquired by a camera proposed by Conci et al (2000) and Kim et al (2005). In this process, the fabric is inspected with the resolution that is achieved by an inspection person at a distance of one metre from the fabric given by Behera et al (2009).


2.2.1 Major Requirements of Automated Inspection mode

i) The system must operate in real-time with good results,

ii) It must reduce escape rates,

iii) It must reduce false alarms,

iv) It must be robust and flexible. Thus, it should adapt itself automatically and achieve consistently high performance despite irregularities in illumination, marking or background conditions and, accommodate uncertainties in angles, positions, etc.,

v) It must be fast and cost efficient,

vi) The system must be simple to operate and maintain the looms

2.2.2 Advantages of Automated Inspection type

The major advantages of this method are

i) Less Computational cost

ii) Correlation between Production and Inspection speeds

iii) Imaging technology is economical, high quality image acquisition

iv) Advances in computer technology for Image Processing and pattern recognition.

v) Reduction of labor costs, rework labor and scrap materials

vi) Increase in efficiency, reduction in production time and compactness.
This automated fabric defect detection work was carried out initially in textile industries. Initially the Fabrics samples were collected in various textiles. The various types of faults such as hole, knots, missing yarn, scratches and stains are analyzed on fabrics.

The automatic inspection process done by Baykut et al (1998), Anstey et al (2006), Roesler (1992), Cheng et al (2008) consists of essentially two steps or phases; learning or training phase and detecting or testing phase. Within the first phase, the system is trained on surface images or image regions which are void of defects. The extreme values of the features are calculated and used for constructing a simple classifier. During the second phase, only the features of interest are considered.

These features have the values of which exceed their own scattering thresholds. Thereby, defect inspection is possible by partitioning a test image into sub windows and calculating the sufficient statistics of each one. If the sufficient statistic set within a window does not agree with that of the original training texture, then it is concluded that, there is a defective region.

Until very recently, machine vision was applied almost exclusively to the inspection of engineering components. Malamas et al (2003) defined the image processing operations as which transform an input image to another one having the desired characteristics. Intelligent image processing systems are used to control automatically the running production processes such as online fabric inspection.

2.2.3 Automated Fabric Defect Inspection Approach Classification

For the two past decades, interesting surveys relevant to automated fabric inspection have been published. It is admitted that all surveys interpreted
the task of detecting defects as a texture analysis problem. Obviously, based on the used approaches till the date of publishing, each survey subtracted its classification.


2.2.3.1 Structural approaches

Structural approaches assume that the textures are composed of primitives given by Kumar (2008), Mahajan et al (2009). These primitives can be as simple as individual pixels, a region with uniform gray levels, or line segments. Consequently, the main objects of these approaches are primarily to extract texture primitives, and secondly to model or generalise the spatial placement rules. The placement rules can be obtained through modelling geometric relationships between primitives or learning statistical properties from texture primitives explained by Mahajan et al (2009), Xie (2008).

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, fabric motion, fibre heap, noise, etc.) which poses severe problems in the extraction of texture primitives from the real fabric samples described by Kumar (2008), Mahajan et al (2009).

2.2.3.2 Statistical approaches

This approach measures the spatial distribution of pixel values described by Xie (2008), Mahajan et al (2009). Kumar (2008) explained the method to separate the image of the inspected fabric into the regions of distinct statistical behaviour.

An important assumption in this process is that the statistics of defect-free regions are stationary, and that these regions extend over a significant portion of inspection images analysed by Kumar (2008) and Mahajan et al (2009). Based on the number of pixels defining the local features, Mahajan et al (2009) classified these approaches into first order, second order and higher order statistics.

The first order statistics estimate properties like the average and variance of individual pixel values, ignoring the spatial interaction between image pixels, second and higher order statistics on the other hand estimate properties of two or more pixel values occurring at specific locations relative to each other. Clearly, the use of statistical approaches is well distinguished in the field of computer vision and has been extensively applied to various tasks.

2.2.3.3 Normalized cross-correlation approach

Normally, correlation is used to locate features in one image that appear in another one and the correlation coefficient can generate a correlation map for defect declaration. The cross-correlation function provides a direct and
accurate measure of similarity between two images. Any significant variation in the value of this measure indicates the presence of a defect analysed by Kumar (2008) and Mahajan et al (2009).

2.2.3.4 Statistical moments approach

Mean, standard deviation, skewness and kurtosis provide statistical information over a region while the values are used for image segmentation. In these techniques, rather large windows are preferred, so that a statistical sample is gathered. Abouelela et al (2005) proposed a method of obtaining texture features directly from the gray-level image by computing the moments in local regions.

The used algorithm has successfully segmented binary images containing textures with iso-second order statistics as well as a number of gray level texture images. Due to the influence of non-uniform illumination conditions on the image, statistical moments reveal the necessity of a pre-processing step to correct the image illumination in-homogeneities. The main advantage of these techniques is their computational simplicity which was described by Anagnostopoulos et al (2001).

2.2.3.5 Fractal dimension approach

In many cases, this method does not cover all possible (FD) ranges for textiles, that is, any value from 2.0 to 3.0, therefore it is not applicable to many types of textiles. Moreover, the method has a poor efficiency and high false alarms rate described by Kumar (2008), Mahajan et al (2009), Conci et al (2000), and Anagnostopoulos et al (2001).

2.2.3.6 Edge detection approach

Edge detection is a traditional technique for image analysis. The distribution of edge amount per unit area is an important feature in the textured images. The amount of gray level transitions in the fabric image can represent lines, edges, point defects and other spatial discontinuities. Thus these features have been largely employed for conformity testing, assembly inspection and fabric defect detection.


2.2.3.7 Eigen filters or independent component analysis approach

The Eigen filter-based approaches are useful in separating pair-wise linear dependencies, rather than higher-order dependencies, between image pixels given by Kumar (2008). As these filters are of particular interest because they adapt automatically to the class of texture to be treated, Unser and Ade (1984) suggested a flexible texture inspection system based on the evaluation of a sequence of local textural features. The measured energy at the output of Eigen filters bank is considered. Their system presents accurate defect detection with an extremely low probability of false alarms.
Monadjemi (2004) introduced the usage of structurally matched Eigen filters to overcome the practical drawbacks of traditional approaches which require an extensive training stage. The proposed algorithm reconstructs a given texture twice using a subset of its own Eigen filter and a subset of a reference banks, and measures the reconstruction error as the level of novelty.

The improved reconstruction is generated by structurally matched Eigen filters through rotation, negation, and mirroring. Sezer et al (2004) developed a new methodology for defect detection based on the Independent Component Analysis (ICA). This method extracts the feature from the non-overlapping sub-windows of texture images and classifies a sub-window as defective or non-defective according to Euclidean distance between the feature obtained from average value of the features of a defect free sample and the feature obtained from one sub-window of a test image.

2.2.3.8 Autocorrelation function (ACF) approach

Autocorrelation is a technique that combines all parts of an image and may be used to characterize repetitive structures proposed by Zhang et al (1995). It measures the correlation between the image itself and the image translated with a displacement vector.

As Autocorrelation measure regular textures, it exhibit peaks and valleys. Autocorrelation function is closely related to the power spectrum of the Fourier transform given by Xie (2008). Tolba and Abu-Rezeq (1997) applies a Self Organizing Feature Map (SOFM) to detect and classify automatically the textile defects.
They first extracted feature vectors from the one-dimensional Auto Correlation Function (ACF). This extracted feature is immune to both continuous variations in the illumination intensity and noise as a result of the noise-rejection property of the (ACF). Then, they used the two-point correlation function to compute the probability of finding a given difference in feature values for any randomly chosen pair of points within the feature space denoted by Fatemi et al (1996).

2.2.3.9 Local binary patterns (LBP) approach

Usually, a simple local contrast measurement is calculated as a complement to the (LBP) value in order to characterise local spatial relationships. The (LBP) operator is computationally simple, gives good performance in texture classification and is relatively invariant with respect to changes in illumination and image rotation says Mallik et al (2000).

For instance, Ojala et al (1996) described the local binary patterns as a shift invariant complementary measure for local image contrast. It uses the gray level of the centre pixel of a sliding window as a threshold for surrounding neighbourhood pixels. Its value is given as a weighted sum of thresholded neighbouring pixels.

2.2.3.10 Spectral approaches

Based on spatial-frequency domain features which are less sensitive to noise and intensity variations than the features extracted from spatial domain, spectral approaches occupy a big part of the latest computer vision research work.
It simulates the human vision system where the psychophysical research has indicated that human visual system analyzes the textured images in the spatial frequency domain. Spectral approaches require a high degree of periodicity thus, it is recommended to be applied only for computer vision of uniform textured materials like fabrics.

For automated defect detection, such approaches are developed to overcome the efficiency drawbacks of many low-level statistical methods. Therefore, these approaches were rendered as a robust solution for online fabric defect detection. The primary objectives Mahajan et al (2009) illustrates of these approaches are primarily to extract texture primitives, and then to model or generalise the spatial placement rules.

2.2.3.11 Wigner distributions approach

The Wigner Distribution Function offers better co-joint resolution 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 this technique says Kumar (2008) is the presence of interference terms between the different components of the image.

2.2.3.12 Model-based approaches

Model-based texture analysis methods try to capture the process that generated the texture. They try to model the texture by determining the parameters of a pre-defined model explained by Malamas et al (2003). Particularly, model-based approaches are suitable for fabric inspection when
the statistical and spectral approaches have not yet shown their utility says Kumar (2008), Mahajan et al (2009), Baykut et al (1998) and Karras (2005).

These approaches often require that the image features at different levels of specificity or detail match one of possible many models of different image classes. This task is very difficult and computationally intensive if the models are complex and if a large number of models must be considered says Malamas et al (2005).

2.2.3.13 Gauss markov random field (GMRF) model approach

As the brightness level at an image point is dependent on the brightness levels of the neighbouring points unless the image is simply random noise, Markov random fields use a precise model of this dependence. They are able to capture the local (spatial) contextual information in an image. These models assume that the intensity at each pixel in the image depends on the intensities of only the neighbouring pixels.


The image of the fabric patch to be inspected was partitioned into non-overlapping windows of size N * N, where each window was classified as defective or non-defective on the basis of a likelihood-ratio test of size x. The test was recast in terms of the sufficient statistics associated with the model parameters.

2.2.3.14 Model-based clustering approach

The problem of locating possible clusters in a data set (image) is a recurrent one with a long history. Campbell et al (1999) combined image-processing techniques with a powerful new statistical technique to inspect denim fabrics. The approach employs model based clustering to detect relatively faint aligned defects.

2.2.3.15 Combination of computational methods

From the previous survey, one may conclude that it is rather difficult to perform a robust individual approach that detects all fabric defects with high accuracy. It is mainly due to the fact that each technique has some advantages but, in the same time its drawbacks. Therefore, many researchers combined two or more different approaches to give better results, than either one individual one.

The main object is to minimize the computational complexity and enhance the detection capability. For instance, Sari-Sarraf et al (1999) described an online automated fabric defect detection system with 100% coverage. The relatively low cost system is synchronized with the loom motion and produces high quality fabric images with either front or back lighting.

The acquired images were then processed by a segmentation algorithm that combines wavelet transform, image fusion, and the correlation dimension. These defects were unicoloured with a size larger than 1 mm².

The model first adaptively learns its parameters on defective samples and subsequently checks for texture defects using the recursive prediction analysis. This method has promising results whereas fails to inspect highly structured textures due to limited low frequencies modelling power of the underlying probabilistic model. Chen and Libert (1998) developed a real-time Automatic Visual Inspection (AVI) system for high speed plane products.

The implemented algorithm combines the connected component labeling, the moment calculation and the pattern recognition. This system is flexible so that inspection algorithms are reusable and new algorithms can easily be evaluated regardless of its hardware. Han et al (2010) presented an efficient and effective novel approach to detect the small fabric defects based on a combination between template matching methods and judgment threshold.

The method learns from statistical information of fabric surface to modify the template. A new classification due to the huge number of fabric defect detection algorithms and techniques, the need of effective methods to compare between these approaches is very important than before.

Fatemi et al (1996) evaluated a variety of different methods for texture segmentation based upon wavelets. The two-point correlation function was proposed as performance measure. They found that, 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.
Also, Zhang et al (1995) studied and compared two software approaches for detecting and classifying knot and slub defects in solid-shade, unpatterned 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. Bodnarova et al (2000) developed a comparative study to examine the suitability of four different detecting algorithms. 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. Conci et al (2004) and Mak et al (2009) compared the Sobel edge detection with those based on thresholding and fractal dimension and found it both robust and fast method to detect twelve fabric defects.

They found that the use of fractal dimension method gives the most reliable results because it correctly detects all defect types with only 2% false alarms while it is faster than the other approaches. Cuenca et al (2003) developed a new texture descriptor based on semi-cover concept and a simplified local measure. The results showed a similar or superior performance to more complex approaches but with greatly saving computational cost.

Finally, Vergados et al (2001) detailed a description of the state of the art techniques for texture segmentation as well as an evaluation of experimental research and results 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.

Automated visual inspection in textile industries was done by Manuel Ferreira et al (1998). Various types of faults were analyzed by Tamnun et al (2008) on textiles. They used the faulty fabric image for analysis and it was interfaced with the design of Feed forward and Back propagation networks. Defects detection in Images and filtering them using Gabor filters was further developed by Mak et al (2006, 2008).

The application of neural networks in textile industries was also reviewed by Chi Leung Parick Hui et al (2010) for a decade of period. A number of attempts have been made to improve automated textile defect inspection. Most of them have concentrated on defect detection, where few of them have concentrated on classification. Mainly three defect detection techniques elaborated by Mitropoulos et al (1999) namely statistical, spectral and model-based have been deployed. A number of techniques have been deployed for classification Mak et al (2009). Among them, NN, Support Vector Machine (SVM), clustering, and statistical inference are notable.

Statistical inference is used for classification and proposed by Anagnostopoulos et al (2002) and Brzakovic et al (1996). They have implemented binary classification, by categorization of only defective and defect-free sections on fabrics. Murino et al (2004) have used Support Vector Machines (SVMs) for classification. They have worked on spatial domain.

They have used the features extracted from gray-scale histogram, shape of defect and co-occurrence matrix. They have implemented SVMs with 1-vs-1 binary decision tree scheme in order to deal with multiclass problem, in distinct categorization of defects.
NNs have been deployed as classifiers in a number of articles. Habib et al (2012) have deployed Counter Propagation Neural network (CPN) in order to classify four types of defects. They concentrated on feature selection rather than giving attention to the CPN model. They have not performed in-depth investigation on the feasibility of CPN model in the context of automated textile defect inspection.

Saeidi et al (2007) have trained their NN by back propagation algorithm so as to deal with multiclass problem that is categorizing defects distinctly. They have first performed off-line experiments and then performed on-line implementation. Their work is on frequency domain. Karayiannis et al (1999) have used an NN trained by back propagate on algorithm in order to solve multiclass problem. They have used statistical texture features.

Kuo et al (2003) have used a NN trained by back propagation algorithm so as to deal with multiclass problem. They have used maximum length, maximum width and gray level of defects as features. Mitropoulos et al (1999) have trained their NN by back propagation algorithm so as to deal with multiclass problem. They have used first and second order statistical features.

Islam et al (2006) have used resilient back propagation algorithm to train their NN. Their networks have been capable of dealing with multiclass problem. Shady et al (2006) have used Learning Vector Quantization (LVQ) algorithm in order to train their NNs. Their NNs have been implemented in order to handle multiclass problem. They have separately worked on both spatial and frequency domains for defect detection. Kumar et al (2003) has used two NNs separately. The first one has been trained by back propagation algorithm.

The network has been designed for binary classification, by categorization of only defective and defect-free. He has shown that the inspection system with this network was not cost-effective. So he has further
used linear NN and trained the network by Least Mean Square Error (LMS) algorithm.

The inspection system with this NN was cost-effective, but it could not deal with multiclass problem. Inability to deal with multiclass problem doesn’t serve the purpose of textile-defect classification. Karras et al (1998) have also separately used two NNs. They have trained one NN by back propagation algorithm. The other NN used by them was Kohonen’s Self-Organizing Feature Maps (SOFM).

They have used first and second order statistical-texture features for both NNs. Both of the networks used by them are capable of handling binary classification problem. Categorization of only defective and defect-free fabrics doesn’t serve the purpose of textile-defect classification and illustrated by Rokonuzzaman et al (2011).

There are some works based on the optical Fourier transform directly obtained from the fabric with optical devices and a laser beam analysed by Huang et al (2001). In these works digital image processing techniques have been increasingly applied to textured samples analysis over the last decades by Comelli et al (1995). Several authors have considered defect detection on textile materials. Umer Farooq et al (2004) discussed about machine vision in deformable webs, but they concentrated on only speed of the lace patterns.

Choi (2001) analysed fabric defects with fuzzy interference technology, but it has the drawback of absence of Charge coupled device irrespective of scanner. Huang et al (2001) applied Fuzzification with image processing technique, but in that case the dimensions of the system are increased with the feature space. Kang et al (2002) described about evaluation of cotton with image processing and neural network but has not focused on fabrics.

Saeidi et al (2007) experimented computer vision aided circular knitting machine to inspect fabric under construction but it has a major drawback of high speed during inspection which is very tedious. Arivazhagan et al (2006) elaborated about the fault segmentation in fabrics with Gabor filters but it has a drawback that it can be applied only to regular textures.

Khan et al (2009) predicted model for wool with ANN using Perceptron and regression network whereas the output is not reliable. Wong et al (2003) investigated on human physiological perceptions of clothing sensory comfort but the performance output is not reliable due to its physical properties.

Banumathi et al (2012) detailed about fabric defect inspection system using neural networks which takes a long procedure for extracting features involving construction, subset generation, evaluation criterion definition and estimation. This takes longer duration and is a major disadvantage of this method.

Jingmi ao et al (2009) analysed about fabric defect detection based on image distance difference which has a disadvantage of higher speed in operation where inspection cannot be done effectively.

Ajaykumar (2003) described about the local textile defects with principal component analysis in neural networks which has a disadvantage that low resolution images cannot be recognised.
Narges et al (2011) explained about fabric defect identification by extracting wavelet coefficients from a perfect fabric with genetic algorithm which is very complicated process and hence avoided.


Figure 2.2 Automated Fabric Inspection Case1

Figure 2.2 and 2.3 represents the automated inspection type in Senthil fabric industries in Tirupur present in Tamilnadu, Sri Guru Fabrics in Coimbatore, Tamilnadu India employs this existing techniques.
Dhivya et al (2013) proposed a hybrid approach for fabric fault identification using wavelet approach but it depends on many sub band values during detection process which seems complicated. Rakesh et al (2013) depicted an approach for textile defect detection which concentrated only on reflective materials on fabrics which is considered as a drawback of this process. Elham et al (2013) analysed defect detection by using auto correlation function which consists of several complicated steps to reach the target as a major drawback.


Now a days textile business is one of the major business all over the world. For example, developing countries like India where textile industry that includes knitwear and readymade garments along with specialized textile products, is the nation's number one export earner. Chan et al (1998) analyzed the sector, which employs 2.2 million workers, accounted for 75 per cent of India's total exports to US$10.53 billion in the financial Year 2005-06, in the
process logging a record growth rate of 24.44 per cent. But one of the greatest weaknesses in this field is the loss of fabric due to defects on those. This loss can be reduced in this textile field up to the maximum by using this "Automated fabric defect Detection Mechanism using microcontroller", in textile industries, showing an average growth of 40% per year since 1990. The association formed by the Exporters of Tirupur is one of the most successful association in India trying hard and been successful in helping the trade in Tirupur, Tamilnadu.

Garment exporters across the country got yet another jolt with the textile mills raising yarn prices by Rs 7 per kg for all counts. While the price of 20s count (term used to define size/weight of yarn usually reflecting the amount of yarn packed in a given area) yarn has gone up to Rs 191 per kg from Rs 184 per kg, 24s count has been increased to Rs 199 per kg from Rs 192 per kg, 30s count to Rs 211 per kg, 34s to Rs 218 and 40s count yarn prices to Rs 225 per kg from Rs 218 per kg. This is the third hike in yarn prices within a month. Textile mills had increased prices across all counts by Rs 7 per kg last on October 26, 2010 and prior to that on October 20, 2010.

In fact, in October 2010 alone, yarn prices have been thrice raised by Rs 7 per kg every time across all the counts. According to Tirupur Exporters Association (TEA), the industry is shocked to note that textile mills have increased yarn prices by Rs 7 per kg for all counts on November 1st, 2010 and the upward revision of yarn prices has been done at a time when cotton prices have just started to fall. For instance, the count 40s combed hosiery yarn price which was quoted at Rs 185 per kg in June 2010 is now priced at Rs 225 per kg. There has been an increase of Rs 40 per kg within just four months. Similarly, in the case of count 30s the price has moved up from Rs 171 per kg in June to the current level of Rs 211 per kg. In order to reduce all these manual defects
the fabric processing is done automatically with image processing, neural networks and Bayesian networks along with PIC16F877 Microcontroller.

2.3 TEXTILE FIELD PROBLEMS AND THEIR IMPACTS

Chi Leung Parick Hui et al (2010) explained the textile field problems and their impacts which involve the interaction of large number of variables. This gives the high degree of variability in raw materials, multistage processing and a lack of precise control on process parameters. Commercial customers have become more exacting in their demand for relative quality of textiles they purchase, as variations in quality can actually damage and disrupt sensitive clothes.

The relation between such variables and the product properties relies on human knowledge but it is not possible for human being to remember all the details of the process-related data over the years. As the computing power has substantially improved over last decade, the Artificial Neural Networks (ANN) is able to learn such datasets to reveal the unknown relation between various variables effectively. Therefore, the application of NN and BNs are more widespread in textiles and clothing industries over the last decade.

The main types of fault occurring in textile industries: holes, gout, knots, missing yarn, scratches and stains are analyzed.

2.4 TEXTILE STANDARDS

Chan et al (1998) discussed about the textile field defect detection methods which require technical solutions and can be implemented without any standardization. However, proper standardization provides important incentives for the implementation of the technical solutions. The textile field standards are mostly concerned with the following three areas:
• Defining the nominal environment
• Defining the terminology
• Limiting the number of textile problems

The International Standardization of Organization (ISO) has proposed their set of textile field standard and is highlighted here:

i) ICS (International Clothing Standard) 59.080.01 standard gives details of Textiles in General including fastness of textiles.

ii) ICS 59.080.20 standard gives details of Yarns including Plied Yarns, Textured yarns and threads.

iii) ICS 59.080.30 standard gives details of textile Fabrics including nonwovens, Felts and Lace.

iv) ICS 59.080.40 standard gives details of Coated Fabrics.

v) ICS 59.080.50 standard gives details of ropes including strings, strap and bands.

vi) ICS 59.080.60 standard gives details of textile floor coverings.

vii) ICS 59.080.70 standard gives details of geotextiles.

viii) ICS 59.080.80 standard gives details of other products in the textile industries.
2.5 METHODOLOGY OF THE RESEARCH

Figure 2.1 Methodology of the Research

1. Fabric Sample is taken from Textile Industries
2. Fabric Sample is given to MATLAB by Programming
3. Noise Removal in Image by Filtering Process
4. Filtered output is processed by Histogram
5. Thresholding is done for fabric image after Histogram
6. Image Processing is done and given to Feed Forward and back propagation network to simulate
7. Simulated output of neural network
8. Output compared with Bayesian Network & Interfaced with Microcontroller
9. PIC Microcontroller input with the motor for rotation
10. Motor rotates if fault is not present or else stops if fault is identified
2.7 CONCLUSION

The current chapter reviews all the major research works presented in the literature in the area of fabric defect detection improvements and briefly discusses on fabric quality issues like Holes, Gout, Missing yarns, Knots, Scratch and Stains.

A brief description of the impact of textile quality and its standards, along with solutions for textile quality improvements are highlighted. Various methods of approaches like Spectral, Statistical, Structural and Model based approach, Combination of computational methods and their drawbacks are discussed.

Hence, this chapter highlights the research gap in textile quality improvement, which requires potential mitigation of textile defects and provide accuracy to the system. Consequently, there is a huge requirement for fast response systems compared with the traditional methods.