A New Fabric Defect Detection Model based on Summed-up Distance Matching Function and Gabor Filter Bank

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***Abstract*—Focusing on the problem of low efficiency and high mistake rate for manual detection of fabric with periodic textures, a new fabric defect detection model based on summed-up distance matching function and optimal Gabor filter bank is proposed. Firstly, the frequency and scale parameters of the filter bank are accurately calculated by the summed-up distance matching function; for the direction parameter, the objective function is constructed by the mean and variance of the energy of the normal fabric images convolved by the Gabor filter bank, then the optimal direction is determined by particle swarm algorithm. The optimal filter bank is used to convolute the fabric image to be measured, and then the Otsu algorithm is used to accurately segment the convolution image. The experimental results show the method has a short learning time and good robustness, and can detect fabric flaws quickly and accurately.**

Keywords-periodic texture; Gabor; Binary Particle Swarm Optimization; defect detection

I. INTRODUCTION

Fabric defect detection is generally aimed at fabrics with simple structures that do not contain complex patterns or fabrics that contain complex patterns but whose patterns have periodic variations [1]. For the detection of fabric defects with simple structure, there have been many more mature methods, such as Gabor filter and so on [2]. Fabric defect detection using the Gabor filter works well, but it needs to determine the parameters. Le Tong, W.K. Wong and C.K. Kwong used differential evolution algorithm to optimize Gabor filter parameters [3]. Hu GH used genetic algorithm to optimize the elliptic Gabor filter [4]. And he also proposed an optimal ring Gabor filter (RGF) for leather and determined the parameters of the filter through simulated annealing (Sa) algorithm [5]. The detection of fabric defects with periodic textures is relatively rare and has only begun in-depth studies in recent years. V. Asha, P. Nagabhushan and N.U. Bhajantri proposed an automatic texture periodicity detection method based on distance matching functions (DMFs) and calculated forward differentials to identify fabric defects with continuous periodic textures automatically [6]. Lizarraga-Morales R A, Sanchez-Yanez R E and Baeza-Serrato R used a simplified single cluster classifier with Reduced Coordinated Cluster Representation (RCCR) as features [7]. And estimate the cell size of a defect-free fabric automatically using a texture periodic algorithm during training to detect defective samples. A model that was proposed by Michael K. Ng, Henry Y. T. Ngan, Xiaoming Yuan and Wenxing Zhang to use the total variation, sparsity, and low rank terms of fabric images with complex pattern [8]. The total variation term is used for regularized defect images, the sparsity and low rank terms are used to control the Dirac comb function. Yundong Li, Weigang Zhao, and Jiahao Pan proposed a discriminative representation for patterned fabric defect detection when only limited negative samples are available by Fisher criterion-based stacked denoising autoencoders (FCSDA) [9].

Based on the advantages of Gabor filter modulation, and the structural characteristics such as periodicity, directionality and uniformity of fabric texture, one new Fabric defect detection model is proposed [10-11]. In this paper, the Gabor filter bank is optimized using the summed-up distance matching function (SDMF) and the binary particle swarm optimization (BPSQ). The experimental results show that the method can detect four kinds of defects, such as hole, stain, thin bar and broken end, which are common in fabrics. The recognition results are better than traditional Gabor filters.

II. SUMMED-UP DISTANCE MATCHING FUNCTION

For fabric images with periodic texture, a summed-up distance matching function (SDMF) is used to describe the periodicity of texture in fabrics. At the expense of low calculation accuracy, SDMF improves the efficiency of the traditional single-window gray-level co-occurrence matrix (GLCM) on the periodicity of texture primitives, aiming to calculate the cumulative amount of high-brightness values in different steps and different directions of the fabric image, and determining the periodic texture period [6]. For a 2-D image of size M×N, the SDMF in the horizontal direction r and the vertical direction c can be expressed as:

$$\Lambda_r(\delta)=\sum_{r=1}^{M}\left(\sum_{i=1}^{N-\delta}\left[f(r,i)-f(r,i+\delta)\right]^2\right) \quad (1)$$

$$\Lambda_c(\delta)=\sum_{c=1}^{N}\left(\sum_{i=1}^{M-\delta}\left[f(i,c)-f(i+\delta,c)\right]^2\right) \quad (2)$$

where δ is the spatial distance between pixels. When the displacement and cycle size are equal, the SDMF satisfies:

$$\Lambda_r(\delta=p_r)=\sum_{r=1}^{N}\left(\sum_{i=1}^{N-\delta}\left[f(r,i)-f(r,i+p_r)\right]^2\right)=0 \quad (3)$$

$$\Lambda_c(\delta=p_c)=\sum_{c=1}^{N}\left(\sum_{i=1}^{M-\delta}\left[f(i,c)-f(i+p_c,c)\right]^2\right)=0 \quad (4)$$

For (a) in Fig. 1, the row SDMF and the column SDMF are shown in Fig 1. (b) (c).

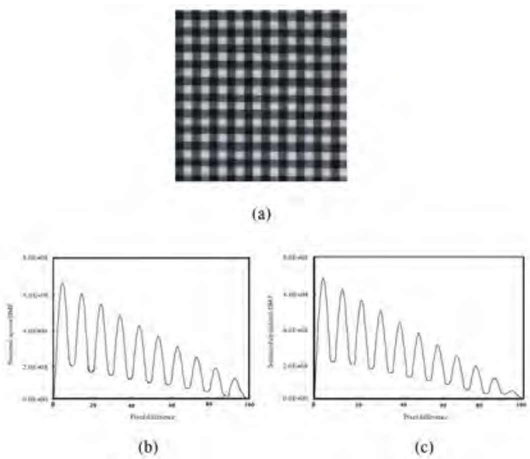

Figure 1. Fabric image with periodic texture and its summed-up distance matching function: (a) Fabric image, (b) The row SDMF, (c) The column SDMF.

III. CONSTRUCT AN OPTIMAL GABOR FILTER BANK

A. 2-D Gabor Filter

The 2-D Gabor filter is a complex exponential function modulated by a Gaussian function and can simulate the filter response of unicellular in the mammalian visual cortex. In the space domain, a two-dimensional Gabor filter is a Gaussian kernel function modulated by sine wave. The mathematical expression of 2-D Gabor function in time domain is as follows:

$$g(x',y')=\frac{1}{2\pi\sigma_x\sigma_y}\exp\left(-\frac{1}{2}\left(\left(\frac{x'}{\sigma_x}\right)^2+\left(\frac{y'}{\sigma_y}\right)^2\right)\right)\exp\left(2\pi iFx'\right) \quad (5)$$

where $x'=x\cos\theta+y\sin\theta$, $y'=-x\sin\theta+y\cos\theta$, σ_x and σ_y is the scale factors of the x-axis and the y-axis, θ is the Gabor filter direction, and F is the center frequency of the Gabor function.

How to determine the optimal Gabor filter parameters is an important issue. Most Gabor filter parameters are set in advance, and the method to get the optimal parameters is generally to extract the parameters and then optimize the specific target. This is followed by training with non-defective sample to produce a high response. Because there is more than one parameter to be optimized, excessive data burden will be generated during the optimization process. Therefore, a method based on SDMF is proposed. Firstly, parameters σ_x , σ_y , and F are accurately calculated, and then the optimization algorithm is used to get θ . This greatly reduces the complexity and redundancy of the algorithm.

B. Parameters of Gabor Filter Bank Obtained by SDMF

For fabric images with periodic texture, an in-depth analysis of the principle of the Gabor filter, as shown in Fig. 2. The dashed lines represent the texture direction and solid lines with arrow represent the Gabor filter direction. When the Gabor filter direction is the fabric texture direction and the size is the period of fabric texture, energy information can be concentrated in the texture direction and the vertical direction of the texture direction after convolution to highlight the texture. So we construct Gabor filter bank composed of two Gabor filters, and optimize the frequency, scale and direction of filter bank. This Gabor filter bank is optimal and can get the best processing results.

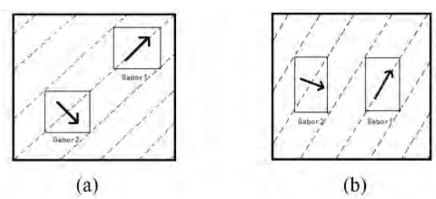

Figure 2. The principle of Gabor filter: (a) 45° direction Gabor schematic, (b) 60° direction Gabor schematic.

- Frequency: If the step length is exactly equal to the texture primitive period, the texture information in this direction can be highlighted effectively. So, $F=1/T$, T is the texture primitive period, and the texture primitive period can be accurately calculated as $T1$ and $T2$ through SDMF. The frequency of the Gabor filter bank is $F=1/T1$ and $F=1/T2$, respectively.
- Scale: σ_x and σ_y can be accurately obtained as $\sigma_x=T1$ and $\sigma_y=T2$ respectively through SDMF. The size of Filter bank is $\sigma=\sigma_x\times\sigma_y$.

The two directions of the periodic fabric texture are perpendicular to each other, so the main direction of the texture is set as θ . And take the Gabor filter bank directions θ_1 and θ_2 as $\theta_1=\theta$ and $\theta_2=\theta+\pi/2$ respectively.

C. Constructing the Objective Function

Single Gabor filter cannot guarantee good performance, so two different directions of Gabor filters are used in paper. $I(x,y)$ is the fabric image after histogram equalization. Energy response diagrams before and after histogram equalization are shown in Fig 1. (d)(e), and histograms are shown in Fig 1. (b)(c). Equation (6) is Gabor convolution.

$$G_i(x,y) = I(x,y) * g_i(x,y) \tag{6}$$

where i=1,2, $g_i(x,y)$ is the Gabor filter. Gabor filter bank formed by two Gabor filters is shown in (7).

$$G(x,y) = \alpha(x,y) \times G_1(x,y) + (1-\alpha(x,y)) \times G_2(x,y) \tag{7}$$

$$\alpha(x,y) = \frac{G_1^2(x,y)}{G_1^2(x,y) + G_2^2(x,y)} \tag{8}$$

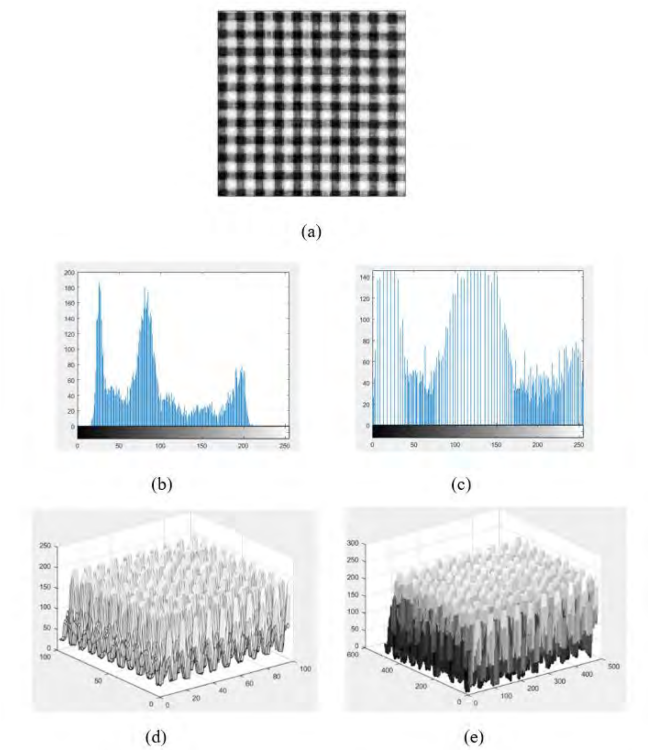

Figure 3. Histogram equalization: (a) The fabric image after histogram equalization, (b) Histogram of Figure 1.(a), (c) Histogram of Figure 3(a), (d) Energy response of Figure 1.(a), (e) Energy response of Figure 3.(a).

For a normal fabric image, the energy mean after convolution of Gabor filter bank is larger than abnormal part, and variance is smaller. So the objective function is

$$\max F = \frac{\delta}{\mu} \tag{9}$$

where $\delta = \left(\frac{1}{n^2 - 1} \sum_{x=1}^{n} \sum_{y=1}^{n} (E(x,y) - \mu)^2 \right)$,

$\mu = \frac{1}{n^2} \sum_{x=1}^{n} \sum_{y=1}^{n} E(x,y)$. $E(x,y)$ is the image energy after Gabor convolution. It can be expressed as

$$E(x,y) = \left[(T(x,y) * G_e(x,y))^2 + (T(x,y) * G_o(x,y))^2 \right]^{\frac{1}{2}} \tag{10}$$

D. BPSO to Solve the Objective Function

The θ is modulated with discrete and real values, so binary particle swarm algorithm (BPSO) [12] is used to optimize the θ of the Gabor filter bank. The principle of BPSO is simple and easy to implement, and the convergence speed is fast. Moreover, there are many measures can avoid it fall into a local optimum. Therefore, BPSO is adopted to select the optimal θ. The optimization steps are as follows:

- Initialize particle position: Set the initial position randomly and initial velocity of the particle within the allowable range and generate a binary code. At this point, the parameter that needs to determine the optimal value is only θ, so the search space is one-dimensional.
- Calculate the fitness function value.
- Update particle position and velocity: Update particle velocity according to (11):

  $$v_{id} = v_{id} + c_1 r_1 (p_{id} - x_{id}) + c_2 r_1 (p_{gd} - x_{id}) \tag{11}$$

  where p_{gd} and x_{id} are integers in {0,1}, the value of v_{id} is expressed in the form of probability, limited to [0.0, 1.0]. Update particle position by (12):

  $$\text{if } (rand() < S(v_{id})) \text{ then } x_{id} = 1$$
  $$\text{else } x_{id} = 0 \tag{12}$$

  where S(v) is a sigmoid function that can limit a to a logical mapping between [0,1]. With $S(v_{id})$ close to 0, the particle's position may be fixed at 0 and there will be less chance of change. Rand() is a random number chosen from [0,1].
- Set the best position of each particle P_i and the global optimum P_g.
- Check the termination condition: when the number of iterations reaches the maximum number, the global best position is the Gabor direction parameter θ value to be determined; otherwise, it is iterative again and go the second step.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

The optimal Gabor filter bank is used to process fabric samples with periodic textures. The normal textures can pass through the filter bank and abnormal textures are suppressed. Then use the Otsu algorithm for binary operations. Because when acquiring the sample image, the brightness of each point of the image is not the same due to the influence of light or other external reasons. The Otsu algorithm is simple and does not suffer from image brightness and contrast.

In order to prove the validity of this method, four representative flaws were selected: hole, stain, thin bar and broken end. All samples are grayscale images of 256×256 pixels. The algorithm proposed in this paper is compared with the classic algorithm proposed in [2]. The evaluation of detection effect of the algorithm is represented by binary images. The detection results are shown in Fig. 4.

The first line is the fabric images of different defects, the second line is the test result of the proposed method, and the third line is the test result of the method in [2].From the detection results of the four defects, it could be concluded that both methods can detect the defects, but the detection results obtained by the proposed algorithm are clearer and the position of defects is more accurate, thus proving the effectiveness of the proposed algorithm.

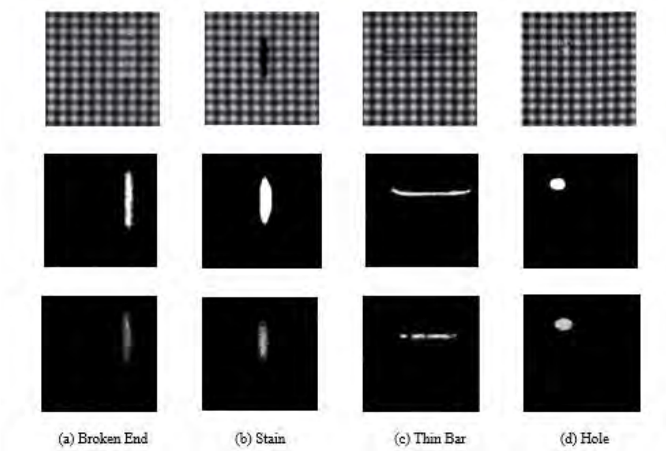

Figure 4. Detection of fabric images with different defects and comparison with [7].

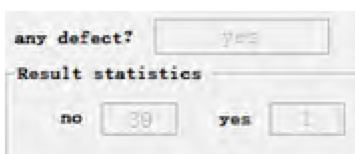

Figure 5. One of the experimental results

In order to get average accuracy, 20 experiments with 40 samples were conducted. One of the experimental results is shown in Fig.5. The table 2 shows the comprehensive accuracy of the two algorithms and the time taken for a single image. It can be seen that the accuracy of the proposed algorithm is higher than the classic algorithm in [2], and takes less time.

TABLE I. ACCURACY AND TIME FOR DEFECT DETECTION RESULTS

Detection Algonithm	Accuracy	Time/s
the optimal Gabor	0.954	0.89
Classic Gabor	0.888	1.71

V. SUMMARY

This paper presents a new method for fabric defect detection with periodic texture. For fabric images without defects, the Gabor filter bank parameters are calculated by SDMF and BPSO. Compared with the classic algorithm using the filter bank, this paper presents the optimal Gabor filter bank composed of two Gabor filters for fabric defect detection. It can detect fabric defects more accurately and efficiently, which is more conducive to industrial production. The objective function is constructed by means and variance of energy so that the Gabor filter bank with optimal parameters is more consistent with defect-free texture features. The proposed algorithm can detect fabric defects faster and more accurately. Experimental results demonstrate the effectiveness of the proposed algorithm.

VI. ACKNOWLEDGMENT

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