A Review of Fabric Defect Detection Techniques

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***Abstract*—In textile industries the texture defect identification and classification is very necessary to maintain good quality of the product. Sometimes, it is very difficult to identify and classify the small fabric defects by human eye and this affects the production tremendously. 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.**

***Index Terms*—About four key words or phrases in alphabetical order, separated by commas.**

I. Introduction

Textile defect identification and classification plays an important role in automated inspection of fabric products. The end product in textile industry is severely affected by weaving defects which in turn reduces the price of fabrics by 45%-65% due to the presence of defects [1]. Most of the textile industries rely on the human visual system for the fabric defect detection task. According to [2] the human visual system can catch only 60% to 70% of the significant fabric defects. Hence, defects detection is a necessary step for quality assurance in fabric production that helps lowering costs and improving the end product's quality. Computer-vision based system [3] plays an important role to reduce the inspection time and to address the human monitoring errors. Computer-vision based inspection systems have been increasingly applied to replace the human-based systems. In this system the human inspector is replaced by a camera. The camera is used for real time detection of fabric defects. Moreover, classification of fabric defects to their original categories is highly desired. The motivations behind the classification of fabric defect lie in the facts that the cause and effect of fabric defects are different from class to class. Based on fabric defect classification, the statistics of the occurrence of each type of defects can be obtained. Compared to fabric defect detection, which has already been commercially available, the classification of fabric defect is much more complex and still remains a research topic presently. The texture materials can be divided into uniform, random or patterned textures. Brazakovic et al. [4] 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 [5] and consistency of printed patterns. Ngan et al. [6] 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.

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II. Fabric defects

Fabric texture refers to the feel of the fabric [3]. It is smooth, rough, soft, velvety, silky, lustrous, and so on. The different textures of the fabric depend upon the types of weaves used. Textures are given to all types of fabrics, cotton, silk, wool, leather etc. There are more than 50 categories of fabric defects in the textile industries. Many of these defects have preferred orientation; either in the direction of motion (warp direction) or perpendicular to it (pick direction). Many defects are caused by machine malfunctions; others are due to faulty yarns. In textile, different types of defects are available i.e. hole, scratch, stretch, fly yarn, dirty spot, cracked point, color bleeding etc. The various types of defects of weaving are given below-

2.1 Broken Ends- If a warp is absent in the fabric for a very short or long distance and then this fabric defect is called broken ends.

2.2 Broken Picks- If a warp is absent in the fabric for a very short or long width and then this fabric defect is called broken picks.

2.3 Float-A float is a kind of defect where a warp or weft yarn floats over the fabric surface for a few container lengths due to missing of interlacement of two series of yarns.

2.4 Slugs-When the weft yarn is unclean and contains slugs and its diameter is irregular.

2.5 Holes-If there is any small hole present in the fabric and then it is a major fabric defect. The occurrence of hole cut or tears which is self-explanatory.

2.6 Oil Spot-Oil Spot on the fabric are caused by too much oiling on loom parts from other sources. Oil stains in most fabrics may be removed by scouring process.

2.7 Irregular Pick Density-If the pick density that is pick per inch varies due to mechanical fault then thick or thin place may be formed in the fabric.

If these defects are not detected properly then it will affect the production process massively. 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 get better 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..

III. 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. In statistical domain approaches, the texture features are generally derived from-

- Defect detection using co-occurrence matrix features.
- Defect detection using edge detection.
- Defect detection using eigenfilters.
- Defect detection using local linear transforms.
- Defect detection using morphological operations.
- Defect detection using bi-level thresholding.
- Defect detection using neural-networks.

Haiqin Zuo et al. [7] proposed a detection methodology for fabric defect based on the gray level co-occurrence matrices (GLCM), which combines the texture enhancement with fabric defect detection. They proved that by using the NL-Means algorithm, the co-occurrence matrices features are more appropriate for the back-end classifiers are extracted, which subsequently improve the detection accuracy. Salem et al. [8] put forward the texture classification of woven fabric based on a GLCM method and multiclass support vector machine. They used a co-occurrence matrix with different offsets. Li et al. [9] projected a novel approach in which, firstly they adopted the local binary pattern method and the gray level co-occurrence matrix to compute the fabric image features. Then, the principal component analysis is utilized to reduce the high dimensional feature data and lastly, a support vector machine is used as a classifier. Tsai et al. [10] have detailed fabric defect detection using co-occurrence matrix and neural network classifier. They used two features, i.e. ASM and CON, and achieved classification rate as high as 96%.

The distribution of the amount of edge per unit area is a significant feature in the textured images. The amount of gray level transitions within the fabric image can correspond to lines, edges, point defects and other spatial discontinuities. These features have been used to identify fabric defects. Conci and Proença [11] have applied Sobel edge detection to detect fabric defects and compared the results with those based on thresholding and fractal dimension. One more useful approach designed for the characterization of low resolution web surface using facet model appears in [12]. The eigenfilter based approaches are useful in separating pair wise linear dependencies, rather than higher-order dependencies, among image pixels. The important information in most fabric textures is contained in higher order relationships among image pixels. For that reason fabric defect detection using Independent Component Analysis (ICA) of fabric texture has been recommended in [13]. Monadjemi [14,15] has suggested the usage of structurally matched eigenfilters, for textured defect detection. One more approach that uses eigenvalues as feature vector and Neyman-Pearson test for defect declaration is described in [16].

Texture properties can be extracted by using several bi-dimensional transform such as Discrete Cosine Transform (DCT), Discrete Sine Transform (DST), Discrete Hadamard Transform (DHT) and Karhunen–Loeve Transform (KLT). Aziz et al. [17] presented a fabric defect detection algorithm in which they used morphological processing followed by DCT, to estimate dynamic thresholds that are applied on the image to detect fabric defects. In [18], Discrete Cosine Transform (DCT) was used with Artificial Neural Network (ANN). The input to the ANN is the estimated DCT coefficients. Ozdemir and Erçil [19] have implemented fabric defect detection using Karhunen-Loève (KL) transform or eigenfilters method. Zhang and Bresee [20] detailed the detection of fabric defects using morphological operations. But the practical utility of this approach is limited. Then Mallik-Goswami and Datta [21] presented an approach of laser-based morphological operations. This approach filters out the periodic structure of fabric in the optical domain by inserting Fouries lens after proper spatial filtering. It overcomes the problems occurred on [22]. Mark et al. [23] proposed morphological filtering methods to segment the fabric image into background and defects. They applied morphological processing to isolate the defective portions. Stojanovic [24] et al. have developed a fabric inspection system that uses thresholding, noise removal followed by local averaging to identify eight category of defects with 86.2% accuracy, however with 4.3% of false alarm. Furthermore Cho et al. [25] have also detailed fabric defect detection by means of bi-level thresholding.

Neural networks are among the preeminent classifiers used for fault detection because of their non-parametric nature with ability to describe complex decision regions. Abdulhady et al. [26] put forward the fabric fault classification by means of competitive neural tree (CNeT). CNeT classifier is very suitable neural network to deal with classes of data which are highly overlapped such as the textile defects. Moreover, the CNeT can be adjusted to accommodate new defects without the need to retrain the network on all previously learned classes [27].The problem of fabric defect segmentation using feed-forward neural networks (FFN) has been investigated in [28]. Ahmed et al [29] presented a novel approaches for detecting fabric fault using artificial neural network with K-fold validation. In [30], wavelet packet and BP neural network are used together to classify the fabric texture. It shows that classification rate can attain 98%.

IV. SPECTRAL APPROACHES

Spectral approaches [31] are robust and efficient computer-vision approaches for fabric defect detection. In this approaches texture is characterized by texture primitives or texture elements, and the spatial arrangement of these primitives [32]. Therefore, the primary goals of these approaches are initially to extract texture primitives, and secondly to model or generalize the spatial placement rules. The high degree of periodicity of basic texture primitives, for example 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 since 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 [33,34], Gabor transform [35,36] and Wavelet transform [37]. They are summarized in the following sections.

A. Defect detection using fourier transform

The Fourier transform (FT) have the advantageous properties of noise immunity and augmentation 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 noticeable as concentration of high-energy bursts in the spectrum. The woven fabric image is a combination of warp and weft yarn patterns. Each of these yarns is effectively 1-D and may be modeled by a comb of impulses that are modulated by the profile of one yarn [38]. Chan and Pang [39] make use of the Fourier analysis intended for fabric defect detection. They extracted seven textural features from the vertical and horizontal frequency components in the Fourier spectrum which are used to discriminate defect types. Later, in [40], the central spatial frequency spectrum is used, from which seven significant characteristic parameters are extracted for detecting the type of defect. A parallel idea was explored in [41], 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. Another detection method was presented in [42]. This method uses histogram equalization and Fast Fourier Transform (FFT) for fault detection. Here FFT has been used to compare the power spectrum plot of an image containing a defect with that of a defect free image. Shengqi Guan [43] presented fabric defect detection based on fusion technology of multiple algorithm in which there is fusion of Fourier transform, wavelet single decomposition, sub-image filtering and neural network.

B. 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 localization in the spatial and frequency domain. The dimension and orientation of local defects generated on the textile web varies randomly. Therefore a general web inspection system using a bank of symmetric and asymmetric Gabors filters has been detailed in [44-46]. Mak and Peng [47] used one Gaussian low pass filter and one Gabor filter which can extract the basic texture features of defect-free fabric image. They used only one optimal Gabor filter that matches with the texture features of defect-free fabric image is used for fabric defect detection. Han and Lingmin Zhang [48] proposed fabric defect detection method based on Gabor filter masks in which, one even symmetric Gabor filter mask and one odd symmetric Gabor filter mask derived from the impulse response of the optimal Gabor filter are used. Kumar and Pang [49] pointed out that the odd symmetric Gabor can be tuned to extract the texture features of defect-free fabric image. Bodnarova et. al. [50] worked out the parameters of a Gabor filter through optimization of Fisher cost function and constrained these parameters to specific values to detect specific defects. Later in [51] they concluded that the optimal Gabor filters perform better than gray level co-occurrence matrix, correlation or FFT based approaches.

C. Defect detection using wavelet transform

In the recent times of yore, multi-resolution decomposition schemes based on wavelet transform have acknowledged considerable attention as alternatives for the extraction of textural features. The multi-resolution 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. Yang et al. [52] designed an adaptive wavelet-based feature extractor method to characterize fabric images with multi-scale wavelet features by using undecimated discrete wavelet transforms. To minimize the error rate in fabric defect classification, they studied six wavelet transform-based feature extractors and classification methods [53]. Kim and Kang [54] evaluated fabric pilling based on the wavelet reconstruction method to attenuate the periodic background and enhance the pills using un-decimated discrete wavelet transform. Later in [55], they used the wavelet packet frame decomposition to extract texture features followed by a Gaussian-mixture-based classifier for texture segmentation and classification. Eric P. Lam [56] discussed a technique of texture image classification using wavelet decomposition with selective wavelet packet node decomposition will be. Jiang et. al. [57] put forward the optimal tree structure of wavelet transform algorithm and extraction of sub-image characterization. Also, calculation of entropy and energy values, as is characteristic quantity of defect detection. Liu et al [58] combined wavelet texture analysis and learning vector quantization neural networks to classify nonwoven uniformity. In further study, in [59], they combined wavelet energy signatures and robust Bayesian neural network for nonwoven uniformity classification. Venkatesan et al. [60] implemented computer aided fabric fault detection in which wavelet transform is performed and the Features are extracted by formulation of GLCM for improved fault classification.

CONCLUSION

This paper has endowed with a survey of fabric defect detection methodologies. These available techniques were classified into two categories: statistical and spectral approaches. The last few years have shown several encouraging trends in fabric defect detection research. Regardless of the significant progress in last decade, the problem of fabric defect detection still remains challenging and requires further attention. The statistical and spectral based approaches give diverse results and consequently the combination of these approaches can give better results, than any one individually, and is recommended for future study.

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