Automatic Fabric Fault Detection Using Morphological Operations on Bit Plane

Vikrant Tiwari, Gaurav Sharma

Vikrant Tiwari, M-Tech IV Semester, CSE, R. K. D. F., Bhopal,
Gaurav Sharma, Asst. Prof., CSE, R. K. D. F., Bhopal.

Abstract
This paper aims at investigating a novel solution to the problem of defect detection from the images of woven fabric. Automated visual inspection systems are an attractive alternative to human visual inspection in the textile industry, especially when the quality control of products in the industry is a significant problem. In manual fault detection systems with trained inspectors, very less percentage of the defects are being detected, and thus insufficient and costly. Therefore, automated visual inspection systems are a long felt need in the textile industry. The development of an automated web inspection system requires robust and efficient fabric defect detection techniques. For the detection of fabric defects, the pre-processed image is decomposed into its bit planes. The lower order bit planes are found to carry significant information of the location and shape of defects. Then we find the exact location by means of weighted morphology. Robustness with respect to the changes in parameters of the algorithm has been examined. The test results obtained exhibit accurate defect detection with low false alarms, thus showing the effectiveness and robustness of the proposed detection scheme.

Keywords
Defect detection, bitplane decomposition, weighted morphology, dilation, erosion, opening, closing.

1. INTRODUCTION

Quality inspection is an important aspect of modern manufacturing industries. One of the industry fields where automated visual inspection systems are highly needed is the textile industry. Since a garment with textile defects usually sells with a massive discount, the garment manufacturing industry is faced with increased pressure to become more competitive by increasing yield while reducing costs. Other than classifying a certain appearance of the fabric, registration of the exact location of the defects and determining their type are also important. Inspection of 100% of fabric is necessary, first to determine its quality and second to detect any disturbance in the weaving process to prevent defects from reoccurring. The advantage for the manufacturer here is to get a warning when a certain amount of defect or imperfection occurs during the production of the fabric so that precautionary measures can be taken before the product hits the market [1]. It has been observed that, price of textile fabric is reduced by 45% to 65% due to defects [2] .Fabric faults or defects are responsible for nearly 85% of the defects found in the garment industry and manufacturers recover only 45-65% of their profit from seconds or off- quality goods [3]. Based on advancements in computer technology, image processing and pattern recognition, automatic visual inspection systems can provide reliable and stable performance.

The work of a human observer in the textile industry is very tedious and time consuming. They have to detect small details that can be located in a wide area that is moving through their visual field at a high speed. It has been reported that the identification rate is only about 70%. The effectiveness of a human observer decreases quickly with fatigue and boredom. Digital image processing techniques have been increasingly applied to textured sample analysis over the past few years.

The task of textile web inspection is particularly complex, since there exists a large variety of fabrics of different structures, compositions, colors, and other properties. Moreover, a massive irregularity in periodic structures of woven fabric introduces a very high degree of noise, which makes the identification and classification of defects difficult. Human visual inspection systems are still preferred in the textile industry since an alternate solution, reliable and versatile enough is not available yet. Owing to the very slow speed of human inspection compared to the production rate in modern manufacturing industries, automatic inspection systems are becoming more important than ever. Therefore, the research in this field is still wide open.

The techniques of morphological image processing are widely used for image analysis and have been a valuable tool in many computer vision applications, especially in the areas of automated inspection [4]. The morphological operations for defect detection in fabric are inherently sensitive to the size and shape of the defect. Therefore, while applying morphological image processing technique on the fabric image for the detection of defects, the software-based morphological operations may give poor result when the defects are relatively small in comparison to the fabric structure. Several techniques have been proposed to overcome this .

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2. BACKGROUND

The defects in fabric are generally classified into three subdivisions according to their occurrence in the fabric. They are, (i) weft-way defects (ii) warp-way defects and (iii) defects with no directional dependence. There are about twenty-two types of defects usually associated with woven fabric due to various processing irregularities. Out of these twenty-two, only few are severe defects and need elimination by rejection at the production stages. These are pick defects, slub or fly, knot, snarl and snug, reed mark or crack and thin place [5]. Apart from the above-mentioned major defects, mechanical defects such as hole piling, oil marks and other anomalies manifest themselves as defects in woven fabric. Numerous approaches were proposed to address the problem of detecting defects in woven fabrics, which can be broadly categorized into three classes: statistical, spectral and model based. Wang et al. [6] demonstrated that 90% of the defects in a plain fabric could be detected simply by thresholding. Table 1 summarizes a comparison between human visual inspection and automated inspection [7]. Zhang et at. [8] Have introduced two approaches to detect defects: gray-level statistical and morphological methods. Lanes [9] has defined a number of convolution masks to detect the defect. These methods, which depend on intensity change on the fabric image, can only capture significant defects such as knot, web, and slub.

TABLE I. Font Sizes for Papers

Inspection Type	**Visual inspection versus automated inspection**	
	Visual	**Automated**
Fabric Types	100%	70%
Defect Detection	70%	80%
Reproducibility	50%	90%
Objective Defect Judgment	50%	100%
Statistics Ability	0%	95%+
Inspection Speed	30m/min	120m/min
Response Time	50%	80%
Information Content	50%	90%+
Information Exchange	20%	90%+

In view of the high degree of periodicity for textile fabrics, Fourier transform based approaches were developed for defect detection by some researchers. Wood [10] has used Fourier and associate transform to characterize carpet patterns, while in [11], the method used is Histogram equalization followed by FFT and central spatial frequency spectrum analysis. It has been reported in the recent past that the detection capability is greatly improved by rank-order filtering which is otherwise termed as generalized morphological operations.

When a piece of textile fabric with defects leaves the production line, the locations, the shapes and the sizes of the defects normally cannot be predetermined. A conventional supervised defect detection approach developed on the basis of some particular defect types therefore may not be very suitable in practice and an unsupervised approach is usually preferred. However, the design of an unsupervised approach is rather complicated and the approach usually requires excessive computational efforts because of the large number of filters used. Thus, most of the algorithms for defect detection in woven fabric are computationally intensive and are less accurate, particularly in the presence of a number of patterns and print. The proposed algorithm is simple and more efficient for computer implementation. There is no mathematical complexity as in the other methods and hence there is a big saving in computational time also.

Page Layout

The margins must be set as follows:

- Top = 1.7cm
- Bottom = 1.7cm
- Left = 1.7cm
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Your paper must be in two column format with a space of 1.27 cm between columns.

3. PRE-PROCESSING

The main purpose of the preprocessing step is to correct the non-uniform illumination and image de-noising. The goal of illumination correction is to remove uneven illumination of the image caused by sensor defaults (vignetting), non uniform illumination of the scene, or orientation of the surface. Textile image pre-processing consists of correction of non-uniform luminosity and contrast enhancement. In this work we use a method of luminosity correction that is based on segmentation of background pixels and subsequent computation of luminosity function based only on the background image. The advantage of this approach is that it does not produce any ringing effect. All paragraphs must be indented. All paragraphs must be justified, i.e. both left-justified and right-justified.

4. Bitplane Decomposition

Slicing a digital image into its component bit planes is useful for analysing the relative importance played by each bit of the image. Instead of highlighting gray level images, highlighting the contribution made to total image appearance by specific bits is examined here [12]. In an n bit gray level image, each pixel in an image is represented by n bits. The image is composed of n, I-bit planes ranging from bit plane 0 (LSB) to bit plane n-l (MSB). In terms of n-bits, plane 0 contains all lowest order bits in the bytes comprising the pixels in the image and plane n-l contains all higher order bits. Thus bitplane decomposition of an n bit image yields n binary images. The grey level of each pixel in a digital image is stored as one or more bytes in the computer. When the grey level is represented as a single byte, it is called an 8 bit image, representing grey level values in the range from 0 to 255. The bit-plane decomposition of an 8 bit image is shown in Fig. 1.

In the pre-processed images of the textile fabric, bit-plane 0 and bit-plane 1 are found to carry vital information corresponding to the position and shape of the defects. Bitplane 0 of the chosen image is shown in Fig. 5. As bit-plane images are binary images, they are highly suited for morphological image processing.

In general, it can be seen that the higher order bit planes contain a majority of visually significant data while the lower order ones contribute to more subtle details in an image. But, on examining the eight bit planes of the pre-processed images, the lower order ones are found to be valuable for the detection of defects.

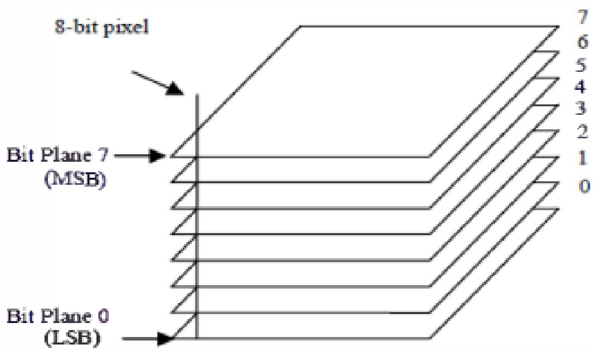
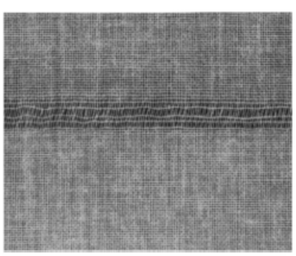


Fig.1 Bitplane Decomposition



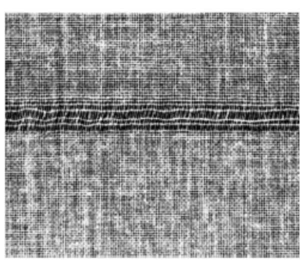
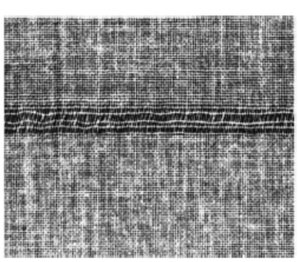


Fig.2 Original Image Fig.3 Contrast Enhanced Image



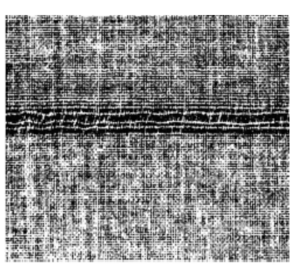


Fig.4 Histogram Equalized Image Fig.5 Bitplane 0

5. Morphological Operations over Bitplane

The language of Mathematical Morphology (MM) is set theory. Sets in MM represent objects in an image. MM is the science of appearance, shape and organization. MM deals with non-linear processes which can be applied to an image to remove details smaller than a certain reference shape called the structuring element[13]. MM is also the foundation of morphological image processing, which consists of a set of operators that transform images according to the above characterizations. The most widely used morphological operations used in image processing are dilation, erosion, opening and closing. Binary images are best suited for performing morphological operations. The images obtained after bit plane decomposition are binary images, which are thus suitable for performing morphological operations. MM was originally developed for binary images, and was later extended to grayscale functions and images. In MM, top-hat transform is an operation that extracts small elements and details from given images. There exist two types of top-hat transforms. The white top-hat transform, which is the difference between the input image and its opening by some structuring element, and the black top-hat transform which is defined as the difference between the closing and the input image. Top-hat transforms are used for various image processing tasks, such as feature extraction, background equalization, image enhancement and others [14]. Dilation is an operation in which the binary image is expanded from its original shape. The amount of expansion is controlled by the structuring element (SE). Dilation is similar to convolution, in which the structuring element is reflected and shifted from left to right and then from top to bottom. In this process, any overlapping pixels under the centre position of the structuring element are assigned with 1 or black values

If X is the reference image and B is the structuring element, the dilation of X by B is represented as

$$X \oplus B = \{Z \mid [(\hat{B})\, z \sqcap X] \subseteq X\}$$

Where $\hat{B}$ is the image B rotated about the origin. When an image X is dilated by a structuring element B, the outcome element Z would be that there will be at least one element in B that intersects with an element in X Erosion process is a thinning operation that shrinks an image. The extent by which shrinking takes place is determined by the structuring element. Here, if there is a complete overlapping with the structuring element, the pixel is set white or o. The erosion of X by B is given as

$$X \ominus B = \{Z \mid [(B)\, z] \subseteq X\}$$

In erosion, the outcome element Z is considered only when the structuring element is a subset or equal to the binary image X Note that dilation and erosion on binary images can be viewed as a function of convolution over a Boolean algebra of operations (NOT, AND, OR, XOR), which are defined between pixels of corresponding locations in two images of equal dimensions.

Opening operation is done by first performing erosion, followed by dilation. Opening smoothens the inside of object contours, breaks narrow strips and eliminate thin portions of the image. It is mathematically represented as

$$\mathbf{X \circ B = (X \ominus B) \oplus B}$$

Closing operation does the opposite of opening. It is dilation followed by erosion. Closing fills small gaps and holes in a single pixel object. The closing process is represented by

$$\mathbf{X \cdot B = (X \oplus B) \ominus B}$$

Closing operation protects coarse structures, closes small gaps and rounds off concave comers. It is well-known that the opening operation will smooth contours, breaks narrow isthmuses, and eliminates small islands and sharp peaks, while the closing operation will smooth contours, fuses narrow breaks and long thin gulfs, and eliminates small holes.

Morphological operations are widely used in the detection of boundaries in a binary image. For an image X, the following can be applied to obtain a boundary image

$$\mathbf{Y = X - (X \ominus B)}$$

$$\mathbf{Y = (X \oplus B) - X}$$

Or

$$\mathbf{Y = (X \oplus B) - (X \ominus B)}$$

Where, the operator '$\oplus$' denotes dilation, ' $\ominus$ ' denotes erosion and '- ' indicates set theoretical subtraction.

Weighted dilation (WDI) and weighted erosion (WER) are defied in [15] as

$$\mathbf{WDI\ (k, l) = max\ (X\ (k - u, l - v)\ X\ B\ (u, v)\}}$$

and

$$\mathbf{WER\ (k, i) = min\ (X(k + u, l + v)/B(u, v)\}.}$$

Operations such as weighted opening (WOP) and Weighted closing (WCL) are simple cascades of WER and WDI. This can be described as

$$\mathbf{WOP(X) = WDI\ (WER(X)\}}$$

and

$$\mathbf{WCL(X) = WER\ (WDI(X)\}.}$$

Weighted open-closing (WOPCL) and weighted close-opening (WCLOP) are denoted as

$$\mathbf{WOPCL(X) = WCL\ (WOP(X)\}}$$

and

$$\mathbf{WCLOP(X) = WOP\ (WCL(X)\}.}$$

The structuring element B has a normalized weight factor and its elements are calculated such that the edge directional points' weights are assigned 1 and the farthest points' weights are assigned with a weight factor w > 1, leading to an emphasis on the effect of edge directional points and a reduction of the effect of the neighborhood points. The rest of the weights are calculated based on an increment

$$\mathbf{\Delta\omega = (\ \omega - 1)/d}$$

where d denotes the distance between the edge directional points and the farthest points from the edge directional points. In vertical and horizontal directions, the weight decreases by $\Delta\omega$, each step starting from the edge directional points. If pixels in the edge corresponding to a defect are present, a high weight factor in B is applied and if it does not exist, a low weight factor in B is put. Once B is fixed, adaptive weighted matrix is adopted to detect the edge corresponding to the defect. The results are that if structuring elements are defined properly, texture background can be removed easily by the opening and closing operations. Also, the defect images left behind will be sharpened by the operations. Hence, alternating sequential filters can be constructed by combining a number of openings and closings.

Most binary morphological operations have natural extensions to gray scale processing. Some, like morphological reconstruction, have applications that are unique to gray scale images, such as peak filtering.

6. Proposed Methodology

The image after pre-processing becomes an illumination corrected and de-noised one. Now contrast of the pre-processed image is further enhanced by a combination of top-hat and bottom-hat transforms. In order to achieve this, the original image obtained after pre-processing is added to the top-hat filtered image, and then the bottom hat filtered image is subtracted from it. Then a histogram equalization operation is performed on this image. Figure 3 shows the contrast enhanced image after applying a combination of top-hat and bottom hat transforms while Fig. 4 shows its corresponding histogram equalized image. Later on, bit plane slicing is performed on this to decompose it into its component bit planes. The lower order bit planes are preserved for further processing and the higher order ones are discarded. Figure 5 shows bit plane 0 for a representative image. Now a series of weighted morphological operations are applied on this image. Bit plane 0 is now complemented and opened by a disc shaped structuring element to obtain a white region corresponding to the defect in the woven material such as shown in Figure 6.

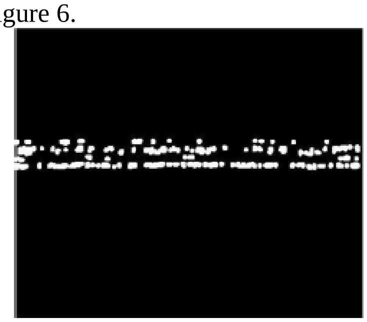


Fig.6 Opened Bitplane 0

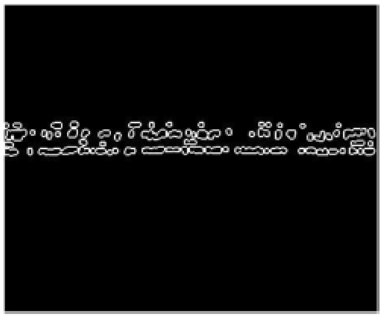


Fig.7 Dilated Outline

The Matlab function bwperim is used to obtain the outline of the defect. This outline is subsequently dilated by a carefully selected structuring element to obtain an image as shown in Figure 7. Finally, the fabric defect can be localized by superimposing the outline on the original grayscale image as shown in Figure 8.

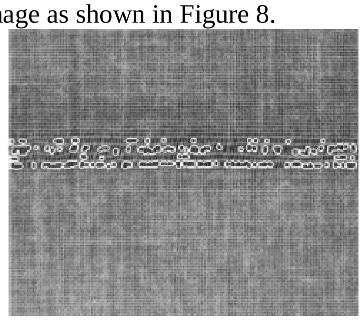


Fig.8 Defect Marked Image

The algorithm has been implemented by using Matlab version 7.9 (Release 2009 b) and is found to be reasonably fast and accurate than the existing computationally intensive methods. The results are promising even when it is applied to localize defects on images with varying lighting or exposure levels. The algorithm has been tested and compared with the commonly used methods and the results show that the method proposed here can not only detect defects but also provide more acceptable location of the defect.

7. Result Analysis

Industrial manufacturing of materials such as fabric, paper, wood, leather, etc. requires a large number of inspection tasks concerning the visual appearance of the material surface (texture, color, fault detection, etc.). The task of textile web inspection is particularly complex, since there is a large variety of fabrics of different structures, compositions, colors, and other properties. Quality control in the textile industry involves, among other tasks, the detection of defects that cause a distortion of the basic structure of the material, which generally shows a high degree of periodicity. Numerous techniques of image analysis have been proposed for this purpose. If the fabric sample exhibits an overall distortion, Fourier-domain-based techniques allow one to obtain successful results to detect shrinking, abrasion and skewness. If the sample has local defects such as holes, stains, broken threads, etc., then it is a common practice to apply methods based on wavelet transforms, used as multi resolution spectral filters that localize and analyze features in both the spatial and the frequency domain. Some other tasks concerning pattern recognition, weave-repeat identification and classification can also be performed using techniques based on Fourier analysis.

In general only uniformly colored materials are usually considered because, the existence of hierarchical structures given by bands, squares, circles, or drawings of varied colors along with the basic woven structure of the material makes the inspection more difficult.

We, human beings, have a unique capability to easily find imperfections in spatial structures. Our visual mechanism works well even when we do not know what the ideal pattern is and what the possible types of defects are. Just by looking at a relatively regular structure containing an imperfection, we can usually identify what is wrong there. But human inspector based defect detection is subject to errors for many reasons.

There are large influences of human errors and subjectivity on the results of inspection. Presence of other factors such as noise, non-uniform illumination and variety of defect types in textiles make the defect detection a challenging problem. Due to these reasons, an expert system for the automatic detection of such anomalies has inspired much research in this direction. The performance of the proposed defect detection scheme has been extensively evaluated by using an off-line test database, which consists of a variety of fabric defects including (1) different types, sizes, and shapes of defects, and (2) different texture backgrounds. The test results obtained have shown that this scheme is a simple and effective defect detection method. This algorithm is more efficient for automation. There is no mathematical complexity as in other methods and hence there is a significant reduction in computational load also. Moreover, this method does not just detect the defect but the shape and size of the defect also. It extracts most defect pixels accurately.

The algorithm is found to be superior to the existing ones in terms of computational speed and accuracy. Several images with different types of defects were also tested using the algorithm. The false alarm rate is found to be 2.2% for the test data set. Our algorithm has an average accuracy of 93.2%. The main attraction of the proposed method is its simplicity, accuracy and computational time. This algorithm demonstrates its strong ability to differentiate defects from other regions in the image even in the presence of certain prints in the fabric. The method works pretty well even when the input image is a low-contrast one. The experimental results demonstrate that the proposed algorithm is fast and robust.

Table 2

Correlation	No. of Samples
True detection	92.67%
False alarm	05.90%
Missed Detection	02.33%

The performance of the scheme is evaluated by visually assessing the quality of the binary output images. True detections (TD) are recorded when (1) the white areas of the binary output image only overlap the areas of the corresponding defects in the fabric image, and (2) no white area appears in the binary output image if the fabric image contains no defect. False alarms (FA) are recorded when the white areas appearing in the binary output image do not only overlap the areas of the corresponding defects in the fabric image, but also appear in some other areas significantly distant from the defect areas, or when white areas appear in the binary output image when the fabric image contains no defect. Overall detection (OD) is the sum of TD and FA. Missed detection (MD) means that no white area appears in the binary output image even if the fabric image contains a defect. Table 2 summarizes the test result.

Further research can be conducted to apply the proposed scheme to detect defects in other products, such as non-woven fabrics, wood or metal castings. In addition, the possibility of developing faster methods of morphological filtering for implementation in the proposed scheme may also be investigated.

8. Conclusion

A method for defect detection and localization in woven fabric is proposed in this paper based on bitplane decomposition and weighted morphology. The algorithm is superior to the existing ones in terms of computational time and accuracy.

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