# A Real-time Computer Vision System for Detecting Defects in Textile Fabrics

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***Abstract*-This paper proposes a real-time computer vision system for detecting defects in textile fabrics. The developments of both the hardware and software platforms are presented. The design of the prototyped defect detection system ensures that the fabric moves smoothly and evenly so that high quality images can be captured. The paper also proposes a new filter selection method to detect fabric defects, which can automatically tune the Gabor functions to match with the texture information. The filter selection method is further developed into a new defect segmentation algorithm. The scheme is tested both on-line and off-line by using a variety of homogeneous textile images with different defects. The results exhibit accurate defect detection with low false alarm, thus confirming the robustness and effectiveness of the proposed system.**

***Keywords:* Defect detection; Gabor filter; Filter selection; Computer vision; Fabrics**

## I. INTRODUCTION

In the textile industry, careful inspections for woven fabrics have to be carried out because fabric defects may reduce the price of a product by 45% or 65% [1]. Currently, the quality assurance of web processing is mainly carried out by manual inspection. However, the reliability of manual inspection is limited by ensuing fatigue and inattentiveness. Sari-Sarraf and Goddard [2] showed that only about 70% of the defects could be detected by the most highly trained inspectors. Furthermore, textile industries are facing increasing pressure to be more efficient and competitive by reducing costs. Therefore, automated detection of fabrics in textile fabrics, which results in high quality products at high-speed production is needed.

The automation of fabric inspection is one of the most intriguing research topics. A variety of algorithms including statistical methods, spectral methods and model-based methods have been deployed to solve the problem. However, many of the detection algorithms developed are only tested off-line and are not applied in the real world. There are also some researchers who tried to develop effective real-time inspection systems for textile fabrics. Sari-Sarraf and Goddard [2] presented a vision-based fabric inspection system, which could perform on-loom detection. The defects were detected by localization of the disruption part in the global homogeneity of the background texture. Stojanovic et al. [3] developed another inspection system for the quality control of web textile fabrics, of which detection speed was up to 120 m/min. Vachtsevanos et al. [4] proposed a method and apparatus for identifying defects, which combined both off-line and on-line learning modules. In their invention, a detection algorithm based on wavelet analysis, neural networks and fuzzy logic was implemented.

Among all the algorithms developed for detecting fabric defects, the methods based on multi-channel Gabor filtering [5, 6, 7] has shown to be one of the most successful ones. The parameter selection of Gabor functions in all these approaches is based on dyadic decomposition, which inevitably causes redundancy and correspondingly need excessive storage of data. Pichler and his colleagues [8, 9] proposed a criterion for choosing Gabor filter parameters, which was derived from the adaptive Gabor transform of the analyzed image. The algorithm reduced the number of Gabor filters required for texture segmentation extensively. However, before segmentation, excessive computation was needed to obtain all those Gabor coefficients. When the spatial resolution became finer, the computational quantity increased exponentially.

This paper proposes a simpler criterion of filter selection for solving the problem of detecting defects in woven fabrics, and applies the criterion to defect segmentation. The criterion can produce a set of optimal filters quickly, in which the number of filters is much less than dyadic decomposition. At the same time, a hardware platform for testing the proposed detection algorithm is constructed, and the design of the platform facilitate the capturing of high-quality fabric images. The paper is organized as follows: Section II describes the architecture of the proposed vision detection system. In Section III, the segmentation algorithm is presented in detail. The performance of the system is evaluated in Section IV. Finally, Section V draws the conclusion of the research undertaken.

## II. THE VISION INSPECTION SYSTEM

The architecture of the proposed defect detection system is depicted in Fig. 1. The system consists of a fabric conveying module, a lighting module, an image acquisition module, a supporting frame and a computer that hosts the detection algorithm. The key issues including (1) the vibration caused; (2) the irregular motion of the fabric; and (3) the system cost that were suggested by Sari-Sarraf and Goddard [2] are considered in the development of our inspection system.

The roller systems located at both sides of the prototype inspection system are designed to ensure smooth and even movement of the fabric sample on the steel plate when the rollers rotate. The system can be adjusted so that appropriate tension can be introduced along the cloth to minimize the effects of wrinkles and mechanical vibration. The rotation of the motor is controlled by a motion control board. The design of the system provides three degrees-of-freedom movement for the camera to keep the photosensor array of the line scan camera and the linear light source to align in the same plane. An extra degree-of-freedom is provide for changing the vertical distance between the camera and the fabric sample in order to adjust the resolution along the pick direction.

Schott DCRIII line light source is used as the back lighting source, which can provide intense and cold illumination for the fabric. Back lighting can easily eliminate shadows and glare effects. Compared with front lighting, back lighting can also enable image with better contrast to be captured. However, in the experimental studies, it can be found that the light intensity around the setup has significant effect on the quality of the images captured, which may deteriorate the performance of the defect detection algorithm. Therefore in the designed apparatus, a common air-cooled fluorescent tube is therefore used as front lighting to eliminate such effects.

In order to achieve an adequate resolution, a Basler L103k-2k line scan camera is chosen, and a disc encoder is installed to ensure the synchronization between the camera and the fabric being transported. The exposure time of the camera is fixed regardless of the speed of the fabric as long as it is less than the period of the TTL line trigger signal. The data transfer rate of images is increased by an interface called the camera link that connects the line scan camera with the frame grabber (Matrox Odyssey XCL). The frame grabber uses a Matrox Oasis chip, which can speed up the data processing of the captured images. The resolution in the pick direction is adjusted by changing the distance between the camera and the fabric, and the resolution in the warp direction is set by the resolution of the encoder, which can be modified by changing the content in the digitizer configuration file.

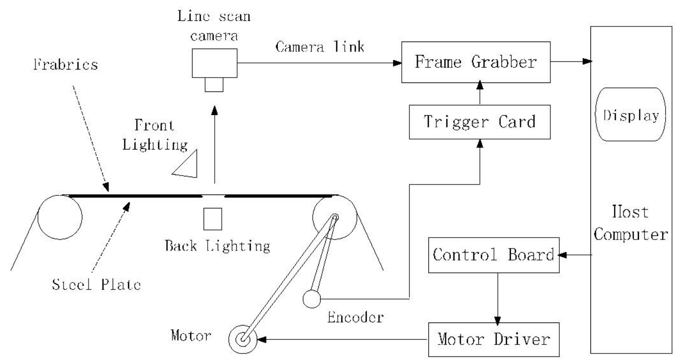


Fig. 1. Architecture of the vision inspection system.

## III. FILTER SELECTION AND DETECTION ALGORITHM

Kumar and Pang [6] claimed that when Gabor functions were used in defect detection, the contribution from the imaginary Gabor function was very small while requiring an additional 50% computation. As such, a filter bank that is only based on real Gabor functions from sixteen different channels obtained from four orientations is used. Therefore, only the real parts of Gabor functions are considered. In this paper, the term real Gabor filter is used to represent the real part of a Gabor function to simplify the descriptions of the following paragraphs. In this section a new filter selection method for detecting defects in woven fabrics is presented, which can automatically tune the parameters of real Gabor functions to match with the texture background.

### *A. Filter Selection Method*

The usual Gabor transform can decompose a studied image into different representations in several levels. The underlying idea of the proposed selection method is to identify the most significant spectral components in every level of the pyramidal Gabor decomposition. Then by combining these features used to identify the spectral component in each level, a set of multi-scale filters can be constructed.

In order to conveniently find a local spectral component of a texture, the real part of a Gabor function is defined by:

$$g_e(x,y)=\exp\left\{-\frac{1}{2}\left[\left(\frac{x'}{\sigma_x}\right)^2+\left(\frac{y'}{\lambda\sigma_x}\right)^2\right]\right\}\cos\left[2\pi u_0 x'\right] \quad (1)$$

where

$$\begin{pmatrix} x' \\ y' \end{pmatrix}=\begin{bmatrix}\cos\theta & -\sin\theta \\ \sin\theta & \cos\theta\end{bmatrix}\left[\begin{pmatrix} x \\ y \end{pmatrix}-\begin{pmatrix} T_x \\ T_y \end{pmatrix}\right],$$

$T_x$, $T_y$ are the translation parameters along the x and y axes respectively, $\theta$ denotes the rotation parameter, $u_0$ is the frequency of a sinusoidal plane wave along the x-axis and $\lambda$ is the ratio between the variances in the y direction and in the x direction. In order to tune a real Gabor function to match with the texture in the i-th level, the following energy function should be minimized:

$$E = \sum_{x,y}\left[IM(x,y) - w^i g_e^{\,i}(x,y)\right]^2 , \qquad (2)$$
$$\forall w^i, T_x^{\,i}, T_y^{\,i}, \lambda^i, \theta^i, u_0^{\,i}$$

where $w^i$ is the Gabor coefficient in the i-th level, $IM$ is a defect-free texture image and the rest are the corresponding parameters of the Gabor function in the i-th level. In order to determine the most important spectral component in the i-th level of Gabor decomposition, the radial frequency $u_0^{\,i}$ is limited to $\left[2u^i/3, 4u^i/3\right]$, and $u^i = 2^{i-1}\sqrt{2}$ ( $\left\{i \mid 1 \le 2^{i-1} \le N_c/4\right\}$). Then $\sigma_x$ can be calculated from the following equation:

$$\sigma_x = 3\sqrt{2\ln 2}/(2\pi u_0). \qquad (3)$$

According to physiological findings, the aspect ratio $\lambda$ of the Gaussian envelopes usually lies between 1.5-2.0 [10, 11]. The results of Kumar and Pang also showed that asymmetric Gabor filters could achieve better segmentation than symmetric filters [12]. In the process of optimization in every level, the ratio $\lambda$ is therefore bound to $[1.0, 2.0]$.

In every level, genetic algorithm [13] is used to minimize the energy function so as to obtain the parameters for the Gabor filters. Fig. 2 shows the chromosome structure, and the population size used is 100. The value of a fitness function is the negative result of (2). Individuals with a higher fitness will have a higher probability for further reproduction. In the algorithm, selection, reproduction, crossover and random mutation are efficiently implemented. The crossover operation is based on a random pair selection that performs an interpolation and extrapolation along the line formed by the two parents. The mutation operation changes one or all parameters of the parent based on a uniform probability distribution. For the new population, the fitness will be evaluated again and the whole process is repeated.

| | | | | | |
|---|---|---|---|---|---|
| $w^i$ | $u_0^i$ | $\lambda^i$ | $\theta^i$ | $T_x^i$ | $T_y^i$ |

Fig. 2. The chromosome structure.

*B. Defect Segmentation*

The filter selection method proposed in the previous section can produce one optimal filter for every level of pyramidal Gabor decomposition. Thus such a set of optimal real Gabor filters are constructed, which are tuned to match the texture background in different resolutions. For an image with the size of $256 \times 256$ pixels, the filter selection method described in Section III(A) can produce 7 real Gabor filters. However, not all the filters obtained are useful to segment defects. Since the size of a defect is usually bigger than that of a yarn, the filtering results from the Gabor filters with finer resolutions than a yarn contribute very little for segmenting defects. Hence, in order to further eliminate those redundant filters, a feature parameter $\alpha^i$ defined by:

$$\alpha^i = \left|w^i\right|\sigma_x^{\,i} \quad i \in \left\{k \mid k = 1,...,n;\, n = \log_2\left(N_c/4\right)\right\}, \qquad (4)$$

can be used to designate the degree of importance of the corresponding Gabor filters in segmenting defects. After the optimization in Section III(A) is performed, the feature parameter $\alpha^i$ should be calculated for every Gabor filter obtained. Then the Gabor wavelets are sorted in descending order of the value of $\sigma_x$, i.e. $\left\{ g_e^{\,i} \mid i = 1,...,n \right\}$. Only the wavelets which satisfy the following condition will be kept for defect segmentation.

$$\left\{ g_e^{\,i} \mid i = 1,...,J;\ \alpha_1 \le \alpha_2 \le \cdots \le \alpha_J > \alpha_{J+1};\ J+1 \le n \right\} \qquad (5)$$

If the condition cannot be satisfied, all the Gabor wavelets obtained from the previous section will be kept. Therefore, it is reasonable to believe that only the Gabor filters that best match with texture background are left.

If the left optimal Gabor filters are directly used to filter a fabric image, the texture background will be enhanced because the optimal filters match best with the background. However, the objective of defect segmentation is to attenuate background information and accentuate defect regions. As this paper mainly considers detecting defects on three mostly commonly used types of weaving fabrics, namely, plain, denim and twill cloth, a simple way to obtain the final optimal Gabor filters for segmenting defects is to rotate the filters obtained by 90 degrees, i.e. the rotation parameters for new filters are set to $\theta_{new}^{\,i} = \theta^i + 90^\circ$.

Based on the optimal Gabor filters obtained from the filter selection method, a complete defect segmentation algorithm is proposed and described in Fig. 3. In the proposed algorithm, image fusion is carried out according to the following equation:

$$O_f = \sum_{i=1}^{J} a^i f^i \quad \left( f^i = IM * g_e^{\,i};\ a^i = \alpha^i / \sum_{k=1}^{J} \alpha^k \right), \qquad (6)$$

where $*$ denotes the convolution operation and $IM$ stands for a fabric sample image. From the figure, it can be noted that after image fusion, the image will be convoluted with a simple median filter. Finally, the final binary segmentation result of a fabric image is obtained by thresholding the output from the median-filtering step.

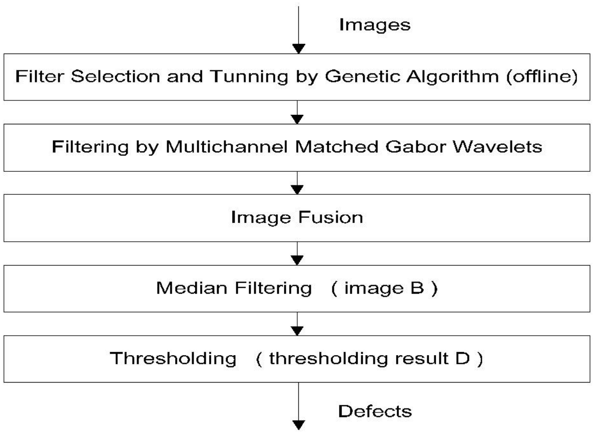


Fig. 3. The Defect Segmentation algorithm.

## IV. SYSTEM PERFORMANCE

The performance of the proposed defect detection scheme has been evaluated both on-line and off-line using the prototyped system. The on-line testing is carried out by inspecting a long piece of twill fabric, and some detection results are summarized according to the tests performed. Since it is very difficult to obtain fabric samples with a great variety of fabric defects, an off-line testing database is also constructed to store the images scanned from a fabric defect handbook [14]. The database contains 32 types of commonly appeared fabric defects in the textile industry.

Generally the fabric defects are categorized into two classes, i.e. global defects and local defects. Since a global defect occupies a relatively large area in a fabric image, it is easier to be detected. Therefore, the main detection objective for this research is to detect local fabric defects, and the resolution of fabric images is chosen to be 7.8 pixels/mm for the on-line experiment. Once a frame of a $2048 \times 256$ image is captured by the frame grabber in the prototype system, the segmentation algorithm is invoked to check whether the captured image contains any fabric defects. If a fabric defect is found, the system will stop the cloth conveying module and wait for the operator to record it. If not, the system will keep running and the frame grabber captures another frame of a fabric image. The process is repeated until the whole piece of fabric is detected. The maximum detection speed of the prototype system is 15 meters/min.

In the on-line test, 276 frames of images are captured and analyzed, in which 17 images contains defects and the rest are defect-free. All these defects occurred in the 17 fabric images are successfully detected, and some of the final segmentation results and the captured fabric samples are presented in Fig. 4. For this experiment, a false alarm (FA) rate of 3.6% is achieved including the FA caused in both the defect-free samples and in the samples with defects.

In the database for the off-line test, there are 78 fabric images with a size of $256 \times 256$ pixels; in which 39 images are defect-free and the other 39 images are with different types of defects. Thirty two defects which commonly appear in the textile industry are tested. The images are scanned with a resolution of 200 dots/in. The test results for the fabric images in the database demonstrated that all the defects are successfully segmented with a false alarm rate of 3.9%.

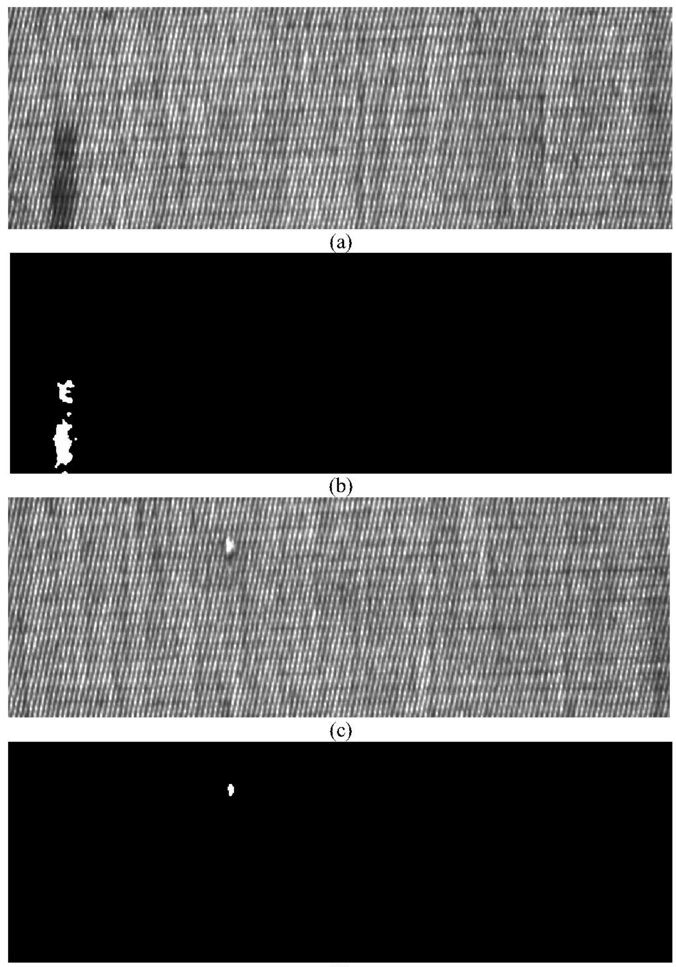


Fig. 4. Fabric samples with oil spot (a) and knot with halos (c), and their corresponding on-line detection results shown in (b) and (d) respectively.

Some of the segmentation results for the images in the database are presented in Fig. 5. The first column in Fig. 5 displays fabric sample images with different types of defects, i.e. harness breakdown (a), mispick (b), warp burl (c) and water damage (d); The second column displays the energy distributions of the output signals from the step called "Filtering by Multichannel Matched Gabor wavelets" in Fig. 3. In fact the defects in the images of this column can be readily detected. The third column shows final defect segmentation results from the proposed algorithm.

Fig. 5(b) and (c) show fabric images with small defects that are difficult to visualize. The scheme successfully detects and segments these defects. Fig. 5(a) presents an example that the defect only alters the spatial arrangement of neighboring pixels and not the mean gray level. The alteration is also increased by the scheme, and finally the defect is segmented. The parameters of the tuned matched real Gabor functions obtained by the filter selection method for this example are listed in the Table I. Fig. 5(d) displays a fabric image with a global defect called water damage. It is shown that the defect is also successfully segmented by the proposed scheme.

Table I
Gabor filter parameters obtained by the selection algorithm

| $u_0$ (cycl./image) | $\theta$ | $\lambda$ |
|---|---|---|
| 1.9 | 15° | 1.49 |
| 6.6 | 179° | 1.98 |
| 9.0 | 92° | 1.42 |
| 28.7 | 130° | 1.49 |

The studied fabric defects in the database include both structural defects and tonal defects. A structural defect, such as those shown by Fig. 5(a) and (b), alters the textural properties, which should not be present in a good quality fabric. A tonal defect on the other hand changes the tonal properties rather than the structural properties, examples of these are shown in Fig. 5(c) and (d).

In the textile industry, when a piece of fabric leaves the production line, the locations and sizes of the contained defects vary randomly. Therefore a supervised detection algorithm that only works on specific defects does not work very satisfactorily in a real application. In this respect, an unsupervised detection scheme will be an ideal alternative. However, the design of an unsupervised detection algorithm is rather complicated and usually needs a set of filters, which may lead to excessive computational effort. Optimal Gabor filter is therefore an alternative, which can be designed to detect a class of textile fabrics. As fewer filters are usually used compared to the unsupervised detection, a faster computational speed can be achieved and less storage requirements of the results are needed.

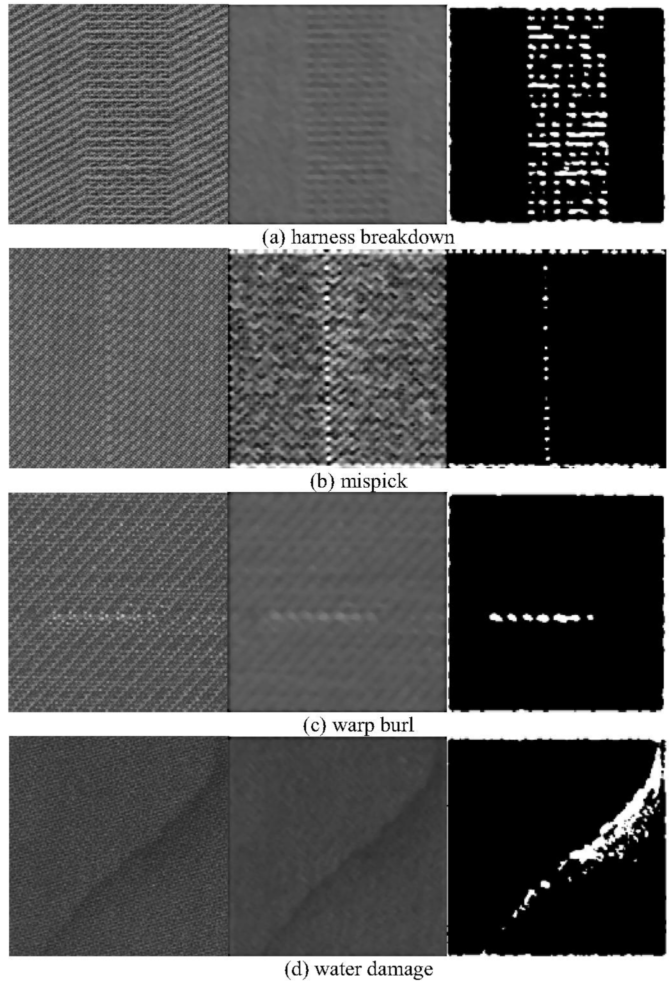


Fig. 5. Fabric samples with harness breakdown, mispick, warp burl and water damage in (a), (b), (c) and (d) respectively and the corresponding final defect segmentation results.

## V. CONCLUSIONS

In this paper a real-time vision-based prototype system for detecting defects in textile fabrics has been proposed and developed. Compared to other systems reported in the literature, the apparatus allow the tension of the fabric to be adjusted so that stable images can be captured.

Besides, a new filter selection method has been demonstrated, which has been developed into a defect segmentation algorithm. The algorithm is based on the analysis of spectral feature of textures, which can automatically find a well matched real Gabor functions in every level of the pyramidal decomposition. The process of filter selection is semi-supervised, and only a non-defective fabric image is needed to obtain a set of optimal Gabor filters.

Indeed, such a set of optimal filters obtained by the algorithm contains much less filters than those generated by the most commonly used dyadic decomposition method.

The performance of the overall defect detection scheme, including the hardware and software has been thoroughly tested both on-line and off-line. The test results have shown that the scheme is effective, robust and can satisfy industrial requirements.

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