Fabric defect detection using morphological filters

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In this paper, a novel defect detection scheme based on morphological filters is proposed to tackle the problem of automated defect detection for woven fabrics. In the proposed scheme, important texture features of the textile fabric are extracted using a pre-trained Gabor wavelet network. These texture features are then used to facilitate the construction of structuring elements in subsequent morphological processing to remove the fabric background and isolate the defects. Since the proposed defect detection scheme requires a few morphological filters only, the amount of computational load involved is not significant. The performance of the proposed scheme is evaluated by using a wide variety of homogeneous textile images with different types of common fabric defects. The test results obtained exhibit accurate defect detection with low false alarms, thus showing the effectiveness and robustness of the proposed detection scheme. In addition, the proposed detection scheme is further evaluated in real time by using a prototyped automated inspection system.

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1. Introduction

The continually changing fashion of garments has generated a greater product variety and shorter life cycle for production. Textile fabrics constitute a large proportion of the total cost of production in garment manufacturing. Since a garment with a textile defects usually sells with a massive discount of 45–65% [1], the garment manufacturing industry is faced with increased pressure to become more competitive by increasing yield while reducing costs. Hence, quality control of fabrics before garment manufacturing is essential to ensure the quality of finished products and to increase the efficiency of the manufacturing process. Indeed, improved performance in the inspection of fabrics leads to good product quality and, in turn, contributes to increased profitability and customer satisfaction. Above all, the general outcome is a better product image and a competitive market place advantage.

Currently, the quality inspection process for textile fabrics is mainly performed manually. However, the reliability of manual inspection is limited by boredom and inattentiveness. Indeed, Sari-Sarraf and Goddard [2] found that only about 70% of fabric defects could be detected by the most highly trained inspectors. Therefore, automated detection of fabric defects, which results in the production of high-quality products at a high production speed is definitely desirable. Automated inspection of textile fabrics has attracted a lot of attentions in recent years. Wang et al. [3] reported that 90% of the defects in a plain fabric could be detected simply by thresholding, and other researchers also started to study the automated inspection of more complicated fabrics, such as twill and denim fabrics [4–8].

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. Among these approaches, statistical approaches were the earliest approaches used to detect fabric defects. Chetverikov and Hanbury [9] used two fundamental structural properties of a texture, namely, structural regularity and local anisotropy, to detect structural defects in regular and flow-like patterns. Bodnarova et al. [10] compared the performance of several common defect detection methods, such as spatial grey-level co-occurrence, normalized cross-correlation, texture blob detection and spectral methods, in terms of detection accuracy and computational efficiency, and claimed that the cross-correlation method was the most promising method for textile fabrics. However, they also pointed out that this method would be computationally very demanding if the template size used was large. Muller and Nickolay [11] used two morphological filters to detect two types of fabric defects, i.e. thread drags and oil spot. Zhang and Bressee [12] also successfully combined morphological operators and autocorrelation relations to inspect two types of fabric defects, i.e. knot and slub. Many other statistical detection methods were also reported in the literature, including edge detection [13], cross-correlation [14], co-occurrence matrix [15] and neural networks [8]. A few model based methods had also been applied successfully to detect defects in textile fabrics. Campbell et al. [16] used the model based clustering method to detect linear pattern production defects, and Ozdemir and Ercil [17] used Gauss Markov random...
fields to detect common defects in textile fabrics. Spectral approaches were the most widely used approaches for detecting fabric defects among the three classes of defect detection approaches. The techniques included in this class were Fourier transform, wavelet transform and Gabor analysis. In view of the high degree of periodicity for textile fabrics, Fourier transform based approaches were adopted for defect detection by some researchers [18,19]. However, since the kernel function of Fourier transform is of infinite length, the contribution from each of the spectral components is difficult to quantify. Therefore, the traditional Fourier transform based approaches are not suitable for detecting local fabric defects, which only cause minor modifications to the frequency spectrum of a studied fabric image. In order to overcome this problem, one way is to apply the short-term Fourier transform [20], thereby allowing localization of spectral effects. However, a suitable window function is needed for this approach to work accurately, which may not be an easy task. Another popular approach is to apply the wavelet transform was used instead [2,21]. Being a special type of wavelet which has an optimal localization in both the spatial domain and the spatial-frequency domain, the Gabor wavelet has been widely used in the field of fabric defect detection [5,6,22].

The development of real-time automated visual fabric inspection systems, in general, consists of three processes, namely, image acquisition, image processing, and image analysis. Typical examples include Elbit Vision System’s I-TEX system, BarcoVision’s Cyclops and Zellweger Uster’s Fabriscan. These systems inspect fabric in full width either at the batterie for greige fabrics or at the exit end of a finishing machine [23]. They are designed to find catalog defects in a wide variety of fabrics including greige fabrics, sheeting, apparel fabrics, upholstery fabrics, industrial fabrics, tire cord, finished fabrics, piece-dyed fabrics and denim. However, they cannot inspect fabrics with very large and complex patterns. Other examples include a fuzzy wavelet analysis system for process control in the weaving process [24], a vision system for on-loom fabric inspection [2], a vision system for on-circular knitting machine [25] and a vision system for fabric detection based on different Gabor filters [26,27]. These systems are rather expensive which prevent them from being widely adopted by small to medium sized factories. Subsequently, Cho et al. [28] proposed a PC-based real-time inspection system to lower the cost. Further research and development efforts are definitely needed to establish cost-effective approaches for solving fabric defect detection problems.

In this paper, a novel defect detection scheme is proposed to facilitate automated inspection of woven fabrics. The proposed scheme consists of a Gabor wavelet network (GWN) and several morphological filters. Unlike the conventional supervised approach, the design of the proposed scheme only requires a non-defective fabric image and no fabric defect information is needed. In addition, it can be shown that the GWN which is used for extracting typical texture features (the basic yarn information) from the non-defective fabric image only requires one imaginary Gabor wavelet in the hidden layer. This reduces significantly the computational load needed in training the GWN. Morphological filters are then designed based on the extracted texture features for detecting textile fabric defects because previous research has demonstrated that the use of morphological filters can significantly lower the false alarm rate [20]. The performance of the proposed scheme is evaluated off-line by using a set of sample fabric images containing some typical fabric defects, and in real time by using a prototype automated inspection system developed in the laboratory. Results of the experiments clearly demonstrate that the proposed scheme is indeed an effective and efficient means for detecting defects in woven fabrics.

2. Fabric defect detection

2.1. Gabor wavelet network for feature extraction

Based on the concept of wavelet transform, Zhang and Benveniste [29] proposed the notion of wavelet network (WN) as an alternative to a feed-forward neural network for approximating arbitrary nonlinear functions. The underlying concept of a WN is to replace the neuron by ‘wavelet’, i.e. computing the units obtained by cascading an affine transform and a multi-dimensional wavelet. Then the affine transform and the ‘synaptic weights’ have to be identified from possibly noise corrupted input/output data in the process of network training. Krueger and Sommer [30,31] used an imaginary part of a Gabor function as the transfer function of the hidden layer in a wavelet network, and proposed the concept of Gabor wavelet network (GWN) for solving 2-D problems in pattern recognition [32]. Assuming that a grey-scale image is given by \( f(x, y) \), where the input vector \([x, y]\) is the position of an image pixel and \( f \) is the grey level of the image pixel. The corresponding representation using a Gabor wavelet network has the following form:

\[
\hat{f}(x, y) = \sum_{i=1}^{N} [w_i g_i(x, y)] + \tilde{f}.
\]

where \([x, y]\) denotes the network input, \( f(x, y) \) denotes the network output, \( w_i \) refers to a network weight from the \( i \)th hidden node to the output node, \( g_i(x, y) \) is the transfer function of the \( i \)th hidden node, \( \tilde{f} \) is introduced to normalize the value of any objective functions, and \( N \) denotes the number of nodes in the hidden layer. The imaginary part of the Gabor function used in (1), i.e. the transfer function of the \( i \)th hidden node, can thus be expressed as

\[
g_i(x, y) = \exp \left\{ -\frac{1}{2} \left[ \frac{(x-t_i^x) \cos \vartheta - (y-t_i^y) \sin \vartheta}{\sigma_x^2} \right]^2 + \left[ \frac{(x-t_i^x) \sin \vartheta + (y-t_i^y) \cos \vartheta}{\sigma_y^2} \right]^2 \right\} \times \sin \left( 2\pi \omega_i \left[ (x-t_i^x) \cos \vartheta - (y-t_i^y) \sin \vartheta \right] \right).
\]

where \((t_i^x, t_i^y)\), \((\sigma_x^2, \sigma_y^2)\), \(\vartheta\) and \(\omega_i\) are the translation parameters, the radial frequency bandwidths, the orientation and the central frequency of the transfer function of the \(i\)th hidden node, respectively. In order to simplify the presentation, the imaginary part of a Gabor wavelet is represented by the term ‘an imaginary Gabor wavelet’ in the following discussion.

It can be noticed easily that each Gabor wavelet in the GWN involves seven parameters, i.e. \([t^x_1, t^y_1, \vartheta_1, \sigma^2_x, \sigma^2_y, \omega_1, w_1]\), which should be determined by using the network training process. The objective function of the network training process (the network optimization) is defined as

\[
E = \| f - \hat{f} \|_2^2.
\]

Hence, any function \( f \in L^2(\mathbb{R}^2) \) can be numerically reconstructed [29] if sufficient appropriate Gabor wavelets are added into such a network.

Since Gabor basis functions are not orthogonal, a direct transform-like solution is not possible. Therefore, an optimization technique called the Levenberg–Marquardt algorithm is used to conduct the network training process. In the process of network training, Gabor wavelets are added into the network one by one. The training process can be briefly described as follows:

(Step 1) \( N = 1 \). Use the LM algorithm to find the optimal values of \([t^x_1, t^y_1, \vartheta_1, \sigma^2_x, \sigma^2_y, \omega_1, w_1]\);
A typical application of this procedure to study textile fabric images is depicted in Fig. 1. Fig. 1(a) shows a fabric image captured from a twill weaving fabric, which is used as a template image for training the GWN. Fig. 1(b) shows the reconstructed template image obtained by using the trained GWN with \( N = 100 \) and Fig. 1(c) shows that the difference between the original template image and the reconstructed template image is not significant. Obviously, the reconstruction of the complete image requires a fairly large \( N \). However, it is interesting to discover that if the fabric image consists of some repetitive patterns, texture features can be extracted easily from the template image for morphological operations without using the full image representation. In this research, the yarn width and the yarn orientation (Fig. 1(d)) have been identified as the two important features for the textile fabric. These features can be extracted by using some of the parameters of the imaginary Gabor wavelets in the trained network. Fig. 2 shows the extracted basic yarn features by using only one imaginary Gabor function in the hidden layer of the trained GWN. In view of the form of the transfer function given by Eq. (2), the yarn information is expressed approximately by using the parameters \( \sigma_y \) and \( \theta \) of a single imaginary Gabor wavelet in the hidden layer of the network as follows:

\[
\begin{align*}
\{ w_y & = 4\sigma_y, \\
\theta = \theta + \frac{\pi}{2} \}
\end{align*}
\]

where \( w_y \) and \( \theta \) denote the yarn width and the yarn orientation of the template image, respectively. Such a GWN can also be used to extract local features for denim weaving fabrics since denim weaving fabrics usually have a similar pattern as that of twill weaving fabrics.

**2.2. Morphological filters design**

After the texture features have been extracted from the non-defective fabric image, morphological filters can be designed to detect defects, if any, from fabrics which have the same texture background as the non-defective fabric image by using sample fabric images captured from such fabrics. Mathematical morphology or simply morphology has been recognized as a technique for the analysis of spatial structures [33], which aims at analyzing the shapes and the forms of objects. The technique was first reported as an image analysis tool in a study about porous materials [34]. An introduction to morphological image processing, both binary and grey level, and containing pictorial examples, is contained in [35]. The following discussions highlight briefly its important aspects which are relevant to this research. Morphological operations are conducted by comparing the object being studied with another object called a structuring element which is chosen with a known shape and size (e.g. a line, a square or a hexagon) for the purpose of object identification, noise elimination, etc. The shape and the size of the structuring element are usually chosen according to some priori knowledge about the geometry of the image structure of the object being studied. Complex operations can usually be achieved by combining some simpler operations. Therefore, morphological filters can usually become a chain of operations.

**2.2.1. Morphological operations**

The language of mathematical morphology is set theory. Sets in mathematical morphology represent objects in an image. In binary images, the sets in question are members of the 2-D integer space \( Z^2 \) where each element of a set is a 2-D vector whose coordinates are the \((x,y)\) coordinates of a black or white pixel in the image. Let \( A \) and \( B \) be sets in \( Z^2 \). For binary images, defining the reflection of set \( B \), denoted by \( \bar{B} \), as \( \bar{B} = \{ w| w = -b \mbox{ for } b \in B \} \) and the translation of set \( A \) by point \( z = (z_1, z_2) \), denoted by \((A)_z\), as \((A)_z = \{ c| c = a + z \mbox{ for } a \in A \} \), the four fundamental morphological operations are as follows:

(a) The dilation of \( A \) by \( B \): \( A \oplus B = \{ z| (\bar{B})_z \cap A \neq \emptyset \} \),

(b) The erosion of \( A \) by \( B \): \( A \ominus B = \{ z| (\bar{B})_z \subseteq A \} \),

(c) The opening of set \( A \) by structuring element \( B \): \( A \circ B = (A \oplus B) \ominus B \),

(d) The closing of set \( A \) by structuring element \( B \): \( A \bullet B = (A \ominus B) \oplus B \).

Note that dilation and erosion on binary images can be viewed as a form 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 [36]. Furthermore,
opening and closing are two higher order operations built on dilation and erosion. Due to the connection with Boolean operations, the erosion and dilation can turn black pixels white and white pixels black when certain conditions are met. This explains why the opening and closing operations can clean up the detections yielded by the Gabor procedure.

These operations can be extended for grey-scale images. In particular, we are dealing with digital image functions of the forms \( f(x,y) \) and \( b(x,y) \), where \( f(x,y) \) is the input image and \( b(x,y) \) is a structuring element. If \( Z \) denotes the set of real integers, the assumption is that \( (x,y) \) are integers from \( Z \times Z \) and that \( f(x,y) \) and \( b(x,y) \) are functions that assigned a grey-level value to each distinct pair of coordinates. Denote \( D_f \) and \( D_b \) as the domains of \( f \) and \( b \), respectively, the four fundamental morphological operations become:

(a) Grey-scale dilation of \( f \) by \( b \): 
\[
(f \oplus b)(s,t) = \max\{f(s-x,t-y) + b(x,y)|(s,x) \in D_f, (y,y) \in D_b\}.
\]
(b) Grey-scale erosion of \( f \) by \( b \): 
\[
(f \ominus b)(s,t) = \min\{f(s+x,t+y) - b(x,y)|(s,x) \in D_f, (y,y) \in D_b\}.
\]
(c) The opening of image \( f \) by structuring element \( b \):
\[
f \circ b = (f \oplus b) \ominus b.
\]
(d) The closing of image \( f \) by structuring element \( b \):
\[
f \bullet b = (f \ominus b) \oplus b.
\]

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 gulls, and eliminates small holes. The results are that if the 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, which is one of the most important filters in mathematical morphology.

2.2.2. Design of filters

Unlike the conventional supervised approach, the GWN with one imaginary Gabor wavelet in the hidden layer is used in this paper as a means to extract local texture features from a non-defective fabric image. Feature extraction is conducted in the network optimization process (the network training process) by using a non-defective template image. After the network has been trained, the parameters of the resulting imaginary Gabor wavelet are directly related to the basic yarn information contained in the template image. Based on the yarn information obtained, a structuring element can be constructed for developing morphological filters which are the key components of the defect detection scheme proposed in this paper.

For 2-D discrete images, a structuring element is usually represented by a set of points \((i,j)\) in the 2-D space indicating its geometry, i.e. \(i,j \in Z\). For example, if the structuring element is a line, the set of points \((i,j)\) are uniformly distributed along the line. In this case, two parameters, the length and the orientation, have to be determined in order to construct an appropriate linear structuring element, so that the texture background can be eliminated as much as possible in the filtered fabric image. Indeed, the length of the linear structuring element is set equal to the yarn width of the fabric image being studied, because the image of a piece of fabric containing defects consists of the images of defects and the texture background formed by the images of yarns, and the size of the image of a defect is usually larger than the width of the image of a yarn. Hence, the linear structuring element with a length of one yarn width can effectively eliminate as much as possible the texture background and prevent losing too much information about the defect. In view of Eq. (4), the length of the linear structuring element is set equal to \(4\sigma_g\), where \(\sigma_g\) is the bandwidth in the \(x\)-axis of the imaginary Gabor wavelet in the trained GWN. The orientation of the linear structuring element depends on the type of fabric under consideration. This paper only considers detecting defects in commonly used fabrics, i.e. plain, twill and denim fabrics. Sari-Sarraf and Goddard [2] reported that in the textile industry, most fabric defects simply appear in some specific orientations (either in the direction of motion (i.e. warp direction) or perpendicular to it (i.e. weft direction)), because of the nature of the weaving process. Therefore, the orientation of the linear structuring element is set to \(\pi/4\) for fabrics without obvious yarn orientation information like plain fabrics, and is set perpendicular to the yarn orientation \(\theta\) obtained by using the trained Gabor wavelet network for the other fabrics like twill and denim fabrics.

Fig. 3 depicts the proposed scheme for detecting defects in woven fabrics. The scheme firstly employs a pair of opening and closing to eliminate as much as possible the texture background in the fabric image. The linear structuring element obtained previously is used in both of the operations. Fig. 4 shows the effect of using these two operations to filter a sample fabric image with a defect. Fig. 4(b) shows that the filtering process has effectively eliminated most of the texture background of the sample fabric image and kept the image which indicates the defect area. This results in a sharp contrast between the resulting texture background and the defect area in the filtered fabric image, which is an essential feature of a good defect detection scheme.

2.3. Post-processing

Fig. 4 also depicts that, in the proposed detection scheme, a \(3 \times 3\) median filter is applied to smooth the filtered fabric image in order to reduce the amount of noise in the image. The smoothed fabric image is then closed again by using a \(3 \times 3\) square structuring element. The last step of the proposed detection scheme is a thresholding step for producing a binary detection result. The thresholding limits \(\lambda_{\text{max}}\) and \(\lambda_{\text{min}}\) in this step satisfy the equation
\[
\begin{align*}
\lambda_{\text{max}} &= \max_{x,y \in W} C(x,y) \\
\lambda_{\text{min}} &= \min_{x,y \in W} C(x,y)
\end{align*}
\]
where \(C\) is the resulting fabric image obtained by applying a pair of opening and closing operations with the linear structuring element designed in Section 2.2.2, the median filter and the closing operation to a defect-free fabric image (a template image). \(W\) is a sub-window of the image \(C\), the size of which should be suitably chosen to avoid the distortion effect caused by the edges of the image, and \(C(x,y)\) is the grey level of the image pixel in position \((x,y)\) of the image. \(\lambda_{\text{max}}\) and \(\lambda_{\text{min}}\) are the maximum value and minimum value of the grey levels of the image pixels in the sub-window. Hence, the output of the binarization step is a binary image \(B\) governed by the equation
\[
B(x,y) = \begin{cases} 
1, & C(x,y) > \lambda_{\text{max}} \text{ or } C(x,y) < \lambda_{\text{min}} \\
0, & \lambda_{\text{min}} \leq C(x,y) \leq \lambda_{\text{max}}
\end{cases}
\]
3. Experiments and results

3.1. Off-line performance analysis

The performance of the proposed defect detection scheme is evaluated off-line by applying the scheme to detect defects in 78 fabric images selected from the Manual of Standard Fabric Defects in the Textile Industry [37]. These images are captured by using a digital flat-bed scanner. There are 39 defect-free images in the database. The other images contain different types of fabric defects including 32 defects commonly appearing in the textile industry. The fabrics in the database are mainly plain, twill, denim weaving fabrics, although other types of fabrics are also included. In the paper, the images have a size of 256 × 256 pixels and an 8-bit grey level.

The performance of the scheme is determined 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 1 summarizes the test results. In the off-line tests, the proposed scheme achieves a 97.4% overall detection (OD) rate with a 2.6% false alarm rate, and only two defective images are missed. Fig. 5 shows some of the detection results. Fabric samples with different fabric defects are displayed in Fig. 5(a), (c), (e), (g), (i), (k), (m), (o), (q), (s), (u), (w), and (y). The pairs of opening and closing operations with the linear structuring elements obtained previously, the median filter and the closing operation are used to process the fabric images and the final binary detection results obtained are displayed in Fig. 5(b), (d), (f), (h), (j), (l), (n), (p), (r), (t), (y), (x), and (z). It can be seen that the proposed scheme can successfully segment the defects with different shapes, different positions and different texture backgrounds.

It can also be seen that the proposed scheme can perform equally well in the case of bright defects with dark texture backgrounds, and in the case of dark defects with bright texture backgrounds. Even when the defect only alters the spatial arrangement of neighboring image pixels and not the mean grey level, the alternation can also be enhanced by the proposed scheme and the defect has been successfully segmented.

The computational complexity of the proposed defect detection scheme is analyzed in order to further evaluate its performance. Assume that the mask size of the structuring elements used in the opening operation and the first closing operation is $1 \times m_1$, that the mask size of the median filter is $m_2 \times m_2$, that the mask size of the structuring element in the second closing operation is $m_3 \times m_3$, and that the size of the image is $n \times n$ pixels. The first two steps of the proposed scheme require $(m_1 - 1) \times n$ comparisons to erode/dilate each image pixel of the image. Thus, $(m_1 - 1) \times (n - (m_1 - 1))$ comparisons are required to erode or dilate the complete image. In this way, it requires $2(m_1 - 1) \times n \times (m_1 - 1)$ comparisons to open or close the image. Similarly, $(m_2 - 1)!$ comparisons are needed to conduct the median filtering for each image pixel, and therefore $(m_2 - 1)! \times n \times (m_2 - 1)$ comparisons are required to filter the entire image. The fourth step requires $2(m_3 - 1) \times n \times (m_3 - 1)$ comparisons. Finally, the thresholding step requires $2n^2$ comparisons. If the proposed defect detection scheme is applied to process the complete image, the number of comparisons needed is

$$4(m_1 - 1)(n - (m_1 - 1)) + (m_2 - 1)!(n - (m_2 - 1))^2 + 2(m_3 - 1)(n - (m_3 - 1))^2 + 2n^2.$$
Hence, when $m_1 = 7$, $m_2 = 3$, $m_3 = 3$, and $n = 256$, 2604 millions comparisons have to be performed in processing each inspected image. If the camera employed can capture four frames per second, the proposed scheme will need to perform approximately 10.4 billions comparisons per second which indeed is not very computationally demanding with a modern computer.

**Fig. 5.** Images of fabrics with different types of defects and the corresponding binary detection results.
3.2. Real-time performance analysis

In order to evaluate the proposed defect detection scheme for real-time implementation, a low-cost prototyped defect detection system has been developed in the laboratory. Fig. 6 shows the architecture of the developed automated defect detection system. The system consists of a fabric conveying module, a lighting module, an image acquisition module, a supporting frame and the proposed detection scheme. Sari-Sarraf and Goddard [2] indicated that the following issues had to be considered when designing an automated system for fabric inspection: (1) the vibration generated by the moving parts; (2) the irregular motion of the fabric; and (3) the system cost. All these issues have been considered in developing the prototype system.

The image acquisition module mainly consists of a line scan camera (Model L103k-2k made by Basler (Germany)) and a frame grabber (Model Matrox Odyssey XCL made by Matrox (US)), and a camera link connects these two components. Thus, an image can be captured by the frame grabber interfaced to the camera by the camera link. Both the frame grabber and the control board are installed in a personal computer with a Pentium IV 2.8 GHz CPU and 1.0 G RAM.

The performance of the proposed detection scheme is evaluated in real time by using the prototyped automatic defect detection system developed in the laboratory. The system is adjusted to capture frames of images having a size of 768 x 256 pixels and an 8-bit grey level, and with an image resolution of about 7.8 pixels per mm in both directions. The fabric conveying speed is about 12 m/min. Comparing to plain weaving fabrics, twill weaving fabrics are more difficult to inspect automatically because they have more complicated texture background. In the experiments, a long piece of twill weaving fabric is used which contains defects, such as oil spot, burl, knot with halos. Two hundred and seventy-six frames of images are captured and analyzed, in which 17 images contain different defects and 259 images are defect-free. Since it is difficult to obtain a long piece of fabric with a variety of fabric defects, most of the defects are deliberately made by hand. The experimental results show that two fabric defects are missed (MD), and that a 3.3% false alarm rate is achieved. Fig. 7 displays a real-time test example, in which a fabric defect is successfully detected by the proposed detection scheme. Indeed, the good detection results achieved clearly demonstrate the efficiency, effectiveness and robustness of the proposed detection scheme. The prototype system developed also has the ability to record information related to the defects appeared, in order to facilitate statistical analyses conducted off-line.

4. Conclusions

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 detec-
tion 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. In this paper, a novel supervised defect detection scheme for automated inspection of textile fabrics has been proposed. The proposed defect detection scheme consists of a Gabor wavelet network with only one imaginary Gabor wavelet in the hidden layer and several simple morphological filters with a suitably designed linear structuring element. The Gabor wavelet network has been utilized to extract from the fabric image under consideration the basic texture features which serve as the priori knowledge for the design of the linear structuring element. 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 the scheme is a simple and effective defect detection method. The proposed scheme has also been further evaluated in real time by conducting experiments with a prototyped automated defect detection system developed in the laboratory. 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 should also be investigated.

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