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Automatic Defect Detection of Patterned Fabric via Combining the Optimal Gabor Filter and Golden Image Subtraction ⋆

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Abstract

A new algorithm based on optimal Gabor filter and the basic Golden Image Subtraction (GIS) is presented for patterned fabric defect detection. Firstly, the defect-free patterned fabric images are processed to search optimal real Gabor filter parameters using traditional Genetic Algorithm (GA). Then test patterned fabric images are filtered according to the obtained optimal real Gabor filter. Furthermore, the basic GIS are adopted to perform subtractions between golden images from referenced fabric images and test images to get resultant images. Finally, thresholding is obtained by training a large amount of defect-free patterned fabric samples to segment defects from fabric background. Experiment results indicate that the average detection success rate is up to 96.31% with ninety defective patterned images and ninety defect-free patterned images. It demonstrates that the proposed method is more efficient.

Keywords: Defect Detection; Gabor Filter; GIS; Genetic Algorithm; Patterned Fabrics

1 Introduction

The market value of patterned fabric is much higher than other fabrics in commercial world. Thus patterned fabric defect detection is an important procedure for fabric quality assurance, and automatic fabric defect detection research has a far-reaching significance, which is an inevitable trend of textile industry development.

Nowadays, existed approaches for fabric defect detection are mainly for non-patterned fabric, which have achieved over 95% recognition success rate [1,2] and have been broadly characterized as statistical, spectral, model-based [3,4]. But it has a few methods for patterned fabrics. One of the reasons is repetitive design that provides more underlying information; the other is complicated and varied fabric texture transform.

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The main theories are presented in patterned fabric detection. Baykal et al. have adopted hash functions [5,6] for the sake of inspecting patterned fabric defect. The method is time-saving, while it is sensitive to noise and cannot outline defect shape. Bollinger Band (BB) method [7] has been basically used in the stock market for overbought and oversold shares, which can segment fabric defect with clean and clear images, but it cannot properly align input images and reference images. Sandy et al. [8], Li et al. [9] have used Traditional Image Subtraction (TIS) method which is based on Exclusive-OR operation on lace patterned fabric. However, TIS cannot do perfectly pixel-by-pixel comparison between golden template and test area. Then, Direct Thresholding (DT) [1] method adopts the fourth level of vertical and horizontal extraction of detailed sub-images with Haar Wavelet decomposition. Although the DT method is immediate and fast, output images are coarse in resolution. Afterwards, the basic GIS method [1, 2] is applied in golden image and test image in order to get resultant image. The GIS method has better performance than TIS but the result is not perfect due to excessive white noises in acquired images. To address this problem, the Wavelet preprocessed Golden Image Subtraction (WGIS) [1, 2] is proposed. Though overall success detection rate is 96.7%, only the common dot-patterned fabric is tested. In the following, the basic Regular Bands (RB) method [10, 11] utilizes distance matching function to determine the periodic distance of length and width of regular band in regular patterned fabrics, the fabric defects are extracted from fabric background by comparing two features of regular band to thresholdbut the method only is appropriate for periodic and regular patterned fabrics.

Kumar et al. [12–16] have summarized that Gabor filter is especially effective for fabric defect detection due to the property of optimal localization in both space domain and frequency domain with multiple dimensions and orientations. In our work, a new method based on Gabor filter and GIS method was presented. The proposed method involves three stages as shown in Fig. 1: training stage, obtaining threshold stage and defect detection stage. In the training stage, a set of fault-free patterned fabric samples are used in obtaining the optimal Gabor filter parameters that match special fabric texture via GA [17]. In the obtaining threshold stage, thresholding for discerning defect-free and defective patterns can be determined by Direct Threshold (DT) [1, 2] method. In the defect detection stage, by means of GIS, resultant images of the test images can be gained. Then, the fabric defect is extracted from the fabric background by comparing thresholding with the energy value of test image.

The paper is organized as follows: Section 2 mainly describes the theories involved, which includes basic Gabor filter, optimal Gabor filter via GA, basic GIS method and Direct Threshold (DT) method. Section 3 presents the proposed method for detecting the presence or absence of defects in an inspection image. Section 4 provides experimental results in fabric defect detection and evaluates the performance of the proposed method. The detail conclusion is described in Section 5.

2 The Theories Involved

2.1 Gabor Filter

Real and imaginary part of a typical Gabor filter are called as real and imaginary Gabor filter, respectively. The real part is even function, which is usually used to derive excellent blob detections in the field of image processing [18]. The imaginary part is odd function, which is an effective edge detection operator and usually utilized to derive excellent edge detectors [19].

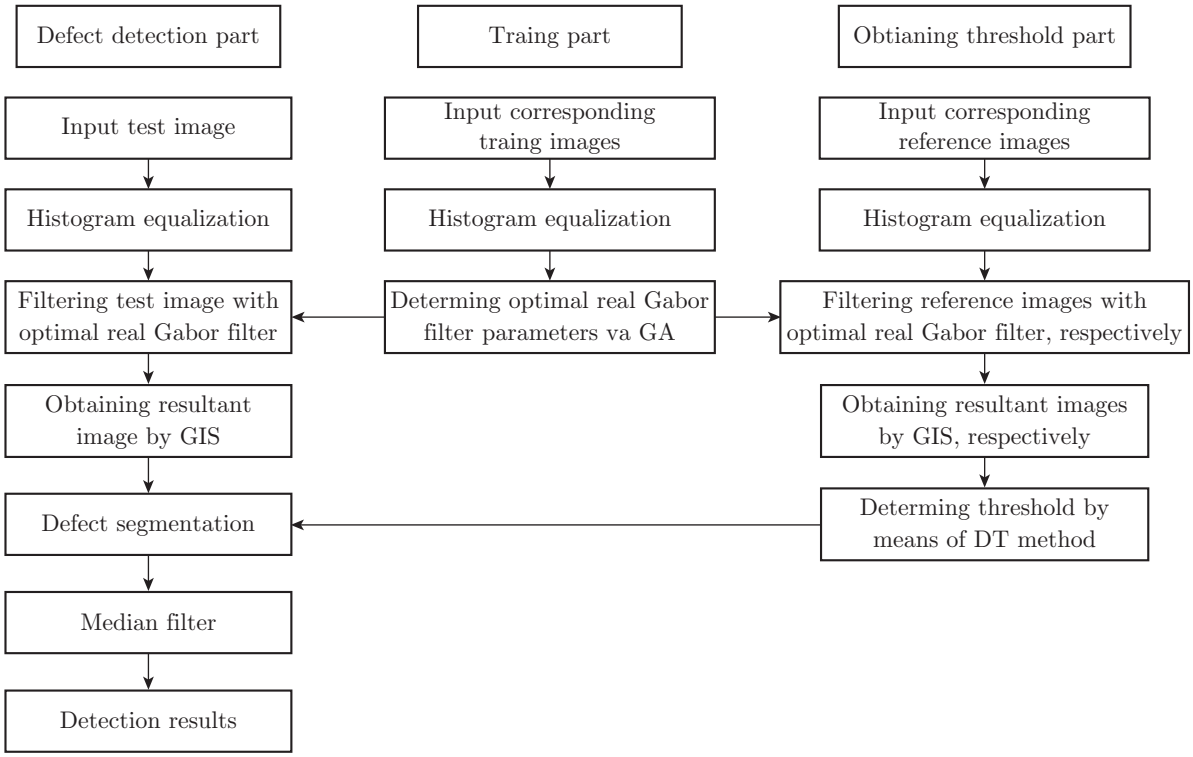


Fig. 1: Defect detection of patterned fabric via combining optimal Gabor filter and GIS

However, some researchers [17, 20–22] find that only the real part is sufficient to inspect fabric defects. The main reason is that the imaginary part not only accounts for nearly 50% of the total computation time, but contributes little to defect detection. Thereby, this paper only utilizes the real Gabor filter as final filter, and the final Gabor filter function can be formulated as Eq. (1):

$$g_e(x,y) = exp\left\{-\frac{1}{2}\left[\left(\frac{x'}{\sigma_x}\right)^2 + \left(\frac{y'}{\sigma_y}\right)^2\right]\right\}\cos\left[2\pi\mu_0 x'\right] \tag{1}$$

where, $\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix}\begin{bmatrix} x - T_1 \\ y - T_2 \end{bmatrix}$ and $\lambda = \sigma_y/\sigma_x$. μ_0 is the center frequency of Gabor filter. θ is the orientation of Gabor filter, which is limited to $[0, \pi]$. σ_x and σ_y are the Gaussian envelope constants along the horizontal and vertical axis, respectively. λ is the aspect ratio between σ_y and σ_x. T_1 and T_2 are conversion parameters. Values x and$y$ are rotated by direction θ to the corresponding x' and y'. Direction rotates the values and to the corresponding and. The specific direction and size represent the particular texture information. Therefore, it plays an important role in searching optimal Gabor filter in arbitrary sizes and orientations.

2.2 Genetic Algorithm

Genetic Algorithm (GA) [23] is a random method of searching optimal parameters by imitating natural evolution process. Its advantages consist of global optimality, robustness and extensive applicability. From the viewpoint of optimization search, GA can obtain approximate or exact solutions to optimizing or searching problems by selection, crossover and mutation operation. In

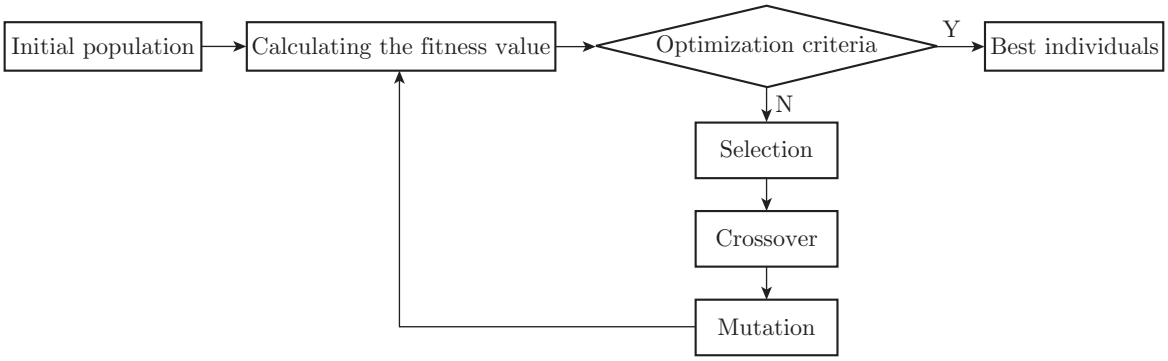


Fig. 2: Flow diagram of Genetic Algorithm

addition, objective function plays an important role in GA due to it could determinate the target of searching. The flow diagram of GA is depicted in Fig. 2 and the detail stages of GA are shown as follows:

Step 1 Initialization: The initial population of binary string is randomly selected from the solution, which generally is called the first generation and limited from 30 to 160.

Step 2 Individual assessment: Calculating fitness of the individuals in groups.

Step 3 Operations: Selecting next generation of individuals by selection, crossover and mutation operation according to the fitness principle. Crossover is mutual exchange in two randomly selected individuals at the same position with the crossover probability (pc) which generally is limited from 0.25 to 0.75. The purpose is to produce a new gene combination, namely producing new individual. Mutation takes some point from each individual into a reverse operation with mutation probability (pm), namely exchanging 0 to 1 or 1 to 0. Mutation probability pm agrees with minimal biological variation, so pm usually ranges from 0.01 to 0.2.

Step 4 Convergence to the global optimum: Termination condition is accomplished when fitness of one individual is zero or maximum number of iteration has been achieved. Otherwise, the process returns to step 2.

2.3 The Basic Golden Image Subtraction (GIS) Method

Description of the basic GIS [1,2] method is shown in Fig. 3. The suitable golden image $G = (g_{ij})$ with size of $m \times n$ pixels is gained from a reference patterned fabric image F of size $M \times N$. Each subtracted image $H_{xy} = H_{xy}(x, y) = (h_{ij})$ with same size of golden image, which is obtained from test image P with same size of reference image. Then, subtractions are executed between golden image and each subtracted image, and the mean of sum of absolute value of all pixels is calculated in order to generate a value r_{xy}. The value r_{xy} is defined as the energy of GIS in Eq. (2). Where $x = 1, \ldots, M - m + 1$, $y = 1, \ldots, N - n + 1$, $i = 1, \ldots, m$ and $j = 1, \ldots, n$ $(0 < n \leq N,\ 0 < m \leq M)$. Finally, $(M - m + 1) \times (N - n + 1)$ matrix is obtained, which is defined as a resultant image $R = (r_{xy})$.

$$R = (r_{xy}) = \frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} |g_{xy} - h_{ij}| \tag{2}$$

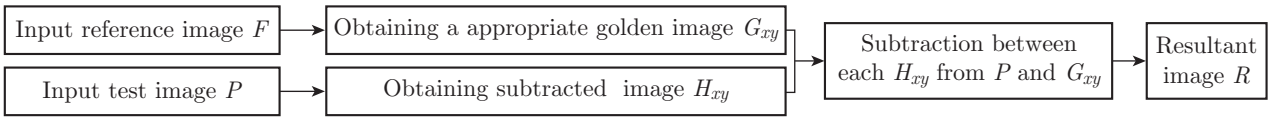


Fig. 3: The structure diagram of the golden image subtraction method

2.4 Direct Threshold Method

Selecting average peak value of the hills from R of reference samples usually is a direct way for the sake of obtaining appropriate thresholding [1, 2]. For example the flawed image in Fig. 4 (d), subtractions on the defective area will cause a distinguish jump in Fig. 4 (f) that is quite different from normal level in Fig. 4 (c).

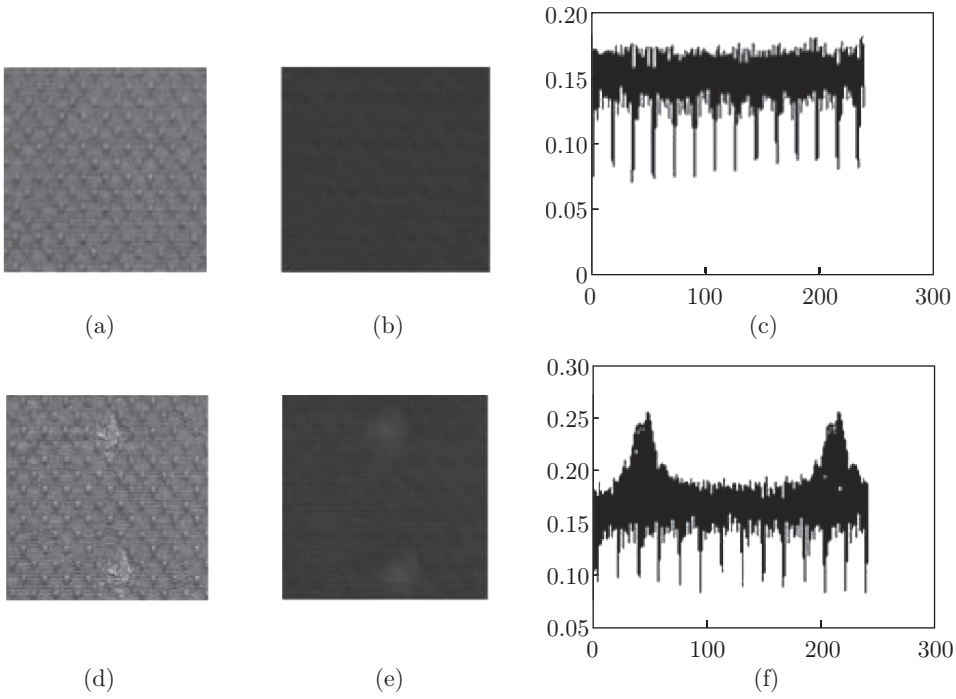


Fig. 4: The plot of resultant images of reference fabric image and defective fabric image. (a) Reference image, (b) Resultant image of reference image, (c) The plot of resultant image, (d) Detective image, (e) Resultant image of detective image, (f) The plot of resultant image

3 Defect Inspection Process

3.1 Obtaining Optimal Gabor Filter Parameters via GA

The key point is to find out a group of optimal Gabor filter parameters that match the texture feature of training samples. GA searches the optimal Gabor filter parameters by utilizing the minimum of objective function E [17] which is given by Eq. (3).

$$E = \min_{\omega, T_x, T_y, \lambda, \theta, u_0} \left[\sum_{xy} (IM(x,y) - \omega g_e(x,y))^2 \right] \tag{3}$$

where ω is Gabor coefficient to harmonize the relevance between the gray-level value $IM(x, y)$ of defect-free image IM and optimal real Gabor function result $g_e(x, y)$.

The detail of obtaining optimal real Gabor filter by GA is described as follows:

Step 1 Initial population: Population is made of all parameter groups which derive from Gabor filter parameters in objective function E given as Eq. (3).

Step 2 Binary coding: The whole parameter groups change into corresponding binary codes.

Step 3 Searching optimal parameter groups: All binary codes of parameters would appear as a whole in GA to realize selection, crossover and mutation operation until the suitable binary codes are selected.

Step 4 Decoding: The selected suitable binary codes are converted into decimal numbers, which represent the optimal Gabor filter parameters and will be applied in real Gabor filter.

3.2 On-line Defect Inspection

For a fabric image under inspection, it is first executed histogram equalization for improving the image contrast. The optimal real Gabor filter operation then follows for each test image, which can be presented as Eq. (4)

$$I_i(x, y) = \left\{ [g_e(x, y) * I(x, y)]^2 \right\}^{\frac{1}{2}} \tag{4}$$

where output images $I_i(x, y)$ is a filtered fabric image. Asterisk $(*)$ is the mark of convolution operation. $g_e(x, y)$ represents the real part of optimal Gabor function and $I(x, y)$ is a sample fabric image.

To obtain resultant image $R = (r_{xy})$ and determine the presence or absence of defects in the test sample $I(x, y)$, the basic GIS operation then follows for the filtered fabric image $I_i(x, y)$. If the test sample exists defects, we expect that a distinguish jump will appear on the plot from the resultant image of defective sample, which will break the periodic hills and valley on the plot from the resultant image of defect-free sample. If the value of resultant image $R = (r_{xy})$ is larger than some pre-determined thresholding, the test sample $I(x, y)$ is identified as a defective one. Otherwise, it is classified as a defect-free fabric image, which is given by

$$D = \begin{cases} 255 & if \quad r_{xy} > Threshold \\ 0 & if \quad r_{xy} \leq Threshold \end{cases} \tag{5}$$

where $D = (d_{ij})$ is a threshold image, r_{xy} is the energy value of resultant image $R = (r_{xy})$ and $i = 1, \ldots, M - m + 1$, $j = 1, \ldots, N - n + 1$.

Eventually, two simple filters are used to smooth threshold image D for lessening the various white impulse noises and enhancing the image for defect on threshold image D, namely Wiener filter and Median filter [24].

4 Experimental Results

This section presents experimental results from a number of patterned images to evaluate performance of the proposed method. The proposed algorithm and experiments were implemented on

Matlab7.11.0 by a personal computer with an Intel Core i5 Quad 3.10 GHz processor. The whole patterned fabric samples are 256×256 pixels, which derive from TILD database [25] and Henry Y. T. Ngan [1, 2] of industrial automation laboratory at the University of Hong Kong.

In this paper, ninety defective images are applied to fabric defect detection. Meanwhile, the corresponding defect-free fabric images are utilized in GA for selecting the optimal Gabor filter parameters to match with specific fabric textures. In order to identify defective patterned fabric image with resultant image $R = (r_{xy})$, reference samples are applied to set the thresholding. It is given by

$$T = (1 - C) \cdot (T_1 + T_2 + \ldots + T_i)/i \tag{6}$$

where T_i is the maxi-mums value of energy of GIS of every reference samples for $i = 1, 2, \ldots, n$. The parameter C is a noise level that generally is set from 1% to 10%. For instance, Table 1 shows that the maximums energy values of resultant image of 4 reference samples that are same of Fig. 4 (a) are 0.1810, 0.1997, 0.1896 and 0.1937, respectively. Hence, the average value is 0.1910, and the thresholding is $T = 0.1910 \cdot (1 - C)$.

Table 1: The maximums values of energy of GIS of reference samples

	Sample (1)	Sample (2)	Sample (3)	Sample (4)
Maximums values	0.1810	0.1997	0.1896	0.1937

In order to evaluate preferably performance of proposed method for patterned fabric defect detection, one common kind of patterned Jacquard fabric is firstly selected from Henry Y. T. Ngan. The defects contain holes, broken end, oil stain, knots and dirty yarn. The number of each defect type is five. Fig. 5 shows partly experimental results. Table 2 summarizes statistical recognition rates for the five test sets, which shows that the average recognition rate is 96% with a maximum of 100%.

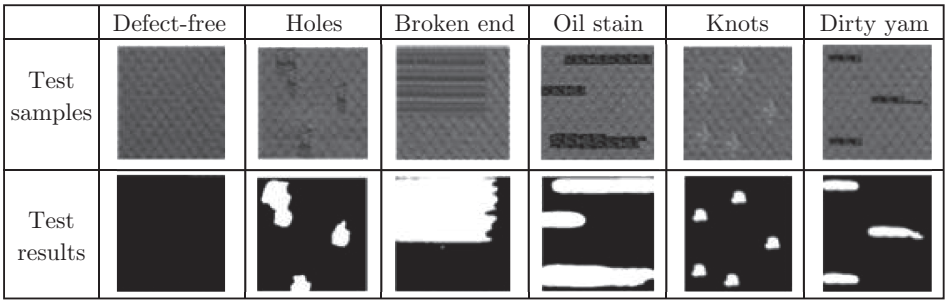


Fig. 5: Detected results of patterned Jacquard fabric images from Henry Y. T. Ngan

The first experiment was conducted to discuss the effect of obtaining optimal Gabor filter parameters by GA. In parameters selection procedure of GA, the target is choosing a minimum result E of Eq. (3) by selection, crossover and mutation operation in initial population. Ideal objective function results E could be received with 100 initial population, pc=0.6 and pm=0.05 in GA [17] based on experimental verification. The determined optimal Gabor filter parameters from patterned Jacquard fabric are spread out in Table 3.

Choosing a golden image and noise level are reasonably key steps for the basic GIS method and DT, respectively. So, the second experiment was conducted to evaluate the effect for test results

due to parameters of GIS and DT. Table 4 shows that different sizes of golden images and noise level have a great influence on detection results. If the size of Golden template keeps in constant and the noise level is adjusted to be too high, a mass of noises will be generated from test results, meanwhile the recognition rate will obviously reduce. If the noise level keeps in constant, the recognition rate will be improved with decreasing the size of Golden template.

Table 2: Recognition rates for patterned Jacquard fabric images

	Holes	Broken end	Oil stain	Knots	Dirty yarn	Overall detection
Successful detected	5/5	4/5	5/5	5/5	5/5	24/25
Detection success rate	100%	80%	100%	100%	100%	96%

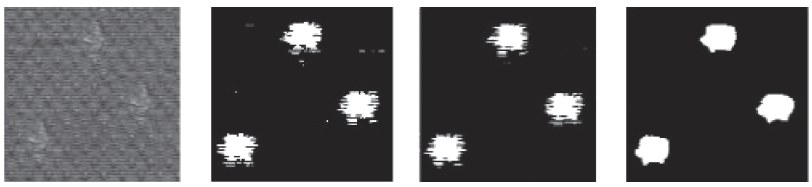
Table 3: The default parameter values Optimal Gabor filter parameters

	ω	T_1	T_2	λ	θ	μ_0
Fig. 6(a)	199.8045	138.8074	186.9990	1.7801	2.8335	12.7291

Table 4: Effect due to the size of golden image and noise level

	Golden template	Noise level	Recognition rate	Noise
(1)	35×25	1%	96%	Small
(2)	35×25	3%	88%	Small
(3)	35×25	5%	80%	Much
(4)	47×41	1%	92%	Small
(5)	47×41	3%	80%	Small
(6)	47×41	5%	76%	Much

The last experiment in this paper is to evaluate the effect of post processing without or with smoothing filtering. The test images used in the experiment is also patterned Jacquard fabric. Fig. 6 (b) shows the test result exists white impulse noises without smoothing filtering, while Fig. 6 (c) and (d) show that the noises can be reduced by Median filter and Wiener filter. Compared with the result of median filtering and wiener filtering, Median filter provides the better detection result. Fig. 6 (c) illustrates that Median filter can effectively remove the noises and perfectly preserve detail of defects. Fig. 6 (d) shows Wiener filter cannot completely filter out noise and makes image edge blurring.



(a) (b) (c) (d)

Fig. 6: Effect due to post processing without or with smoothing filtering. (a) Defective sample, (b) Without smoothing filtering, (c) Using Wiener filter, (d) Using median filter

Afterwards, altogether sixty-five defective images of size 256×256 and sixty-five defect-free images of same size have been utilized for this experiment. Twelve defective images of sixty-five defective images are shown in the paper and other defective images are not listed. Perfect consequences of diversiform defect detections distribute in Fig. 7 including defective images and detection results. Table 5 shows corresponding Gabor filter parameters, the size of golden image and noise level, which indicates different patterned fabric texture will need to choose corresponding Gabor filter parameters and template size, in order to obtain better test results. Sixty-three

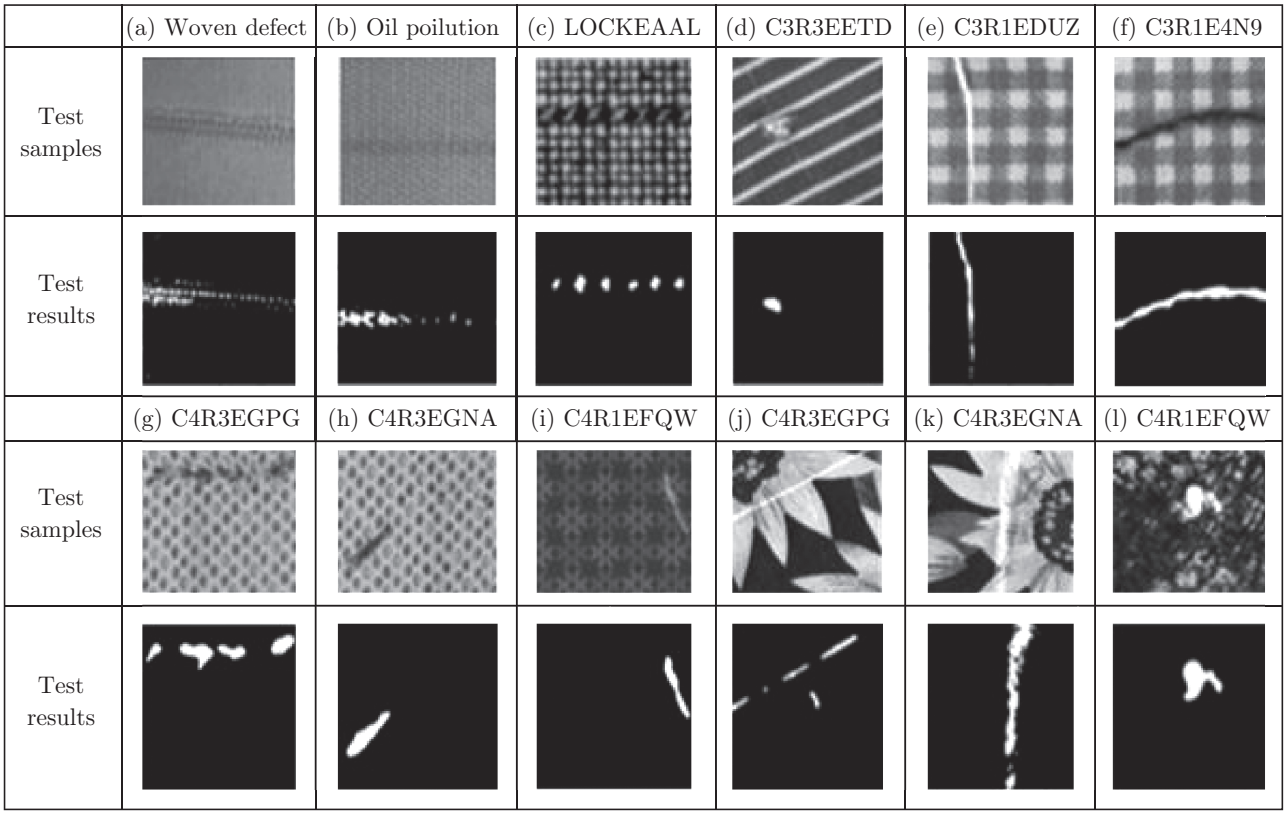


Fig. 7: Detected results of patterned fabric images from TILD database

Table 5: Corresponding Gabor filter parameters, the size of golden image and noise level

	Gabor filter parameters						Golden template	Noise level
	ω	T_1	T_2	λ	θ	μ_0		
Fig. 4 (a)	237.4389	107.0381	109.9707	1.6383	2.6651	8.9848	4×4	1%
Fig. 4 (b)	186.1193	113.8807	194.1349	1.4184	2.6784	7.9995	2×2	1%
Fig. 4 (c)	449.5601	126.9795	112.6100	1.3500	2.6610	14.1597	7×7	1%
Fig. 4 (d)	253.1769	178.0059	119.5503	1.7957	3.1211	7.5178	7×7	1%
Fig. 4 (e)-(f)	362.6588	198.4360	101.7595	1.0186	2.6702	7.9119	3×3	1%
Fig. 4 (g)-(h)	646.6276	179.2766	188.6608	1.0528	3.1124	12.5393	17×17	1%
Fig. 4 (i)	186.1193	113.8807	100.4888	1.6784	3.1145	8.0068	6×6	1%
Fig. 4 (j)-(k)	390.7136	109.2864	171.7498	1.2278	2.8294	7.9119	2×2	1%
Fig. 4 (l)	173.8025	177.3216	143.5484	1.2374	3.0534	10.4377	9×9	1%

defect-free images and sixty defective images could be correctly detected. So, the detection success rates are 96.92% and 92.31% for defect-free and defective images, respectively.

Eventually, Table 6 summarizes statistical recognition rates of patterned fabric images from TILD database and Henry Y. T. Ngan. It shows that overall detection success rates for all test patterned fabric images is 96.31%.

Table 6: Overall detection success rates for all test patterned fabric images

	50 test samples from Henry Y. T. Ngan	130 test samples from TILD database
Defect-free images	25/25=100%	63/65=96.92%
Detection success rate		
Defective images	24/25=96%	60/65=92.31%
Detection success rate		
Average detection success rate	49/50=98%	123/130=94.62%
Overall detection success rate	96.31%	

5 Conclusion

A novel method based on optimal Gabor filter and GIS is explored to realize automatic patterned fabric defect detection in this paper. The proposed method has been evaluated with ninety defective patterned images and ninety defect-free patterned images. The overall detection success rate is up to 96.31% according to the whole inspection results, which shows that the proposed method is more efficient and convenient for patterned fabric defect detection. The improved algorithm has several mainly contributions. First, compared with the basic GIS method, the proposed method avoids a big obstacle of excessive noise on defect detection. Second, the proposed method can identify location of a variety of fabric defects with finer shapes. Third, the proposed method can detect regular and partially irregular fabrics. Fourth, the means can automatically research optimal real Gabor filter parameters that match with special patterned fabric texture through GA, which eliminates the blindly artificial experiment of selecting parameter groups. However, shorter computational time, higher complexity and instability during random GA searching procedure are our further study.

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