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Detection of Defects in Fabric by Morphological Image Processing

Asit K. Datta¹ and Jayanta K. Chandra²

¹*Department of Applied Optics and Photonics, University of Calcutta, Kolkata 700009*

²*Future Institute of Engineering and Management, Kolkata 700150
India*

1. Introduction

Defects are generated in woven fabric due to improper treatments in weaving machines, spinning errors and inadequate preparations of fiber at the spinning stage. The economic viability of a weaving plant is significantly influenced by the extent of its success in eliminating defects in fabric. Detection of defects is generally carried out by time consuming and tedious human inspection. Such manual inspection procedures are commonly agreed upon to be inefficient with detection efficiency suffering from deterioration due to boredom and lack of vigilance. The problem is accentuated by the presence of several types of defects those may occur in woven fabric at random.

In textile industry, imaging and image processing techniques are investigated for off-line and on-line visual inspection of fabric for the detection of defects (Zhang & Bresse, 1995; Drobino & Mechnio, 2006). The basic philosophy of detection of defects by such techniques is guided by the analysis of the image of fabric for distinguishing properties, those can be used to discriminate between defective and first quality fabric. In most cases, measurements are made on the first quality fabric and are then compared with the measurements made on the test fabric. Severe deviations in the measured parameters are used to indicate the presence of defects. Defects are then categorized into several types. However, the recognition of a particular type of defect amongst various classified types always remains a problem even in the context of presently available advanced image processing technology. Moreover, massive irregularities in periodic structures of woven fabric (particularly for fabrics manufactured from natural fibers) introduce very high degree of noise, which make identification and classification of defects difficult. The problem is accentuated very much due to the hairiness of natural fibers.

Elaborate image processing algorithms are usually adopted for detection and recognition of defects (Sakaguchi et al, 2001). Recent reviews are available on various techniques, those can be applied for such tasks (Xie, 2008). In this chapter we are interested to explore one of such techniques which can be termed as morphological image processing, for the detection of defects in woven fabric.

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 area of automated inspection (Haralick et al, 1987). Many successful machine vision algorithms used in character recognition, chromosome analysis and finger print classification are based

on morphological image processing techniques (Maragos, 1987). It has relevance to conditioning, labeling, grouping, extracting and matching operations on image (Dougherty, 1993). Thus, from low level to high-level computer vision, morphological techniques are important in operation such as noise removal and median filtering (Heijmans, 1994). Indeed many successful machine vision algorithms employed in industry, processing thousands of images are based on morphological techniques.

For the quality control in the textile industry, the technique of morphological image analysis has been used for assessing fiber composite material (Serra & Verchery, 1973) and carpet appearance (Xu et al, 1991) and texture analysis (Wermen & Peleg, 1985). Morphological image processing based technique has also been investigated for detection and classification of defects in fabric (Chetverikov & Hanbury, 2002). 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. The testing involves two stages of operations. First a structuring element is selected from the heuristic knowledge of the likely defects. Secondly, the test image is thresholded and then morphological operations are applied on the thresholded image of the test fabric for the identification of defects.

1.1 Types of commonly occurring defects in woven fabric

The defects in fabric are generally classified into three subdivisions according to the 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 severe defects are:

- a. **Broken pick, short pick, double pick and pick' inhomogeneity:** These defects are sometimes referred to as mispick (float) or missing pick and result in a void in the fabric due to missing yarns. Sometimes, two adjacent threads with same interlacing are beaten up together as a result of broken picks. Double pick defect is mainly due to extraneous thread in the fabric.
- b. **Slub (fly):** These defects usually appear in the fabric as abnormally thick places of varying length.
- c. **Knot:** These defects usually appear in fabric as hardly discernible change in yarn thickness. Knots in fabric usually arise due to fastening of yarns.
- d. **Snarl and snag:** A defect, where warp or weft yarns are twisted on itself and the loop is termed as snarl. A snag is produced when one or more pick is snagged on a knitted yarn.
- e. **Reed mark (crack):** It is due to improper irregular interspacing of yarns and appears as a transparent strip.
- f. **Thin place:** This defect arises out of insufficient density of yarns.

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.

In general, all defects alter the normal regular structure of fabric pattern and also modify the statistical and physical properties of the first quality fabric. The effects of defects are also dependent on the textural types of woven fabric.

2. Morphological image processing operations

Mathematical morphology is a tool for extracting image components that are useful in the representation and description of region shape (Serra, 1988). As a discipline within imaging, mathematical morphology concerns with the applications of its basic operators in all aspects of image processing. Conceptually, morphological operations are rooted in planar geometric structure which is altered by probing with a structuring element. Each operation uses the structuring element to determine the geometrical filtering process, satisfying four properties: translation invariance, antiextensivity, increasing monotonically and idempotence. The structuring element of a morphological operator is therefore a function defined in the domain of the spatial pattern. The value of each pixel of the domain is the weight or coefficient employed by the morphological operator at the pixel position.

The concepts of image processing using mathematical morphology were developed mainly as an application of set theory (Matheron, 1975; Serra 1988; Heijmans & Ronse 1990). The evolution of the theory closely follows the evolution and applications of pipeline and cellular computing techniques (Danielsson & Levialdi, 1981). By nineties many image-processing algorithms for morphological operations are evolved using electronic and optical techniques (Liu, 1989; Casasent, 1990; Botha et al, 1989; Mallick-Goswami & Datta, 2000). Optical morphological image processing was also applied for feature extraction and shape description (Gracia et.al, 1993).

The morphological image processing technique has its roots in texture analysis and in the problems of determining properties of the texture. Its underlying idea is to use a so-called structuring element to define neighbourhood of points in an image. Operations with the structuring element may smooth the contours of the objects or may decompose an image into its fundamental geometrical shapes. Morphological operations can be applied not only on binary image but also on gray level images (Vincent, 1993).

Fundamental morphological operations are erosion and dilation. These operations remove or add pixels from a binary image according to rules that depend on the pattern of the neighboring pixels. The erosion operation reduces the size of an image, while the dilation operation enlarges geometrical size the image. Two other derived morphological operations are opening and closing. An opening is an erosion operation followed by dilation, and a closing operation is a dilation followed by an erosion operation. Each of these operations uses the structuring element to determine the geometrical filtering process.

In morphological operations, the choice of structuring element is very critical and is generally guided by apriori knowledge of processing tasks. However, there are several studies, where the selection of structuring element is guided by a training phase for a particular situation (Camps et al, 1996).

2.1 Binary morphological image processing operations

We restrict ourselves to the specific case of a gray fabric image $F:Z \rightarrow \bar{R}$ defined on a subsection of the two-dimensional Euclidean space R^2 . The notation $\bar{R}$ indicates the set $R \cup \{-$

$\infty, +\infty$. In other words, the function assigns a grey-level to each point $x \in Z$ of the fabric image. In practice, however, the Euclidean space is replaced by a discrete space Z^2 . The gray values taken by F are often limited to integers and the pixel value at position x is denoted by $F(x)$. For 8 bit gray scale images, $F(x): Z \rightarrow \{0, 1, 2, \dots, 255\}$.

The morphological operations are defined as set operations and can be applied for processing of fabric images by defining another selected image S called structuring element. Therefore S is a subset in the two dimension Euclidean space. S can be a binary image or a gray image. The classical Minkowsky set addition and subtraction of these two images F and S are defined in set notation as,

$$\text{Addition: } F \oplus S = \{x+a: x \in F, a \in S\} = \bigcup_{a \in S} F_a = \bigcup_{a \in S} S_a \mid F \in S \quad (1)$$

$$\text{Subtraction: } F \ominus S = \bigcap_{a \in S} F_a \quad (2)$$

where F_a is the translate of the image set along a and is defined as,

$$F_a = \{F + a : x \in F\} \quad (3)$$

The transformation $F \rightarrow F \oplus S$ and $F \rightarrow F \ominus S$ are called a dilation and erosion operation by structuring element S . According to standard convention the morphological dilation operation on the image F by the structuring element image S is given by,

$$\text{Dilation: } F \oplus \bar{S} = \left\{ h \in E : (\bar{S})h \cap \frac{F}{\phi} \right\} \quad (4)$$

$$\text{Erosion: } F \ominus \bar{S} = \{h \in E : S_h \subseteq F\} \quad (5)$$

where h is an element in Euclidean space and, ϕ denotes the empty set.

The reflected or the symmetric set $\bar{S}$ is related to S by the following equation,

$$S = \{-a : a \in S\} \quad (6)$$

Self complementation of the set yields a duality relation and the dilation operation is also expressed as:

$$F \oplus \bar{S} = (F^c \ominus \bar{S})^c \quad (7)$$

where, F^c is the complement of the set constituting the image F .

By definition, morphological opening is erosion followed by dilation and the closing operation is viewed as the complimentary process of opening. Therefore, the opening and closing operation are denoted in set notation as,

$$\text{Open: } (F, S) = (F \ominus \bar{S}) \oplus \bar{S} \quad (8)$$

$$\text{Close: } (F, S) = (F \oplus \bar{S}) \ominus \bar{S} \quad (9)$$

The opening is the union of all translates of the structuring element that is included in the set F . It may be noted that both opening and closing operations are translation invariant. Opening and closing are related to Boolean duality by,

$$\text{Close: } (F, \bar{S}) = \text{open: } (F^c, S)^c \quad (10)$$

2.2 Gray morphological image processing operations

Binary morphological operations are performed for the sets whose elements are vectors corresponding to pixel positions and therefore are *set-set operations*. A grayscale image can be considered as a three-dimensional set where the first two elements are the x and y coordinates of a pixel and the third element is the gray-scale value. The key issue is to use the infima/suprema (minima and maxima in discrete cases) to define gray-scale morphological operators (Chu-Song et al. 1999; Heijmans 1999). The structuring elements of the gray-scale morphological operations could have the same domains as those in binary morphology. However, a gray-scale structuring element is also possible having certain values instead of having only value 1 or 0. Therefore, morphological operation of gray scale images with binary structuring element is a function-set operations and the operation for gray images and gray structuring element are function-function operations (Sternberg, 1986). The pixel value of a gray fabric image F at position x is expressed by a function $f(x)$. The gray scale erosion and dilation with as binary structuring element S can then be defined as,

$$\text{Function set erosion: } [f \ominus \bar{S}](x) = \inf_{x \in S_x} f(x) \quad (11a)$$

$$\text{Function set dilation: } [f \oplus \bar{S}](x) = \sup_{x \in S_x} f(x) \quad (11b)$$

However, in case of operations with gray scale structuring element g^S , the gray morphological operations are defined as,

$$\text{Function – function – erosion: } [f \oplus g^S](x) = \max_{y \in G} \{f(x+y) + g(y)\} \quad (12a)$$

$$\text{Function – function – dilation: } [f \ominus g^S](x) = \min_{y \in G} \{f(x+y) - g(y)\} \quad (12b)$$

Gray-scale opening and closing are defined in a similar manner as the binary case. The only difference is, when the operations are carried out, these opening and closing operations use gray-scale dilation and erosion. As binary morphological operations do, gray-scale opening is anti-extensive and gray-scale closing is extensive. Both operations make an original image smooth along to the nature of minimum and maximum functions.

3. Morphological operations on image of fabric

It is evident that F is the image of test fabric and S is the image of structuring element, which in most of the cases is a binary image. Selection of structuring element image is important in morphological image processing for defect detection in fabric. A particular defect in the fabric image can be detected by eroding the image with a structuring element that is slightly

smaller than the shape of the defect. For example, if the dimension of the structuring element is made slightly smaller than the average dimension of a knot, then the erosion operation of the fabric image with the structuring element will result in the complete elimination of the weft and warp structure. However, the selection of structuring element is not easy for the detection of thick yarn as the yarn may run through out the entire length of the fabric.

While applying the binary morphological image processing operations as defined, it is necessary to obtain binary image of the fabric. Segmenting the gray level pixel values of fabric image into two gray level values are all that is required to produce a binary image of fabric. Let, $I(i, j)$ is the gray level pixel value at point (i, j) of the input fabric image and $F(i, j)$ is the gray level of point (i, j) of the output fabric image. The binary image is obtained from the gray level image by converting the pixel value to 1 (white pixel) if the value is greater than the preselected threshold value: otherwise the pixel value is returned to 0 (black pixel). It is assumed that the threshold value does not depend on the spatial coordinates (i, j) and also threshold value is independent of local properties of the point.

3.1 Extracting defects from image of fabric

Detection of defects by morphological operators are carried out for few test samples of woven fabric. For example, three types of typical defects such as a knot (fig. 1a), thick weft (fig.1b) and missing weft (fig. 1c) are subjected to morphological operations with a 3×3 structuring element. Since the fabric images are gray images, gray to binary image conversion by thresholding is necessary for defect detection. The thresholded binary images are shown in figures 1d, 1e and 1f. The morphological erosion and opening operations on the thresholded images are shown in set of figures 1g, 1h and 1i and figures 1j, 1k and 1l. It has been observed that a rectangular structuring element of 3×3 pixel size is sufficient for extracting the defects such as knot from the test fabric either by erosion or by opening operations. However, in case of detection of thick weft by opening operation is not very efficient though the detection is better than erosion operation. The detection of missing weft by erosion and opening operations needs higher size structuring element. A 5×5 rectangular structuring element gives better results than using a 3×3 structuring element. This is because of the continuity of the defective yarn throughout the length / breadth of the test fabric.

From the results, it is shown that the presence of knot and thick yarns are detected more clearly by the erosion operation than the by opening operation. However for opening operation a structuring element of 5×5 is used. The detection of missing weft by erosion and by opening operations, however, is hopelessly useless even by using structuring elements of higher areas.

3.2 Morphological operations by removal of interlaced grating structure of fabric

While detecting defects of various sizes in test fabrics, the results of morphological operations are much better, if the basic grating structure of the fabric due to weft and warp interlacing is removed by spatial filtering. To accentuate the gray values of the pixel positions of defects and to properly distinguish them from the cross-points, it is necessary to process the fabric image with a view to smooth out or remove the cross points. The processing is done by optical or digital spatial filtering of the de-noised image F_{dn} to yield the spatial filtered image F_{sf} . A binary fabric image F_b can then be obtained from the spatial

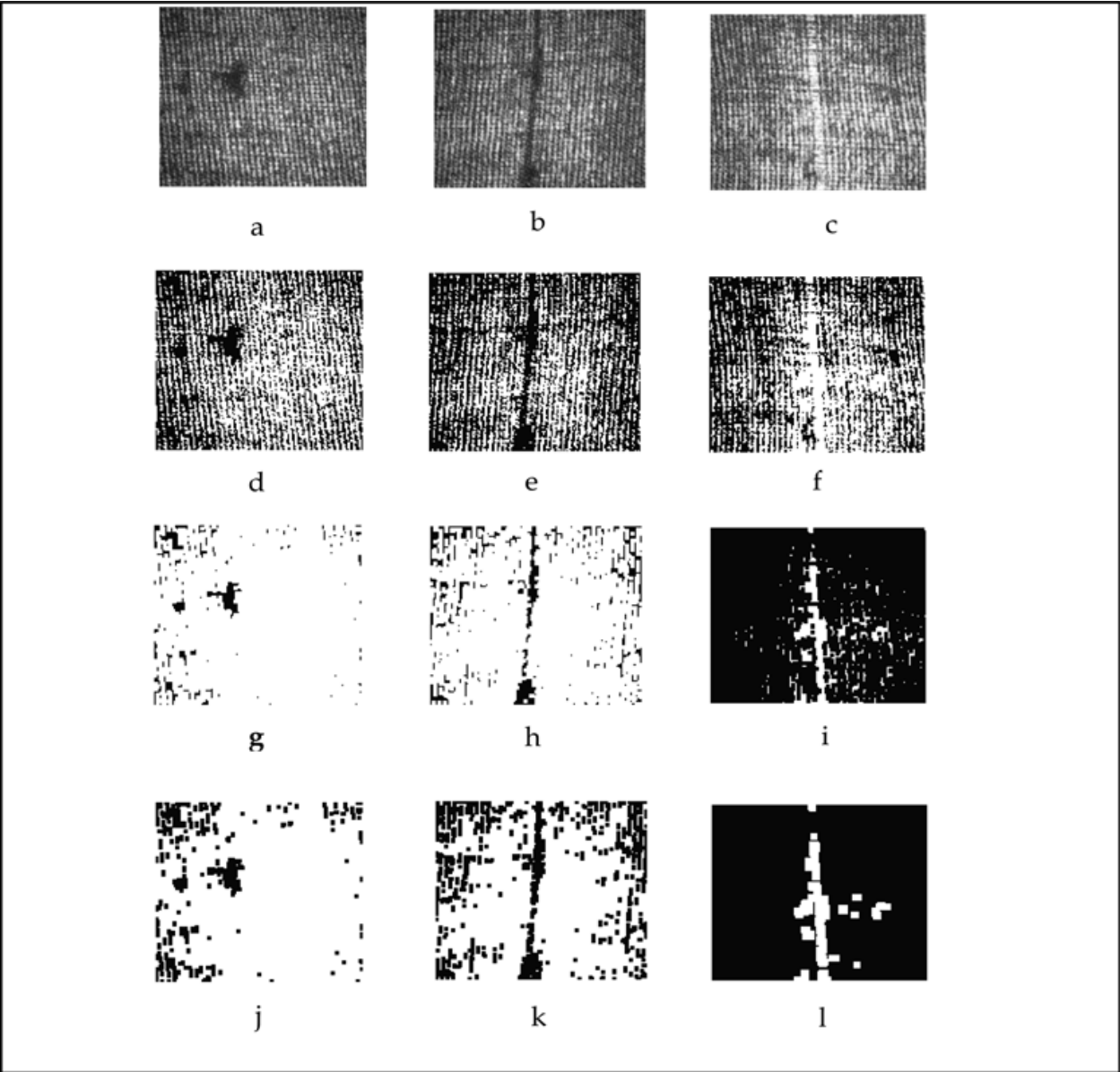


Fig. 1. Test fabrics with defects (row 1), thresholded images (row 2) and results of defect detection by morphological erosion (row 3) and opening operations (row 4).

filtered image, when the pixels are converted to either 1 or 0, if it is above or below a pre-selected threshold value P_{th} . Therefore, $F_b=1$, if $F_{fs}>P_{th}$ and $F_b=0$ if $F_{sf}<P_{th}$. The threshold value P_{th} is however, depended on the type of fabric.

The test results of morphological operations after the removal of grating structures of fine, medium and coarse fabric are shown in Fig. 2. Some general conclusions can be drawn from the results. It is not possible to remove the grating structure of warp and weft yarns by digital spatial filterig, particularly for coarse fabric when the size of defects are comparable or slightly bigger than the yarn diameter (row 2 of fig. 2). In fine and medium fabrics, it is possible to remove the interlaces grating completely by suitably selecting the diameter of spatial filter and the threshold value. For defect detection opening, dilation, erosion and closing operations are performed. The type of morphological operations to be performed depends on the types of defects present in the test fabric. The result follows the expected

pattern for long defects, since the connectivity of the yarn in the whole image set is higher than that of the defects. In fig. 2, for the detection of defect present in the first type of test fabric opening operations are carried out. For defects in the second, third and fourth types, dialtion, erosion and opening operations are carried out respectively.

4. Morphological filtering operations for noise removal from fabric image

Before applying the morphological operations for the detection of defects in woven fabric, the gray fabric image F is *de-noised* by using morphological filtering technique. This preprocessing is necessary particularly for cotton fabric, where the presence of hairiness is more likely to occur. Since noise in an image should be removed wherever it is located, the translation invariance property of filter is required for noise removal. Translation invariant operations are justifiable also for a fabric image where noise in the image is dimensionally

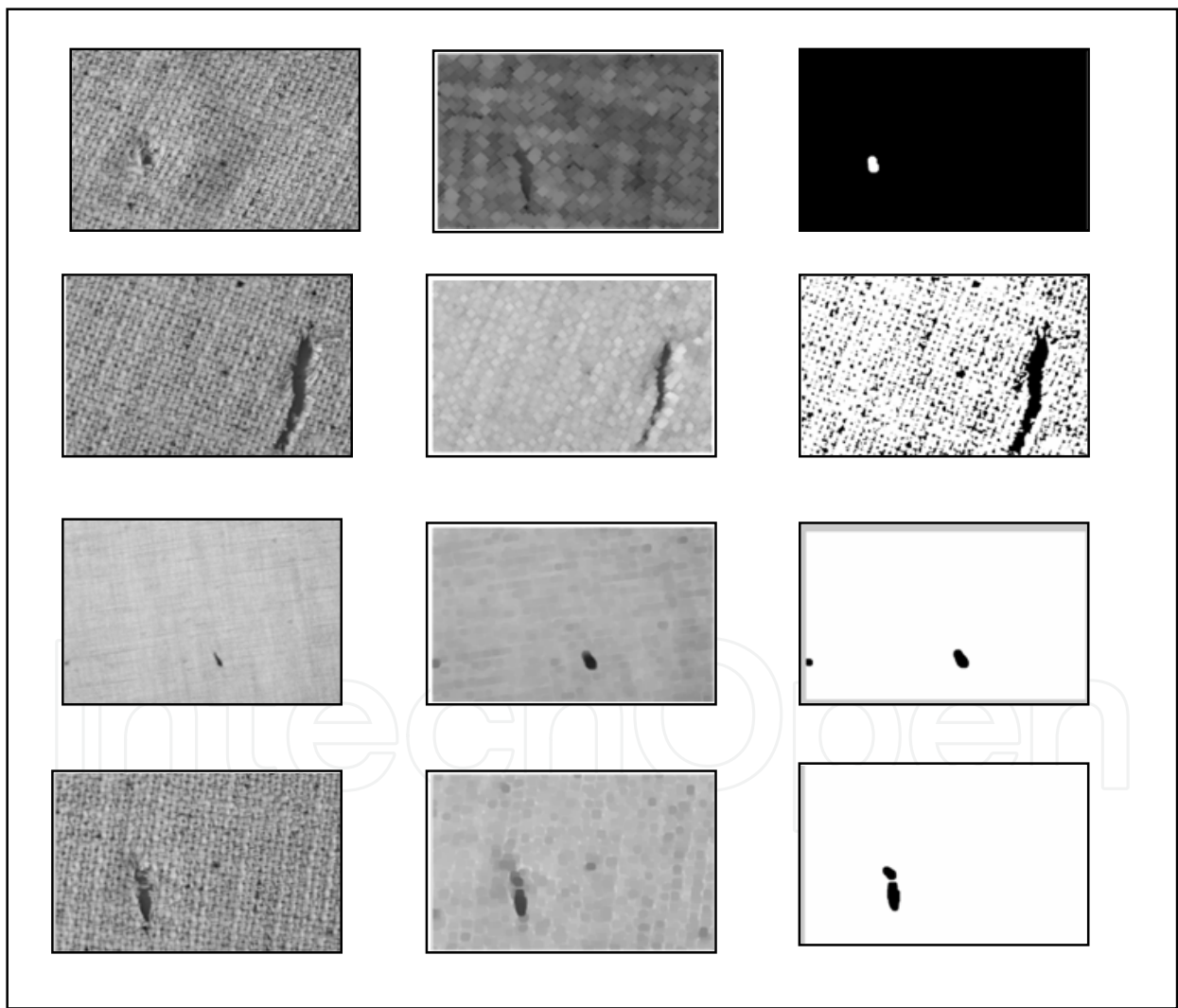


Fig. 2. Test results of morphological operations after removal of interlaced grating structure. Column 1 shows the images of test fabrics, column 2 shows the spatially filtered images of column 1. Column 3 shows the detection of defects by morphological operations on images of column 2.

smaller than the defects. The morphological filter, which can be constructed on the basis of the underlying morphological operations, are more suitable for noise removal than the standard linear filters since the latter sometimes distort the underlying geometric form of the image (Maragos & Schafer, 1987). Therefore, these filters are more suitable for noise removal (Podaru & Stanomir, 2003).

The morphological filtering is restricted to all image-image transformations that are translation invariant and increasing idempotent operations characterized by $\phi[\phi(F)] = \phi(F)$, where ϕ is an operation. The filter $\phi(F)$ is decomposed into OR operation of erosions by a structuring element S and is expressed as,

$$\phi(F) = \bigcup_{S \in \ker[\phi]} F \ominus \bar{S} \quad (13)$$

where F is a fabric image and $\ker[\phi]$ is the kernel of ϕ given by, $\ker[\phi] = \{F \mid 0 \in \phi(F)\}$.

Extensivity and anti-extensivity of the operations are not always useful for practical situation of noise removal. Since median filter is not extensive or anti-extensive, but handles white objects and black backgrounds equivalently, morphological representation of median filter is very useful for de-noising. The cascades of opening and closing with an elementary (2×2) binary structuring element S is used for this purpose. Since the structuring element is symmetric, reflection of S is the S itself. The de-noised image F_{dn} is obtained from gray fabric image F by the following processing steps:

$$\text{open}(F) = (F \ominus S) \oplus S \quad (14)$$

$$F_{dn} = \text{close}[\text{open}(F)] = ([\text{open}(F)] \oplus S) \ominus S \quad (15)$$

By this process most of the noise present in the fabric image is removed while maintaining the shape and size of the defects almost intact.

5. Rank order operator: generalized morphological operations

The detection of small defects such as knots and broken picks in woven fabric is difficult because of the presence of confused background due to the interlaced periodic structure of the warp and weft, which result a large number of almost regular crossover points. Moreover, hairiness of the fabric introduces high dose of noise into the image pattern of the fabric.

In the Section 3, it has been shown that the morphological erosion operation can erode the grating structure of the fabric to a certain extent and might be suitable for the identification of defects. However, complete erosion of the background is not possible unless very judicious choice of the structuring element is made. For detection of defects of small size in woven fabric, simple morphological erosion operation with a comparatively large structuring element is not efficient. In such cases, there are always chances of complete erosion of the image. Dilation also may cause the entire cross point background of the image to fill in resulting in a completely dark search space (background). In many cases, there is a need to erode first by a small structuring element and then apply a larger one. This may somewhat solve the problem, however this is not always possible, particularly for the detection of defects in fabric where the failure rate of such a solution is frustratingly high.

It is shown in this section, that the binary rank order operation (Heygster, 1980; Arce & Foster, 1989) gives satisfactory result when the expected size of defect is considered in

selecting of structuring element. Moreover, the rank order operator has unique property of image smoothing and presenting edges and at the same time it is very efficient for noise removal. In a woven fabric, repetition of the interlaced grating structure is not very accurate and therefore rank order operation proves to be an efficient tool for defect detection.

It may be noted that the rank-order operator is a generalization of the morphological erosion and dilation operations. Erosions and dilations are convolutions with maximum and minimum threshold value respectively. Therefore rank order operations require a structuring element as well. Rank order operator rotates in planar geometric structure, which is altered by probing with a structuring element called reference image. Each operation uses the reference image to determine the geometrical filtering process. The reference image or the structuring element of the operator is therefore a function defined in the domain of the spatial pattern of the operator.

5.1 Binary convolution operation

The rank order operation can be performed by a linear convolution between input image and reference image (structuring element image) followed by thresholding of the convolution output. Simplest image convolution operation of image is a process that copies one image at each pixel location of another while allowing for the effects of all pixel values in the area where the copy takes place. A multiplying, adding and shifting operation accomplish this. A convolution $c(p)$ of a binary fabric image $F(u)$ by structuring element $S(u)$ is given by,

$$c(p) = \sum_u F(p-u)S(u) = F * S \quad (16)$$

where, p and u are two-dimensional spatial vectors, $u, p \in Z^2$, and the summation is over the Z domain of the image.

5.2 Binary nonlinear rank order filter

In recent years, several rank-order structuring filters are proposed. These filters are roughly divided into two categories. The set of adaptive rank-order filters fall under the first category (Lee & Fam, 1987), while the second class encompasses structure preserving rank-order filters (Niemnien et al, 1987). Adaptive rank-order filters are used on images with low signal-to-noise ratios and some a priori knowledge or local statistics are required for processing (Stevenson & Arce, 1987). The main advantage of the non-adaptive type lies in the fact that the extensive use of local statistics is not necessary.

The rank order filter while applied on binary image is also called an order statistic filter or a Ξ filter (Preston, 1983). A binary rank order operations can be replaced by operations of counting the number of image points that contacts the points of the structuring element probe and marks the reference point in the output image if at least a given percentage of points contact the probe. The percent point or the threshold is a variable and is adjusted for good performance in a particular application.

Widely employed nonlinear and locally adoptive filters are rank order filters. The threshold operation X_t is applied to eq.16, at threshold t , to get the output result after rank order filter operation and is given by,

$$R_t(F,S)(p) = X_t\left(\sum F(p-u)S(u)\right) = X_t(F * S) \quad (17)$$

For a rank order operator R_t expressed in this form, threshold t is the rank. The threshold operation X_t is performed under the conditions that,

$$X_t = \begin{cases} 1 & \text{if } c(p) \geq t \\ 0 & \text{otherwise} \end{cases} \quad (18)$$

5.3 Choice of the proper rank of the rank order operator

Two problems are encountered while applying the rank order operator for defect detection in fabric. They are related to the (a) choice of reference image (i.e. structuring element) and (b) the choice of the rank. The value of each pixel of the domain is the weight or coefficient employed by the pixel position. The selection of the size and shape of the reference image is hence an important step for defect detection. When the size of the reference image is almost same to the size of the defect to be detected the most efficient and optimum detection capability is expected. Evidently the size of the domain can be ascertained from priory knowledge of the likely defect in woven fabric.

The rank selection is based on the boundary characteristics. One of the most important aspects in selecting a rank is the capability of reliably identifying the mode peaks in a given image histogram. This is particularly important for automatic threshold selection in situations where image characteristics can change over a broad range of intensity distributions as in the case of woven fabric. Therefore the rank of the operator has to be decided also from a priori knowledge of the periodicity of the fabric structure and the diameters of the warp and weft yarns.

The rank of a particular operation is a function of the reference image or the structuring element S and the intensity values of the test fabric F . A simple relation is established between the rank R and the dimension D of the structuring element S and the maximum value M of the convoluted matrices for quick selection of a rank for a particular operation. The relation is given by,

$$R = 255(k)(D) - M \quad (19)$$

where, k is a positive low value and M is obtained by dilation operation as $M = \max(F \oplus S)$.

If F (the test fabric) is a $(m \times n)$ matrix and if S (the structuring element or the reference image) is a $(m_1 \times n_1)$ matrix, then the convoluted matrix has dimension $(m \times n) \times (m_1 \times n_1)$. So the dimension of the output matrix increases correspondingly. The conversion of $(m \times n) \times (m_1 \times n_1)$ matrix to $(m \times n)$ output matrix eliminates the data outside the region of interest.

5.4 Defect detection of fabric by rank order operator

Fig. 3 shows the presence of a knot, oil mark and thick yarns respectively, as defects in the test fabrics. A structuring element of size 15×15 is used for rank order filtering of the basic grating structure of the fabric at the value of $k = 0.657$.

It is seen that the knot is extracted efficiently (fig. 3, first column). In contrast to the erosion operation (Fig 2), the size of the knot is not reduced and is maintained in the detection process of the rank order filtering. The oilmark is also detected as defect by the same process (fig. 3, second column). The detection of thick yarns in the test image of fig. 3 is shown in third column. A scrutiny of fig. 3f will shows the existence of not only a thick weft at the

bottom but also the existence of a slightly thicker yarn (weft) on the upper portion of the fabric. Also existence of the defect of slightly thicker yarn escapes visual inspection and the can not be detected by morphological operations described in sections 3 and 4. However, by selecting an elongated structuring element 4 X 132 and the value of $k = 0.657$ (which matches closely the diameter of the yarn) and the defect is detected by rank order filtering.

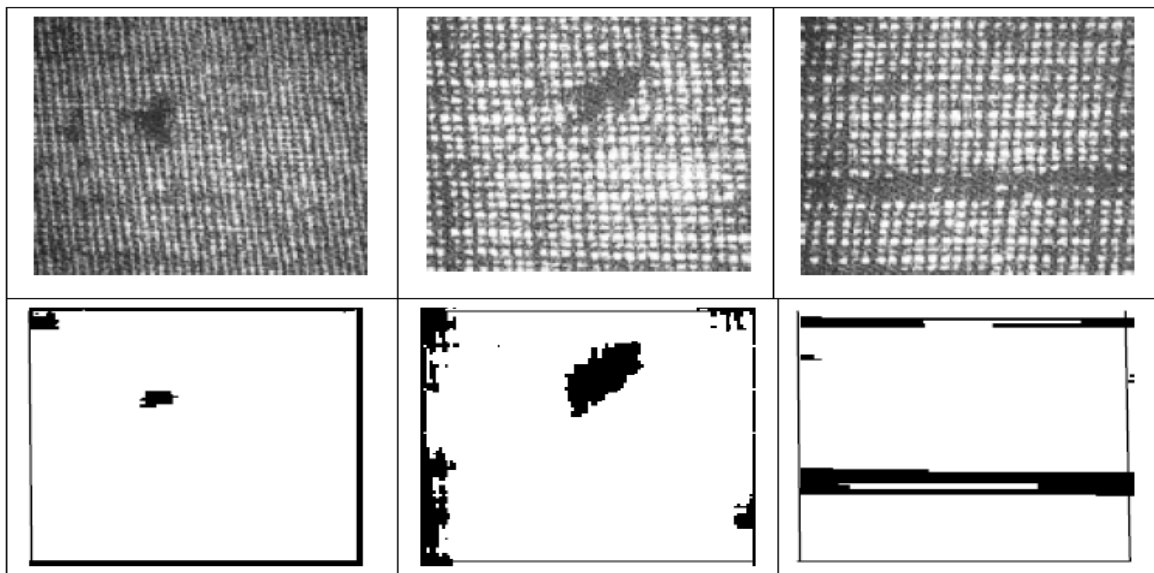


Fig. 3. Shows the presence of defects, knot, oilmark and thick yarns (top row). The bottom row shows the detection process by rank order filtering.

6. Selection of the size structuring element by artificial neural network

Selection of structuring element in all morphological operations is one of the major problems while detecting defects in woven fabric. The size and shape of structuring element has to be different for different textures of fabric and also has to be different for identification of different types of defects. In general, the selection of structuring element is done heuristically or by trial and error basis. In order to overcome the problem of selection of the size of the structuring element, decomposition of the structuring element is proposed (Park & Chin, 1995; Roerdink & Heijmans, 1988). One can also process (e.g., extract or eliminate) differently scaled objects of interest in the image by adapting the size of the structuring element(s) to the local intensity range (Masayasu, Masayoshi, & Akira, 2003). Attempt has been made to use optimally selected structuring element (Schonfeld, 1994) and optimal selection is applied for the defect detections in fabric (Mak, Peng, & Lau, 2005). Since biological neurons can adopt itself to a new situation and can be trained, the selection of structuring element can be done by training from the image data to be processed for a specific application. Any simple artificial neural network model may be useful for training (Lippman, 1989). However, particularly defect detection problems where association of a single class is required for many disjoint regions in the pattern space, a multi layer perceptron (MLP) model with a hidden layer of neurons is necessary (Widrow, & Lehr, 1990). The signal flow in a MLP model is shown in Fig. 4, where w denotes the weight, I and O are the input and output signals with proper subscripts h and o for hidden and output layer. The hidden layer neurons generate hyper planes that are building blocks of decision

regions. In MLP architecture, linear threshold unit is used for generating activation function from input layer neurons to the hidden layer neurons and sigmoidal threshold function $S[.]$ is required for generating activation functions from hidden to output layer neurons. A real parameter λ determines the sigmoidal activation gain. Each neuron of the input layer is connected to each neuron of the hidden layer after being multiplied by the weight vectors and similarly each neuron of the hidden layer is also connected to each neuron of the output layer after being multiplied by the weight vectors. During the training process, up-gradation of the weight vectors takes place and continues till an error term ε goes below a certain predefined tolerance value. A learning rate coefficient η determines the size of the weight adjustments made at each iterations and hence influences the rate of convergence. The learning rate has to be kept small in order to maintain smooth trajectory in weight space. Large learning rate leads to oscillations during learning and it is necessary to introduce a momentum term α into weight update procedure. Many algorithms exist for training and testing in MLP model (Haykin, 2008).

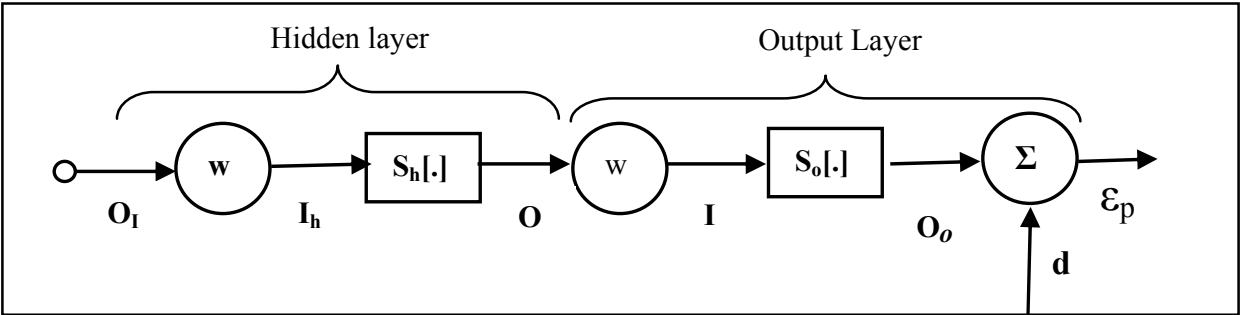


Fig. 4. Signal flow in artificial neural network model

If $(u \times v)$ is the size of the structuring element needed for the morphological operation, then this parameter should relate to the fabric parameters for training the ANN. For this purpose each sample of fabric is assigned a set of two normalized numbers Z_1 and Z_2 for their identification. Z_1 is a normalized number related to threads per centimeter of fabric along the weft direction (say x -axis) divided by an integer number (say N , where $N > 1$), so that Z_1 can be expressed as a fraction. Similarly, Z_2 is a normalized number related to number of threads per centimeter of the fabric along warp direction (say y -axis). Z_2 is also expressed as a fraction by dividing by N . Given a training set vector pairs of fabric parameters Z_1 and Z_2 for P different types of fabrics, the network is trained for different types of defects to yield trained size of structuring element required for morphological operation.

7. Conclusion

It has been shown in this chapter that morphological operations can be exploited for detection of various types of defects in the woven fabric. However, the erosion operation on fabric image helps in detecting defects to a major extent. Binarization of the fabric image is necessary before applying the morphological operations. The detection capability improves if the image is spatially filtered and then thresholded to remove the interlaced grating structure of the fabric. Moreover, gray morphological operations is possible for the defect detection and more accurate detection is possible than the binary morphological processing. In this chapter it is also shown that detection capability is greatly improved by rank-order filtering which is termed as generalized morphological operations. The method offers two

flexible controls. The structural element can be selected according to *a priori* knowledge of the defect. Secondly, the rank can be selected to suit a particular noisy situation. It has been established that very good detection is possible for small size defects (such as a knot) in all types of fabric by rank order filtering technique.

Proper selection of the structuring element in all morphological operations enhances the chance of detection of defects which otherwise may not be very distinct even during visual inspection. A method has been shown where the size of the structuring element can be selected as a result of training of the system by artificial neural network.

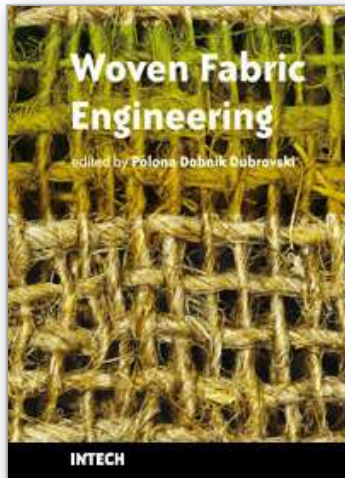
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Woven Fabric Engineering

Edited by Polona Dobnik Dubrovski

ISBN 978-953-307-194-7

Hard cover, 414 pages

Publisher Sciyo

Published online 18, August, 2010

Published in print edition August, 2010

The main goal in preparing this book was to publish contemporary concepts, new discoveries and innovative ideas in the field of woven fabric engineering, predominantly for the technical applications, as well as in the field of production engineering and to stress some problems connected with the use of woven fabrics in composites. The advantage of the book Woven Fabric Engineering is its open access fully searchable by anyone anywhere, and in this way it provides the forum for dissemination and exchange of the latest scientific information on theoretical as well as applied areas of knowledge in the field of woven fabric engineering. It is strongly recommended for all those who are connected with woven fabrics, for industrial engineers, researchers and graduate students.

How to reference

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Asit Datta and Jayanta Kumar Chandra (2010). Detection of Defects in Fabric by Morphological Image Processing, Woven Fabric Engineering, Polona Dobnik Dubrovski (Ed.), ISBN: 978-953-307-194-7, InTech, Available from: <http://www.intechopen.com/books/woven-fabric-engineering/detection-of-defects-in-fabric-by-morphological-image-processing>

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University Campus STeP Ri
Slavka Krautzeka 83/A
51000 Rijeka, Croatia
Phone: +385 (51) 770 447
Fax: +385 (51) 686 166
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InTech China

Unit 405, Office Block, Hotel Equatorial Shanghai
No.65, Yan An Road (West), Shanghai, 200040, China
中国上海市延安西路65号上海国际贵都大饭店办公楼405单元
Phone: +86-21-62489820
Fax: +86-21-62489821

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