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A review of automatic fabric defect detection techniques

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Abstract- Quality inspection is an important aspect of modern industrial manufacturing. In textile industry production, automate fabric inspection is important for maintain the fabric quality. For a long time the fabric defects inspection process is still carried out with human visual inspection, and thus, insufficient and costly. Therefore, automatic fabric defect inspection is required to reduce the cost and time waste caused by defects. The development of fully automated web inspection system requires robust and efficient fabric defect detection algorithms. The detection of local fabric defects is one of the most intriguing problems in computer vision. Texture analysis plays an important role in the automated visual inspection of texture images to detect their defects. Various approaches for fabric defect detection have been proposed in past and the purpose of this paper is to categorize and describe these algorithms. This paper attempts to present the survey on fabric defect detection techniques, with a comprehensive list of references to some recent works. The aim is to review the state-of-the-art techniques for the purposes of visual inspection and decision making schemes that are able to discriminate the features extracted from normal and defective regions. Therefore, on the basis of nature of features from the fabric surfaces, the proposed approaches have been characterized into three categories; statistical, spectral and model-based.

1. Introduction

In textile industry, inspection of fabric defects plays on important role in the quality control. However, the current inspection task is primarily performed by human inspectors and this intensive labour cannot always give consistent evaluation of products. Fabric Automatic Visual Inspection (FAVI) system is an attractive alternative to human vision inspection. Based on advances in computer technology, image processing and pattern recognition, FAVI system can provide reliable, objective and stable performance on fabric defects inspection. A good automated system means lower labor cost [1] and shorter production time [2]. There are numerous reported works in the past two decades during which computer vision based inspection has become one of the most important application areas. The texture materials can be further divided into uniform, random or patterned textures. Brazakovic et al. [3] have detailed a model based approach for the inspection of random textured materials. The problem of printed textures (e.g. wall paper scanning, ceramic flaw detection and printed fabric detection) requires evaluation of color uniformity [4] and consistency of printed patterns. Ngan et al. [5] have introduced the new regular bands (RB) methods which is effective approach for pattern texture inspection. This paper focuses on the inspection of uniform textured materials and presents a survey on the available techniques for the inspection of fabric defects.

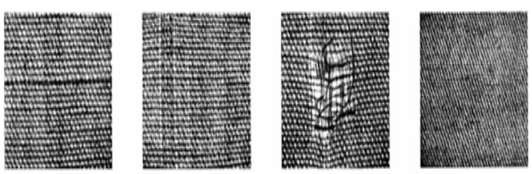
2. Fabric defects

Fabric faults or defects are responsible for nearly 85% of the defects found in the garment industry [6]. Manufactures recover only 45-65% of their profit from second or off quality goods [7]. It is imperative therefore to detect, to identify and to prevent these defects from reoccurring. There are many kinds of fabric defects. Much of them are caused by machine malfunctions and have the orientation along pick direction (broken pick yarns or missing pick yarns), they tend to be long and narrow. Other defects are caused by faulty yarns or machine spoils. Slubs are often appeared as point defects; machine oil spoils are often along with the direction along the warp direction, and they are wide and irregular. An automated defect detection and identification system enhances the product quality and results in improved productivity to meet both customer needs and to reduce the costs associated with off-quality. Recently, the fault detection is done manually after a sufficient amount of fabric has been produced, removed from the production machine and then batched into larger rolls and then sent to the inspection frame. An optimal solution for this would be to automatically inspect from the fabric as it is being produced and to alert the maintenance personnel when the machine needs attention to prevent production of defects or to change process parameters to prevent automatically to improve product quality. This is done by identifying the faults in fabric using the image processing techniques and then based on the dimension of the faults; the fabric is classified and then graded accordingly. Nickoloy et al. [8] have shown that the investment in the automated fabric inspection system is economically attractive when reduction in personnel cost and associated benefits are considered.

2.1 Texture analysis techniques for fabric defect inspection

Texture is one of the most important characteristics in identifying defects or flaws.

Figure1.shows some example of defects in various fabric materials. It provides important information for recognition and interpolation. In facts, the task of detecting defects has been largely viewed as a texture analysis problem. With reference to several texture analysis survey papers [9-14], we categorized texture analysis techniques use for visual inspection into four ways: statistical approaches, structural approaches, filter based approaches and model based approaches. A variety of techniques for describing image texture have been proposed in the research literature. M. Tuceryan and Jain [15], on the other hand, defined five major categories of features for texture analysis: statistical, geometrical, structural, model based and signal processing features. Geometrical and structural methods try to describe the primitives and the rules governing their special organization by considering texture to be composed of texture primitives .These two approaches have not been attempted in fabric defect detection, mainly due to the stochastic variations in the fabric structures (due to elasticity of yarns, fabric motion, fiber heap, noise etc.) which poses severe problems in the extraction of texture primitives from the real fabric samples. Therefore, in this paper the proposed defect detection techniques have been classified in three categories: statistical, spectral and model-based. Table 1 shows a summary list of some of the key texture analysis method that have been applied to defect detection.



(a) (b) (c) (d)

Fig. 1- Fabric defect samples: (a) Double yarn; (b) Missing yarn; (c) Broken yarn; (d) Variation of yarn

3. Statistical approaches

Statistical texture analysis methods measure the spatial distribution of pixel values. An important assumption in this approach is that the statistics of defects free regions are stationary, and these regions extend over a significant portion of inspection images. Statistical methods can be classified into first- order (one pixel), second-order (two pixels) and higher- order (three or more pixels) statistics based on a number of pixels defining the local features. 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. The defect detection methods employing texture features extracted from fractal dimensions, first order statistics, cross correlation, edged detection, morphological operations, co-occurrence matrix, eigenfilters, rank order functions, and many local linear transforms have been categorized into this class.

3.1 Defect detection using co-occurrence matrix features

The co-occurrence matrix method, known also as the spatial gray-level dependence method, has been widely used in texture analysis. It is based in repeated occurrences of different grey level configurations in a texture. Automatic visual inspection techniques for textured images generally compute a set of textural features in the spatial domain or in the spectral domain. Siew and Hogdson [16] presented the assessment of carpet wear using Spatial Gray Level Dependence Matrix (SGLDM), neighboring Gray Level Dependence Matrix (GLDM), Gray Level Difference method (GLD), and the Gray Level Run Length Method. Also it has been applied to wood inspection [17], surface defect detection [18], and fabric defect detection [19]. The original investigation into SGLDM features was pioneered by Haralick et.al. [20]. Texture features, such as energy, entropy, contrast, homogeneity, and correlation are then derived from the co-occurrence matrix. However only six of such features have been used for the defect detection on wood and fabric defect detection has been shown with only two of these six features. Several works have been reported using co-occurrence matrices to detect defects, such as [17, 19, 21, 22, 23] for example in [21] Iivarinen et al. applied co-occurrence texture features to detecting defects in paper web where the normal texture have characteristic frequency. Conners et al. [17] have used six features of co-occurrence matrix, to identify nine different kinds of surface defect in wood. Tsai et al. [19] have detailed fabric defect detection while using only two features, and achieved a classification rate as high as 96%. Rosler [22] has also developed a real fabric defect detection system, using co-occurrence matrix features, which can maintain 95% of the defects as small as 1mm2 in size. In order to derive maximum texture information using co-occurrence matrix, the values parameter ɵ should agree with the orientation of the fabric pattern and distance d should be equal to the pattern period [24]. Bodnarova el al. [25] have examined this issue on the optimal displacement vector d for the fabric defect detection. The co-occurrence matrix features suffer from a number of difficulties. It appears there is no generally accepted solution for optimising the displacement vector [4, 26]. The number of gray levels is usually reduced in order to keep the size of the co occurrence matrix manageable. For a given displacement vector , a large number of features can be computed, which implies dedicated feature selection procedure .This technique can be computationally expensive for the demands of a real-time defect inspection system , but it have been exploited in many studies as highly accurate technique.

3.2 Defect detection using local linear transforms

Texture properties can be extracted by using several bidimensional transform such as Discrete Cosine Transform (DCT), Discrete Sine Transform (DST), Discrete Hadamard Transform (DHT), Karhunen –Loeve Transform (KLT) and eigenfiltering. Unser [27] tested different local linear transforms for texture classification and found KLT as the best algorithm. Also Ade et al. [28] compared Laws filters, KLT, DCT and DHT for textile defect detection. In their experiments, the KLT performance, particularly on larger window size, was amongst the best. Neubauer [29] has detected fabric defect using texture energy features from low mask on 10×10 windows of inspection images. In his approach, three 5x5 Laws masks corresponding to ripple, edge, and weave features [30] are used to extract histogram features from every window of the image. These features are then used for the classification of the corresponding window into defect-free of defect class, using a three-layer neural network. Using eigenvalues of covariance matrix as a feature Őzdemir and Ercil [31] have implemented fabric defect detection using an approach which is a variation of the Karhunen-Loeve (KL) transform or eigenfilters method. A novel scheme of characterizing and classifying defects in woven textile fabrics has been attempted in [32]. This back propagation based neural network coupled with the DCT technique can lead to outstanding results for classification of various fabric defects. In online fabric inspection, the local transforms such as DCT or DST could be preferable to eigenfilters or KL transforms, since DCT or DST can be directly obtained from the camera hardware using commercially available chips that perform fast and efficient DCT or DST transforms.

3.3 Defect detection using fractal dimension (fd)

Fractal-based texture analysis was introduced by Pentland [33]. Voss [34] refers to box counting as the process of estimating the probability that m points lie in the box. Keller et al. [35] proposed a modification of method due to Voss, which presents satisfactory results up to FD = 2.75. The utilization of fractal dimension is investigated by Conci and Proenca [36] for discriminating defective areas. The decision for defect declaration is based on the variation of FD. This method is infact computationally enough to be suitable for PC implementation, but presents very limited experimental results which suggest 96% detection on eight types of defects. The localization accuracy of these defected defects is very poor and high false alarm.

3.4 Defect detection using edge detection

Edges can be detected either as micro edges using small edge operator masks or as macro edges using large masks [37]. The distribution of amount of edges per unit area is an important feature in the textured images. The amount of gray level transitions in the fabric image can represents line, edges, spots, ripples and other spatial discontinuities. These features have been used to detect fabric defects [38, 39, 40]. Conci and Proenca [39] have used sobel edge detection to detect fabric defects and compared the results with those based on thresholding and fractal dimension. J.S.Lane [40] has detailed a systematic approach to detect fabric defect. [41] gives useful approach for the characterization of low resolution web surface using facet model. These approaches using edge detection are suitable for plain weave fabrics imaged at low-resolution.

3.5 Defect detection using cross-correlation

Correlation is used for locating features in one image that appear in another and therefore provides a direct and accurate measure of similarity between two images. Any significant variation in the values of resulting measure indicates the presence of a defect. Bodnarova et al. [42] have used the correlation coefficient from multiple templates to generate a correlation map for defect declaration. The correlation approach in [43] yields satisfactory results when detecting imperfections in regularly textured backgrounds. On the other hand, randomly textured backgrounds do not correlate well and demonstrate a limitation of this approach.

3.6 Defect detection using bi-level thresholding

Use of gray level thresholding enables to detect high contrast defects. The occurrence of a defect causes the signal level to rise or fall locally; the presence of a peak or trough then indicates a defect. This defect is detected when the signal crosses a decision threshold. This idea is used to detect fabric defects [44, 45] on moving textile web. The defect detection can be effective even when web is covered by a fine and complex pattern. Cho et al. [46] proposed algorithm for finding defect in textile fabrics with fine web surface which shows 80% recognition rate on warp and pick float. The fabric inspection system that uses thresholding, proposed by Stojanovic et al. [47], gives high detection rate with good localization accuracy and low rate of false alarm.

3.7 Defect detection using morphological operations

Zhang and Bresee [48] have detailed on morphological operations for detection of fabric defects. The practical utility of this approach is limited as most of the commonly occurring fabric defects will be missing from the binary image generated from the simple thresholding operation. Detecting defects morphologically on spatially filtered images of fabrics produces better results [49], particularly when the fabric is fine and contains defect of small size. In their experiments the morphological operations are only performed on a periodic images defect, unlike the case in [48] where the entire structure of thresholded fabric image was utilized.

3.8 Defect detection using neural networks

Neural networks are one of the fastest most flexible classifier used for fault detection due to their non-parametric nature and ability to describe complex decision regions. A new approach for the segmentation of local textile defects using feed-forward neural network (FFN) and also a new low-cost solution for the task web inspection using linear neural network is presented in [50]. The usefulness of these two proposed approaches is shown by experimental results obtained from the real fabric defects. Hung and Chen [51] have used back propagation neural network, with fuzzy logic, to achieve the classification of eight different kinds of fabric defects along with defect-free fabric. A compact fabric inspection system using neural network is presented in [52] but is not adequately detailed. Recently, H.M.Elragal [53] proposes an automated visual inspection system using Adaptive Neural Fuzzy Interface System (ANFIS) that can detect and classify knitting machine fabric defects. [54] Investigates two methods for the detection of defects on textured surfaces using neural networks and Support Vector Machines (SVM). The real-time implementation of defect segmentation scheme using FFN is computationally costly. Although the real time computational complexity of SVM is also similar, but do not suffer from the problem of local minimum and is computationally simple to train. Another analogous work for texture defect detection using cellular neural networks is detailed in L.Occhipinti [55]. The FFN and SVM require training from the known classes of fabric defects. Yuen et al. [56], presented a novel hybrid model through integration of genetic algorithm (GA) and neural network to classify the type of garment defects. They developed a segmented window technique to segment images into several classes using monochrome single-loop ribwork of knitted garment. Four characteristic variables were collected and input into a back propagation (BP) neural network to classify the sample images. Their experimental result shows very high accuracy rate of recognition and thus provides decision support in defect classification. M. Shi et.al. [57] describes an adaptive image-segmentation method based on a simplified pulse-coupled neural network (PCNN) for detecting fabric defects. They introduce a new parameter called the deviation of the contrast (DOC) to describe the contrast difference in row and column between the analyzed image and a defect – free image of the same fabric. The simplification of PCNN reduces the number of the network parameters by utilizing the local and global DOC information for the parameter selections. Castilho et al. [58] presents a real-time fabric defect detection based intelligent techniques. Neural networks (NN), fuzzy modeling (FM) based on product – space fuzzy clustering and adaptive network based fuzzy inference system (ANFIS) were used to obtain a clearly classification for defect detection. Experimental results for real fabric defect detection, shows the usefulness of the three intelligent techniques and they further stated that NN has a faster performance. Online implementation of the algorithms showed they can be easily implemented and may be adapted to industrial applications without great efforts. Recently, another method of textile flaw detection and classification based on wavelet reconstruction and BP neural network is detailed in [59]. They detected two types of textile flaws, namely oil stain and hole. For the extraction of flaw features, histograms of hole and oil stain are computed as the input of BP neural network. Their experimental result shows that this method can effectively detect defects and classify the types of defects with high recognition correct rate.

3.9 Defect detection using histogram

Histogram and the rank function provide exactly the same information. Natale [60] has used rank order functions for the detection of artificially introduced defect in some Brodatz textures [61]. H. Kauppines [62] detailed the parquet slab grading using cumulative histogram. Defect detection in ceramic tile using a set of adaptive rank order function is discussed in [63]. The colour information in textured images can also be used to extract colour histograms and this has been used in [64, 65] to detect defects.

4. Spectral approaches

These are robust and efficient computer-vision approaches for fabric defect detection. In this approaches texture is characterised by texture primitives or texture elements, and the spatial arrangement of these primitives [66] .Thus, the primary goals of these approaches are firstly to extract texture primitives, and secondly to model or generalise the spatial placement rules. The high degree of periodicity of basic texture primitives, such as yarns in the case of textile fabric, permits the usage of spectral features for the detection of defects. However, random textured images cannot be described in terms of primitives and displacement rules as the distribution of gray levels in such images is rather stochastic. Therefore, spectral approaches are not suitable for the detection of defects in random texture materials. Various approaches for the detection of defects in uniform textured material using frequency and spatial- frequency domain features have been reported in the literature. In spectral- domain approaches, the texture features are generally derived from the Fourier transform [67, 68], Gabor transform [69, 70] and Wavelet transform [71]. They are summarized in the following sections.

4.1 Defect detection using discrete fourier transform

The Fourier transform (FT) has the desirable properties of noise immunity and enhancement of periodic features. The FT characterizes the textured image in terms of frequency components. The periodically occurring features can be observed from the magnitude of frequency components. These global texture patterns are easily distinguishable as concentration of high-energy bursts in the spectrum. Liu and Jernigan [72] reviewed a set of 28 textural features extracted in the Fourier spectrum for texture analysis. Escofet et al. [73] used the angular correlation of the Fourier spectra to evaluate fabric web resistance to abrasion. Chan and Pang [74] used the Fourier analysis for fabric defect detection. Seven textural features extracted from the vertical and horizontal frequency components in the Fourier spectrum are used to discriminate four defect types including double yarn, missing yarn, webs and yarn densities. Later, in [75], an approach based Fourier transform has been used to detect the various types of fabric defects. The central spatial frequency spectrum is used, from which seven significant characteristic parameters are extracted for detecting the type of defect. Further, they carried out experiments to detect only two classes of defects namely double yarn and missing yarn which found to be consistent for a number of samples. In [76], the author used the Fourier transform to reconstruct textile images for the defect detection. The line patterns in the textile images, supposed to be defects, were taken out by removing high energy frequency components in the Fourier domain using a one-dimensional Hough transform. The difference between the restored image and the original image were considered as potential defects. A similar idea was explored in [77], but low pass filtering was used to remove the periodic information. The Fourier transform of textile fabric can also be obtained in optical domain by using lenses and spatial filters. The fabric defect detection system using the measurements of the first- and the zero-order intensities have been developed [78, 79, 80, and 81]. Ciamberlini et al. [82] have described the design of spatial filters: a fixed filter adaptable for different types of fabric and a universal spatial filter for the detection of defects in textured materials. Campbell and Murtagh [83] have detailed a Windowed Fourier transform based method to detect defect on denim fabric samples.

4.2 Defect detection using gabor filter

The Fourier transform is an analysis of the global frequency content in the signal, it is not able to localise the defective regions in the spatial dependency into Fourier analysis is through the windowed Fourier transform. If the window function is Gaussian, the windowed Fourier transform becomes the well known Gabor transform, which can be achieving optimal localisation in the spatial and frequency domain [84]. Jain and Farrokhnia [85] used it in segmentation and classification of textures with dyadic coverage of the radial spatial frequency range. The Gabor filter bank has been extensively studied in visual inspection. Kumar and Pang [86] perform fabric defect detection using only real Gabor functions. Later in [87], they used a class of self similar Gabor functions to classify fabric defects. They also investigated defect detection using only imaginary Gabor functions as an edge detector. Bodnarova et al. [88] applied a Fisher cost function to select a subset of Gabor functions based on the mean and standard deviation of the template feature images to perform textile flaw detection. Shu et al. [89] detailed a method of detecting the fabric defects automatically based on multi-channel and multi-scale Gabor filtering. It is based on energy response from the convolution of Gabor filter banks in different frequency and orientation domains. Experiments on various simulated defect fabric images have shown the effectiveness of this method. This method has accurate location and fine detection of fabric defects. Han and Zhang [90] proposed a fabric defect detection method based on Gabor filter masks. The performance is evaluated off-line by using a group of fabric sample images containing many kinds of fabric defects. Their experimental result shows accurate defect detection with low false alarms. In [91], Gabor filters are designed on the basis of the texture features extracted optimally from a non-defective fabric image by using a Gabor wavelet network (GWN). Their result exhibits accurate defect detection with low false alarms, showing the effectiveness and robustness of the scheme. Gabor wavelet transform is applied to detect the defects in fabrics [92]. Gabor filter scheme that imitates the early human vision process is applied to the sample under construction. The result obtained by proper thresholding ensures segmentation of the defect, which in turn confirms efficiency of this method. Hou and Parker [93] investigate a method for detecting defects on textured surfaces using a Support Vector Machines (SVM) classification approach with Gabor wavelet features. Instead of using all the filters in the Gabor wavelets, an adaptive filter selection scheme is applied to reduce the computational cost on feature extraction while keeping a reasonable detection rate. Their experimental result shows, this method can successfully detect and segment defects in texture images.

4.3 Defect detection using wavelet transform

In the recent past, multiresolution decomposition schemes based on wavelet transform have received considerable attention as alternatives for the extraction of textural features. The multiresolution wavelet representation allows an image to be decomposed into a hierarchy of localized sub images at different spatial frequencies. It divides the 2D frequency spectrum of an image into a low pass (smooth) sub image and a set of high pass (detail) sub images. The textural features are then extracted from the decomposed sub images in different frequency channels and different resolution levels. In [94], Sari-Sarraf and Goddard have developed a fabric defect detection system that can detect small defects with an overall detection rate of 89%. Their defect detection scheme uses the low-pass and the high-pass 'Daubechies' D2 filter [95]. Scharcanski [96] used the discrete wavelet transform to classify stochastic textile texture. Rather using fixed scales, Kim et al. [97] employed a learning process to choose the wavelet scales for maximising the defect ability of fabric defects. Latif-Amet et al. [98] extracted co-occurrence and MRF-based features from wavelet transform coefficients for fabric defect detection. Gray level diference-based features from sub bands of the wavelet transform were also applied in classifying fabric defects. Jasper et al. [99, 100] have detailed the design of a texture specific wavelet basis filter, which can be tuned to a particular texture. The design of adaptive orthonormal wavelet bases has been shown [101] to achieve the best performance in the characterization of fabric defects. Later, in [102], the authors detailed the adaptive wavelet – based methodology from the use of a single adaptive wavelet to multiple adaptive wavelets. For each class of fabric defect, a defect – specific adaptive wavelet was designed to enhance the defect region at one channel of the wavelet transform, where the defect region can be detected by using a simple threshold classifier. This multiple adaptive wavelets method has been evaluated on the inspection of 56 images containing eight classes of fabric defects, and 64 images without defects, where 98.2% detection rate and 1.5% false alarm rate were achieved in defect detection. The detection of fabric defects using wavelet packet decomposition and Independent Component Analysis has been investigated in [103]. Kumar and Gupta [104] have used mean and variance of "Haar" wavelet coefficient for the identification of surface defects. The fabric texture can also be considered as noise and removed using wavelet shrinkage. Recently, Truchetet and Laligant [105] gave a detailed review on wavelet analysis in industrial application. On the basis of wavelet and singular signal characteristic analysis, Guan et.al. [106] presented a new defect detection method based on wavelet characteristics. The detail signal feature after wavelet decomposition of fabric image is extracted, and it is compared with the detail signal feature of normal fabric image decomposition to determine fabric defects. Their experimental result shows the defect detection accuracy is over 92.5%. An extracted sub-image features approach based on wavelet transition with one resolution level and Fourier transform is presented in [107]. By using restoration scheme of the Fourier transform, the normal fabric textures of smooth sub-image in the spatial domain are removed by detecting the high-energy frequency components of sub-image in the Fourier domain, setting them to zero using frequency-domain filter, and back-transforming to a spatial domain sub-image. Then, the smooth and detail sub-images are segmented into many sub-windows, in which standard deviation are calculated as extracted features. These extracted features are compared with normal sub-windows features to determine whether there exists defect. Ngan et.al. [108] have developed the method of wavelet preprocesses golden image substraction (WGIS) for defect detection on patterned fabric. They concluded that the WGIS method provides the best detection result. The overall detection success rate is 96.7% with 30 defect-free images and 30 defective patterned images for one common kind of patterned Jacquard fabric.

5. Model-based approaches

Model - based texture analysis methods are based on the construction of an image model that can be used not only to describe texture, but also to synthesize it. Model-based approaches are particularly suitable for fabric images with stochastic surface variations (possibly due to fiber heap or noise) or for randomly textured fabrics for which the statistical and spectral approaches have not yet shown their utility. The model parameters capture the essential perceived qualities of texture. Markov random fields (MRF) have been popular for modeling images. MRF theory provides a convenient and consistent way for modelling context dependent entities such as pixels, through characterising mutual influences among such entities using condition MRF distribution [109]. Several probabilistic models of the textures have been proposed and used for defect detection. In [110], Cohen et al. used Gaussian Markov Random Fields (GRMF) to model defect free textile web. The inspection process was treated as a hypothesis testing problem on the statistics derived from the GMRF model. The images of fabric to be inspected are divided into small windows in inspection process; a likelihood ratio test is then used to classify the windows as non–defective or defective. The testing image was partitioned into non-overlapping sub-blocks where each window was then classified as defective or non-defective. Baykut et al. [111] implemented this method in a real-time application with a dedicated DSP system. In [112], the authors showed that MRF based methods were competitive in a comparative study against other statistical and spectral based methods in defect detection. Brzakovic et al. [113, 114] discuss a theoretical approach based on a poissonian model for inspection of web materials. The inspection objective is to quantify the randomness and homogeneity across the material. Campbell et al. [115] detects an alignment pattern in preprocessed images via model based clustering and uses an approximate Bayes factor to assess the evidence for the presence of a defect.

6. Comparative studies

A classification of fabric defect detection techniques is shown in Table 1. The statistical and structural approaches have been in favour in terms of the amount of research reported. It is also worth noting that the categorisation of texture analysis techniques used for fabric defect detection as describe above and listed in table 1 is not a crisp classification. There are several comparative studies in the literature that evaluate texture analysis methods in applications to fabric defect detection. It must be noted that different studies use different datasets and possibly different parameter settings. Also resolution of the acquired images is an important factor in selecting the suitability of an approach for the defect detection. Therefore comments / conclusions on the suitability of some approaches, recently cited in the literature, based on the image resolution, computational complexity, and performance would be useful. The approaches discussed in this survey have been evaluated on image sample with various resolutions. The high resolution images are highly suitable for detecting defects with very subtle intensity variations, but their use will require a high volume of online computations for unsupervised defect detection. However, supervised defect detection on these high-resolution images is a real possibility and is therefore suggested for its practical usage. Ozdemir et al. [116] compared six texture features, consisting of MRF, KL transform, 2D lattice filters, Laws filters, Co-occurrence matrices, and a FFT - based method, for detecting textile defects. For each method, the effects of various parameters have been examined and concluded that, although many of the methods gave promising results, texture modeling using the 9th order Markov Random Field model gave the best results. Also, by considering the results obtained with respect to speed and reliability, MRF approach seems feasible for a real-time factory implementation. Also Bodnarova et al. [117] have concluded that the optimal Gabor filters (optimized to detect five types of defects) perform better than gray level co-occurrence matrix, correlation or FFT based approaches. However this comparison is very limited on a set of 25 images and the information about the image resolution is also missing. Lee Tin Chi [118], compares the performance of three methods which utilize matched masks, wavelet transform and neural network for fabric defect detection. An evaluation of the performance of the methods was conducted on eight classes of fabric defects (Broken End, Dirty Yarn, Mispick, Netting Multiples, Stack End, Thick Bar, and Wrong Draw). In the first method, a multichannel filtering bank equipped with five matched mask was used. Matched masks are 2-D filters that characterize specific texture properties. Using this method, 96% of fabric defects were successfully detected, and the false alarm rate was 6%. The second method employed wavelet transform to decompose fabric images into multi-scales and orientations. During the training stage, the parameters to be optimized include the rotation angles and the two thresholds applied on the horizontal and vertical transformed images. Using this method, only 76% of fabric defects were identified, and the false alarm rate was 7%. The last method took advantage of the fault tolerance and learning ability of neural networks. They explored the texture structure of defect-free images so that feature extraction was conducted on repeating units with proper selection of locations. For defect images, similar feature vectors were extracted and passed to the neural network. Using this method, the detection rate was as high as 92% and the false alarm rate was 6%. They further concluded that, the method employing matched masks proved the most effective in detecting fabric defects. The neural network method was next best. The wavelet transform method was the least effective, because it was only able to detect effectively certain classes of fabric defects. Comparative studies performed by Randen et.al. [119, 120] and Chen et al. [121] indicate that the Gabor features in most of the cases outperform the other methods regarding the complexity and overall error rate. But the Gabor features suffer from a number of difficulties. A major difficulty of this method is how to determine the number of Gabor channels at the same radial frequency and the size of the Gabor filter window in the application. Although a solid conclusion cannot be drawn to determine the best method for defect detection, it is clearly evident that filtering approaches, in particular Gabor filtering has been more popularly applied in these areas. The recent texture inspection approach by Chetverikov and Henbury [122] using the measure of structural regularity and texture antisotropy gives quite convincing experimental results. Therefore, a combination of these two approaches can offer the best performance for textile web inspection and is suggested for future investigation and comparison.

7. Conclusion

The review of fabric defect detection methodologies using image processing techniques gives us possible trend of this application area. These available techniques were classified into three categories: statistical, spectral and model-based. Although the research on visual inspection is diverse and ever-changing, the following observations can be made.

1. The core ides of these methodologies along with their drawbacks / critics were discussed whenever known.
2. Filter bank based methods have been very popular in fabric defect detection. The filters can be manipulated and designed in all sorts of directions and scales to decompose textures in order to highlight defects. However, it is notable that recent researches suggest contextual analysis which directly based on local neighbourhoods without dedicated filtering is a promising alternative approach.
3. In order to understand the formation and nature of the defects, it is important to be able to accurately localise the defective regions rather than classifying the surface as a whole. This can provide possibilities of classifying the defects and further studies of the characteristics of the defects.
4. Due to lack of uniformity in the image database, performance evaluation and the nature of intended application, is not prudent to explicitly declare the best available methods for fabric defect detection. Therefore, the effective performance evaluation requires careful selection of data sets along with its clear definition of scope.
5. The statistical, spectral and model – based approaches gives different results and hence the combination of the approaches can give better results, than either one individually and is suggested for future research. There is also a need of some standard datasets in order to carry out fair comparative analysis.

8. References

[1] Chin R. T. and Harlow C. A. (1982) *IEEE Trans .Pattern Anal. Machine Intell.*, 4(6), 557-573.

[2] Smith M. L. and Stamp R. J. (2000) *Computer Ind.* 43,73-82.

[3] Chin R.T. (1987) *Computer Vision, Graphics, and Image Processing*, 41(3), 346-381.

[4] Yang X. Pang G., and Yung N (2005) *IEE Proceedings Vision, Image Processing,* 152(6) 715-723.

[5] Ngan H.Y.T. and Pang G.K.H. (2009) *IEEE Trans. on Automation Science and Engineering,* 6(1).

[6] Sengottuvelan P., Wahi A. and Shanmugam A. (2008) *Research Journal of Applied Sciences,* 3(1) pp 26-31.

[7] Srinivasan K., Dastor P. H., Radhakrishnaihan P., and Jayaraman S.(1992) *J. text. Inst.,* vol. 83, no. 3, pp. 431-447.

[8] Nickolay B. N. and Schmalfub H. (1993) *Mellind Textilberichte,* vol. 73, 33-37.

[9] Harlick R. (1979) *Proceedings of IEEE,* 67(5) 786-804.

[10] Wechsler H. (1980) *Signal processing,* 2 271-282.

[11] Van Gool L., Dewaele P., and Oosterlinck A. (1985) *Computer Vision, Graphics and Image Processing,* 29, 336-357.

[12] Vilnrotter F., Nevatia R., and Price K. (1986) *IEEE Transactions on Pattern Analysis and Machine Intelligence,* 8,76-89.

[13] Reed T. and Buf J. (1993) *Computer Vision, Image Processing and Graphics,* 57(3),359-372.

[14] Kumar A. (Jan-2008) *IEEE Trans. of Industrial Electronics,* 55(1).

[15] Tuceryan M. and Jain A. (1998) *In Handbook of Pattern recognition and computer vision,* 235-276.

[16] Siew L. H., Hodgson R. M., and Wood E. J. (1988) *IEEE Trans. Patt. Anal .Machine Intell.,* 10(6), 92-105.

[17] Conners R. W., McMillan C. W., Lin K., and Vasquez-Espinosa R. E. (May 1980) *IEEE Trans .Patt. Anal. Machine Intell.*, 3(6),204-222.

[18] Iivarinen J. (2000) *Proceedings of SPIE 4197,* 140-145.

[19] Tsai I., Lin C., and Lin J. (Mar 1995) T*ext. Res. J.,* 65, 123-130.

[20] Harlick R. M., Shanmugam K. and Dinstein I. (1973) *IEEE trans. Sys. Man Cybern.,* 3, 610-621.

[21] Iivarinen J., Rauhamaa J., and Visa A., (1996) *In International Conference on Pattern Recognition,* 4, 356–360.

[22] Rosler R. N. U. (1992*) Mellind Texilberichte,* 73, 292.

[23] Amet A. L., Ertüzün A., and Erçil A. (1998) *Proc. IEEE Southwest Symposium on Image Analysis and Interpretation,* 205-210.

[24] Zucker S. W., and Terzopoulos D. (1990) *Image Modelling, A. Rosenfield (Ed.),* 423-445.

[25] Bodnarova A., Williams J. A., Bennamoun M., and Kubik K. K. (1997) *Proc. IEEE TENCON'97 Conf.,* Brisbane (Aus.), 307-310.

[26] Monadjemi A. (2004) *PhD thesis, University of Bristol, UK.*

[27] Unser M. (1986) *Signal Processing,* 11,61-79.

[28] Ade F., Lins N. and Unser M. (1984) *In ICPR,* 1, 428-431.

[29] Neubauer Claus. (1992) *Proc. 11th Intl. Conf. Pattern Recognition, The Hague (The Netherlands),* 688-691.

[30] David E. R. (1997) *Machine Vision: Theory, Algorithms, and Practicalities, 2nd ed. New York ,* 569-572.

[31] Őzdemir S. and Erçil A. (1996) *Proc. IEEE Conf. Emerging Technologies and Factory Automation, EFTA'96,* 2, 697-703.

[32] Behra B. K., Mani M. P. (Dec. 2007) *Indian Journal of Fibre and Textile research,* .32, 421-426.

[33] Pentland A.P. (1984) *IEEE Trans. On Pattern Analysis and Machine Intelligence*, 6 , 661-674.

[34] Voss R. I (1986) *R.Pynn and A. Skjeltorp Eds.*

[35] Keller J., Crownover R. and Chen S. (1989) *Computer Vision Graphics Image Proc.,* 150-160.

[36] Conci A. and Proença C. B. (1998) *Computer Networks and ISDN Systems*, 30, 1887-1895.

[37] Davis L. S. and Mitiche A. (1980) *Computer Graphics and Image Processing,* 12, 25- 39.

[38] Jasper W. J. and Potapalli H. (1995) *Text. Res. J.,* 65, 683-692.

[39] Conci A. and Proença C. B. (2000) *Text. Res. J.,* 70, 347-350.

[40] Lane J. S. (June 1998) US Patent No. 5,774,177.

[41] Abidi B. R., Sari-Sarraf H., Goddard J. S., and Haunt M.A. *Scientific Literature Digital Library,* http://citeseer.ist.psu.edu/284961.html

[42] Bodnarova A., Bennamoun M.,and Kubik K. K. (1998) *Proc. IEEE SMC'98 Conf., San Diego (U.S.*), 4423-4428.

[43] Bennamoun M. and Bodnarova A. (1998) *Proc. IEEE Conf. SMC,* 4340-4343.

[44] Norton-Wayne L., Bradshaw M., and Jewell A. J. (1992) *Proc. British Machine Vision Conf., Leeds (U.K),* 217-226.

[45] Norton-Wayne L., Bradshaw M., and Sandby C. (1993*) Proc. SPIE 1989,* 2-13.

[46] Cho C.S., Chung B. M. and M-J. (Aug. 2005*) IEEE Trans. Industrial Electronics,* 52(4).

[47] Stojanovic R., Mitropulos P., Koulamas C., Karayiannis Y., Koubias S., and Papadopoulos G. (2001) *Real-Time Imaging,* 7, 507-518.

[48] Zhang Y. F. and Bresee R. R. (1995) *Text. Res. J.,* 65, 1-9.

[49] Mallick-Goswami B. and Datta A. K. (2000) *Text. Res. J.,* 70, 758-762.

[50] Kumar A. (2003) *Pattern Recognition,* 36, 1645-1659.

[51] Hung C. C. and Chen I. C. (2001) *Text. Res. J.,* 71(3), 220- 224.

[52] Rohrmus D. (Jun. 2000) *Proc. IEEE Conf. Computer Vision & Pattern Recogn.,* 2, 794-795.

[53] Elragal H. M. (2006) *Proc.of 23rd National Radio Science Conference.*

[54] Kumar A. and Shen H. C. (2002) *Proc. Intl. Conf. Image Process.,* ICIP-2002, 353-356,.

[55] Occhipinti L., Spoto G., Branciforte M., and Doddo F. (2001) *Proc. IEEE Conf. Circuts & Sys.,* ISCAS 2001, pp.481-484.

[56] Yuen C. W. M., Wong W. K., Qian S. Q., Chan L. K. and Fung E. H. K.. (2009) *Expert Systems with Applications: An International Journal*, 36(2), 2037-2047.

[57] Shi M., Jiang S., Wang H. and Xu B. (2009) *Machine Vision and Applications,* 20(2)131-138.

[58] Castilho H. P., Goncalves P. J. S., Pinto J. R.C. and Serafim A. L. (2007) *Image Analysis and Recognition,* SpringerLink, 4633.

[59] yin Y., Lu W. B., Zhang K. and Jing L. (2009) *Global Congress on Intelligent System,* 4, 167- 171.

[60] De Natale F. G. B. (1986) *Intl. J. Pattern Recognition and Artificial Intell*., 10(8).

[61] Brodatz P. (1966) *Texture: A Photographic album for artists and designers, Dover, New York.*

[62] Kauppinen H. (2000) *Proc. IEEE Conf. Pattern Recognition, Barcelona (Spain),* 4, 803-806.

[63] Desoli G. S., Fioravanti S., Fioravanti R., and Corso D.,(1993) *Proc. Intl. Conf. Industrial Electronics,* 3, 1871-1876.

[64] Boukouvalas C., Kittler J, Marik R, and Petrou M., (1999) *IEEE Trans. Industrial Electronics,* 46, 219-226.
[65] Bergsa L., Duffy N., Laecy G., and Mazo M., (2000) *Image and Vision Computing,* 18, 951-957.
[66] F. Vilnrotter, R. Nevatia, and K. Price, (1986) *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 8:76–89.
[67] Wechsler H. (1980) *Signal Processing,* 2, 271-282.
[68] Azencott R., Wang J. –P., and Younes L., (1997) *IEEE Trans. Pattern Anal. Mach. Intell.* 19,148-153.
[69] Daugman J. G. (1985) *Journal of the Optical Society of America* 2, 1160-1169.
[70] Clark M. and Bovik A. C., (1987) *Pattern Recognition Letters* 6, 261-267.
[71] Mallat S. G., (1989) *IEEE Trans. Pattern Anal. Mach. Intell.,* 11, 674-693.
[72] Liu S. –S., Jernigan M. E., (1990) *Computer Vision, Graphics and Image Processing* 49, 52-67.
[73] Escofet J., Millan M. S., Abril H., Torrecilla E.,(1998) *Proceedings of SPIE 3490,* 207-210.
[74] Chan C. –H., Pang K. H., (2000) *IEEE Trans. Industry Applications* 36, 1267-1276.
[75] Sengottuvelan P, Wahi A and Shanmugam A, (2008) *Research Journal of Applied Sciences,* 3 (1), 26-31.
[76] Tsai D. and Heish C., (1999) *Image and Vision Computing*, 18(1),49–62.
[77] Tsai D. and Huang T., (2003) *Image and Vision Computing*, 21, 307–323.
[78] Mead D. C., Kasdan H. L., and Dorrity J. L. (1978) *US Patent No. 4,124,300*.
[79] Castellini C., Francini F., Longobardi G., and Tirbilli B., (1992) *Opt. Lasers Eng.*, 24, 19-32.
[80] Ribolzi S, Merckle J., and Gresser J. (1993) *Text. Res. J.,* 63, 61-71.
[81] Ciamberlini C., Francini F., Longobardi G., Poggi P., Sansoni P., and Tiribili T., (1996) *Proc. SPIE 2786,* 9-18.
[82] Ciamberlini C, Francini F., Longobardi G., Sansoni P., and Tiribili B.,(1996) *Opt. Eng.,* 35, 835-844.
[83] Campbell J. G. and Murtagh F. (1998) *Opt. Eng.,* 37, 2536-2542.
[84] Daugman J. (1980) *Vision Research*, 20,847–856.
[85] Jain A. and Farrokhnia F., (1991) *Pattern Recognition*, 24, 1167–1186.
[86] Kumar A. and Pang G., (2000) *Optical Engineering, 39(12), 3176–3190*.
[87] Kumar A .and Pang G., (2002) *IEEE Trans. on Industry Applications,* 38(2), 425–440.
[88] Bodnarova A., Bennamoun M., and Latham S. (2002) *Pattern Recognition,* 35, 2973–2991.
[89] Shu Y. and Tan Z. (2004) *Proceedings of the 5th World Congress on Intelligent Control and Automation,* 3378-3380.
[90] Han R. and Zhang L. (2009) *Global Congress on Intelligent Systems*, 184-188.
[91] Mak K. L. and Peng P. (2008) *Robotics and Computer-Integrated Manufacturing,* 24(3),359-369.
[92] Arivazhagan S., Ganesan L. and Bama S. (2006) *Machine Vision and Applications,*16 (6).
[93] Hou Z. and Parker J. M. (2005) *Proc. of seventh IEEE Workshop on Application of Computer.*
[94] Sari-Sarraf H. and Goddard J. S. (1999) *IEEE Trans. Ind. Appl.*, 35, 1252-1259.
[95] Bracewell R. N. (2000) *The Fourier transform and its applications, Boston: McGraw-Hill, 3rd ed.*
[96] Scharcanski J. (2005) *Pattern Recognition Letters*, 26, 1701–1709.
[97] Kim S., Lee M., and Woo K. (1999) *In Proceedings of IEEE International Symposium on Industrial Electronics,* 3, 1406–1409.
[98] Latif-Amet L., Ertuzun A., and Ercil A. (2000*) Image and Vision Computing*, 18(6-7),543–553.
[99] Jasper W. J., Garnier S.J., and Potapalli H. (1996) *Optical. Eng.,* 35, 3140-3149.
[100] Jasper W., Joines J. and Brenzovich J. (2004) *J. Textile Institute*, 96, 43-54.
[101] Yang X., Pang G. and Yung N. (2004) *Pattern Recognition,* 37889-899.
[102] Yang X., Pang G. and Yung N. (2005*) IEE Proc.- Vis. Image Signal Process*,152(6),715-723.
[103] Serdaroglu A., Ertuzun A., and Ercil A. (2006) *Pattern Recognition & Image Analysis*, 61-64.
[104] Kumar A. and Gupta S.(2000) *Proc. IEEE Conf. Industrial Technology,* 2, 113-118.
[105] Truchetet F. and Laligant O. (2008) *Journal of Electronic Imaging*.
[106] Guan S., Shi X., Cui H. and Song Y. (2008) *IEEE Pacific – Asia Workshop on Computational Intelligence and Industrial Application*, 266-370.
[107] Guan S. and Shi X.(2008) *International Symposium on Information Science and Engineering*, 281-285.
[108] Ngan H. Y. T., Pang G. K. H., Yung S. and Michael K. Ng (2005) *Pattern recognition,* 38(4), 559-576.
[109] Li S. (2001) *Markov Random Filed Modeling in Image Analysis.*

[110] Cohen F., Fan Z., and Attali S. (1991) *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 13(8) 803–809.
[111] Baykut A., Atalay A., Ercil A., and G¨uler M. (2000) *Real- Time Imaging* 6, 17–27.
[112] Ozdemir S., Baykut A., Meylani R., Ercil A., and Ert¨uz¨un A (1998*) International Conference on Pattern Recognition* 1738–1740.
[113] Brzaković D.P., Bakić P. R, Vuiovic N. S., and Sari-Sarraf H. (1997) *Proc. IEEE Intl. Conf. Robotics and Automation,* 1-8.
[114] Brzaković D. P., Bakić P. R., and Liakopoulos A. (1995) *Proc. SPIE* 2597. 60-69.
[115] Campbell J. G., Fraley C., Murtagh F., and Raftery A. E. (1996) *Technical Report No. 314, Dept. of Statistics, University of Washington, Seattle*, 1-15.
[116] Ozdemir S., Baykut A., Meylani R., Ercil A., and Ert¨uz¨un A. (1998) *International Conference on Pattern Recognition,* 1738–1740.
[117] Bodnarova A., Bennamoun M., and Latham S. J. (2002) *Pattern Recognition,* 35, 2973-2991.
[118] Lee, Tin-Chi (2004) *Fabric defect detection by wavelet transform and neural network," University of Hong Kong*.
[119] Randen T and Husoy J. H. (1999) *IEEE. Trans. PAMI*, 21 (4), 291-310.
[120] Randen T., Husoy J. (1994) *Optical Engineering*, 33 (8), 2617-2625.
[121] Chien-Chang Chen, Chaur-Chin Chen (1999) *Pattern Recognition Letters,* 20, 783-790.
[122] Chetverikov D. and Henbury A. (2002) *Pattern Recognition*, 35, 2165-2180.

Table 1- In exhaustive list of fabric defect detection methods

Approach	Method	References
Statistical	1. Co-occurrence matrix	[17, 19, 21, 22, 23, 24, 25]
	2. Local linear transforms	[27, 28, 29, 30, 31, 32]
	3. Fractal dimension	[33, 34, 35, 36]
	4. Edge detection	[38, 39, 40, 41]
	5. Cross-correlation	[42, 43]
	6. Bi-level thresholding	[44, 45, 46, 47]
	7. Morphological operations	[48, 49]
	8. Neural networks	[50, 51, 52, 53, 54, 55, 56, 57, 58, 59]
	9. Histogram	[60, 62, 63]
Spectral	1. Discrete Fourier transform	[67, 68, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83]
		[69, 70, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93]
	2. Gabor filter	[71, 94, 95, 96, 97, 98, 99, 100, 101, 102, 103, 104, 105, 106, 107, 108]
	3. Wavelet transform	
Model based	1. Gauss Markov random field	[109, 110, 111, 112]
	2. Poissonian model	[113, 114]
	3. Model-based clustering	[115]