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Adaptive Gabor Filtering for Fabric Defect Inspection

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Abstract. Based on the characteristics of mini-jacquard fabrics, an adaptive detection and localization method for mini-jacquard fabric by local-local and local-integral texture features is proposed. Gabor filters have been successfully utilized to characterize texture. However, their parameters are often predefined, which may not be optimal for specific tasks such as fabric defect detection. In this paper, we propose to adaptively choose the optimal Gabor filter parameters with the Particle Swarm Optimization (PSO) algorithm. After a defect patch is identified, fuzzy c-means clustering (FCM) algorithm is utilized to locate the defect region. Experimental results demonstrate that the proposed method is able to achieve improved detection accuracy in real-time.

Keywords: detection, gabor filter, mini-jacquard fabrics, PSO

1 Introduction

Whether it is from raw materials, processes or finished products, the types of textiles are very prosperous [1]. Fabric evolves through human history from the cotton and hemp to silk, chemical and fibre cheeses, from the hand-crafted woven textiles to modern electronic textiles produced by machines [2]. Textile is used in multiple products such as clothing, filters, wipes, and decoration and transportation materials. Although the method of fabricating the fabric has undergone a revolutionary change, due to machine failure, yarn problems and other reasons, there are still defects on the surface of the fabric. The flaw is called defect, and the presence of which in fabrics can reduce prices with losses reaching 45%-65% [3]. Detection, identification and localization of fabric defects is a powerful means to control fabric quality [4]. And today, it's necessary to replace the fastidious manual inspection [5] with automatic inspection [6] for better productivity and improving quality of fabric, which enhance the efficiency of detection in fabric defect. But the automatic inspection is not easy to implement mainly due to the various fabric patterns and the diverse defects which could be categorized into more than 70 types [5].

Automatic detection is a method based on computer vision, which means the defects are detected by analyzing and characterizing with two-dimensional (2D) texture of fabric surface [7]. All fabrics can be classified into 17 established wallpaper groups which are lattices composed of elementary elements called motifs, those are organized repetitively along parallelogram, rectangular, rhombic, square, or hexagonal shapes [8]. Considering the classification of inspected fabric types, Ngan et al. have proposed a taxonomy for defect detection methods, which broadly categorizes the methods into two main groups, which are motif-based and non-motif based. Essentially, both segmentation methods are based on whether the given method is built on the sub-image segmentation according to the wallpaper groups. Most of non-motif based algorithms are designed for the plain and twill fabrics categorized as p1 in wallpaper groups; a few have the capabilities to process other types. And the typical theories of methods processing fabric textures: auto correlation [8-9], morphology [8, 10-11], Fourier transform [12-13], wavelet transform [9, 14-15], autoregressive model (AR) [16], etc. The core purpose of all methods is to reduce the loss. Although it can not be repaired when serious defects occur, it can repair as much as possible to reduce. Therefore, automated fabric inspection is beneficial, but the challenges are: (A) the variety of raw materials which make up the fabric; (B) different compositions of various wallpaper-like

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fabric textures; (C) The similarity in shape between the defect and the background texture. It's not easy to solving all problems in a single way or achieving high detection success rates for large numbers of samples from different groups.

Fabric defect detection has been a popular research topic for many years. The imperceptibility of defects is a major problem in the defect detection. How to detect fabric defects efficiently is an urgent problem to be solved in modern textile industry. Among the existing basic methods for solving such problems, each basic method has its own advantages and disadvantages, the key is that most of them can only detect a single or a few defects, and the jacquard fabric (non-p1 groups) is more remarkable than the plain fabric (p1 group), so the algorithm is more demanding. When the basic method fails to meet the requirements, a combination of various methods has emerged to meet the requirements, such as the combination with mathematical morphology and fourier transform, and learning approach and Gabor transform. Paper [14, 17] proposes methods suitable for mini-jacquard fabric defect detection. Paper [14] suppresses the normal texture by Fourier transform and morphological filtering, which highlights the defect area to obtain the saliency of the image, and then introduces the visual saliency model of graph theory and the maximum entropy method to locate the defect. In the mini-jacquard defect detection experiment, the detection rate of this method is up to 90%, but it takes a long time. Aiming at the problem of long time-consuming with high accuracy in the detection of mini-jacquard, reference and learn the method of detection of plain fabric. The detection rate and running speed of Jacquard fabric are slightly better than other methods when using the method of paper [18] to detect defects. The paper [18] provides a method of modulating Gabor filter, which consists of two stages: In learning stage, modulated the 2D Gabor filter with defectless fabric image, and the optimization algorithm is used to optimize the parameters of the filter to obtain the optimal parameters. In detection stage, the Gabor filter with best parameters is used to obtain the measured image, and binarized the filtered image. Then the defect location is pointed out. The experimental results show that the method has higher accuracy and more precise location in plain fabrics with shorter comprehensive running time, which is suitable for the defects detection in mini-jacquard fabrics.

In this paper, a method combining modulable Gabor wavelet and correlation function is proposed. Under the unsupervised condition, combination the advantage of wavelet and correlation function, and the periodic texture feature is also used to detect the fabric flaw. Modulable Gabor wavelet is used to obtain the texture information with few amount of texture and high efficient in fabric defect detection to meet different patterns. The texture feature image is composed of two parts: $P = P_1 \oplus P_2$, where P_1 is represented as a normal feature in the image and P_2 is represented as a abnormal feature, it's means the fabric is flawless, when the value of P_2 is zero. The perfect state of Gabor filter means the energy of P_1 is a constant C; If the value of P_2 is not zero, the value of P is not equal to C, then marked the defects. In view of the unsupervised condition, this paper introduces the similarity calculation, which calculates and obtains the similarity matrix between each block and integral before and after filtering with different parameters of Gabor filter, then obtaining the fitness values based on the similarity matrix in the adaptive function of optimization algorithm, the final value of fitness used to judge whether the fabric contains defects. After comparing the advantages and disadvantages of optimization algorithms, particle swarm optimization (PSO) is retained, which seeks the optimal solution through the cooperation between groups and it is simple and easy to implement. Ideally, after the optimization completed, the defect areas in the filtered image differ greatly from the normal texture, then the binary function can easily and accurately locate the defect. However, it is difficult to achieve the ideal state in the actual operation, which leads to the binary function in the defect location error prone, so this paper introduces FCM algorithm to locate the defect accurately to improve the accuracy of location. To summarize, this paper makes the following contributions:

An unsupervised self-learning method was proposed for fabric defect detection, which based on the periodicity of normal texture in mechanized fabrics. This method is not need flawless fabric images, compared with the traditional learning algorithm, it is further reducing manual intervention.

The method can be applied with different textures in defect detection, it is based on the characteristics of fabric texture diversity but periodicity, and combined with modulatable Gabor filter and similarity calculation.

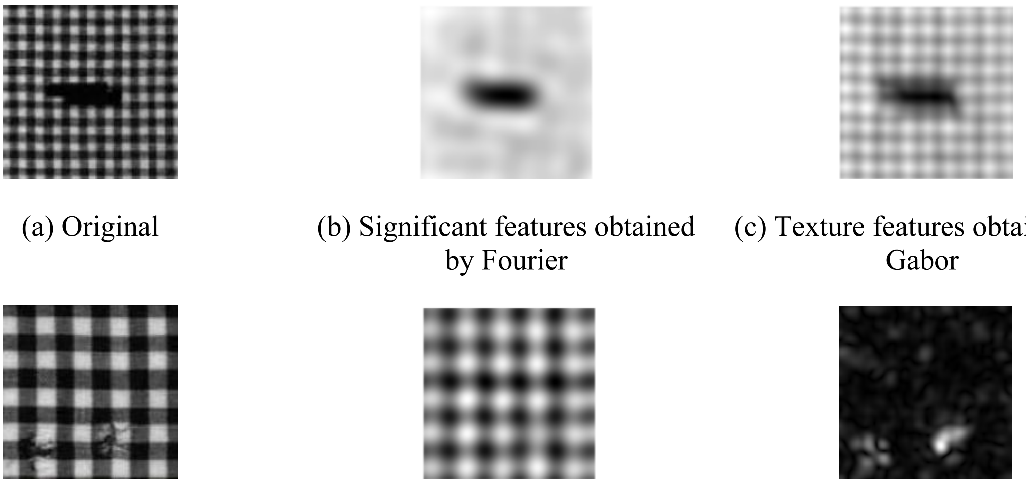
The remainder of this paper is organized as follows. In Section 2, the work related to Gabor is briefly reviewed. Section 3 outlines the method and its procedures. In Section 4, the proposed is compared with other methods. Section 5 concludes the paper. Lastly, Section 6 is acknowledgement.

2 Background

The method relies on feature extraction, similarity calculation and parameter optimization. The following literature review briefly discusses various components related to fabric defect detection.

2.1 Feature Extraction

There are many methods for feature extraction, such as auto correlation [8-9], morphology [8, 10-11], Fourier transform [12-13], wavelet transform [9, 14-15], autoregressive model (AR) [16] and so on. As a repeated and periodic texture image, fabric image has certain characteristics in its spectrum. Therefore, the frequency domain based method in fabric flaw detection is a classic. In recent years, there are still a large number of such articles published [12-25]. Because of the poor temporal resolution, the extracted features are mostly global features, so it is difficult to detect some minor defects which cannot affect the global texture [13]. Wavelet transform is a multi- resolution analysis method, which can extract local information better, Gabor transform, as a special Fourier transform in wavelet transform, has improved some shortcomings of the Fourier transform, making it take into account the resolution in time domain and frequency domain. The window size of Gabor transform changes with frequency and has good directivity, which is widely used in fabric detection [17-25]. As shown in Fig. 1.



(a) Original | (b) Significant features obtained by Fourier | (c) Texture features obtained by Gabor

(d) Original | (e) Significant features obtained by Fourier | (f) Texture features obtained by Gabor

Fig. 1.

Gabor wavelet can obtain few amount of texture information with high efficient, so Gabor wavelet is retained as filter function in this paper. Which expressed as:

$$g(x,y)=\frac{1}{2\pi\sigma_x\sigma_y}\exp(-\frac{1}{2}(\frac{x^2}{\sigma_x{}^2}+\frac{y^2}{\sigma_y{}^2})) \quad \textbf{(1)}$$

$$Gabor(x,y)=g(x',y')\exp(2\pi j(Ux'+Vy')) \quad \textbf{(2)}$$

$$\begin{cases} x'=x\cos(\theta)+y\sin(\theta) \\ y'=-x\sin(\theta)+y\cos(\theta) \end{cases} \quad \textbf{(3)}$$

Where $g(x,y)$ is a Gaussian kernel function, σ_x and σ_y are the standard deviations on x-axis and y-axis; U and V are the center frequencies directions in x-axis and y-axis; θ is the rotation angle. The filter formula is:

$$\mathrm{Im}(x,y) = im(x,y) * Gabor(x,y) \quad \textbf{(4)}$$

Where $im(x,y)$ is the image data of the fabric to be inspected; $\mathrm{Im}(x,y)$ is the texture feature data filtered by the Gabor filter. The Gabor filtering function of different directions and scales can be obtained by proper expansion, contraction or rotation, which modifying the values of σ_x, σ_y, U, V and θ. A single Gabor filter is determined by a set of $(\sigma_x, \sigma_y, U, V, \theta)$. This paper defines the fitness function: $fit = f(\sigma_x, \sigma_y, U, V, \theta)$, and the value of fit is used to judge the optimal parameters of the Gabor filter.

2.2 Similarity Operation

Similarity operation is generally used to judge whether two signal sources are consistent, such as judging whether two images are consistent through statistics. Because of the algorithm in this paper belongs to the unsupervised method, the similarity algorithm is introduced to judge the similarity degree of block-block after filtering and then locate the flaw. The periodic size of fabric texture is not fixed, so it is impossible to adopt a fixed partition size. Based on the characteristics of strong periodicity of fabric, this paper calculates the partition size by similarity. This part mainly implements two functions: 1. Calculate the appropriate block size under different textures; 2. Participate in the fitness function value of the particle swarm optimization algorithm.

2.3 Particle Swarm Optimization

Particle swarm optimization (PSO) searches for the optimal solution through the cooperation between groups, which has the advantages of simple implementation and few parameters to be adjusted. Therefore, this paper selects PSO algorithm as the optimization algorithm, and gives concrete steps to realize. The flow chart of PSO algorithm is shown in Fig. 2. which is also shown the links between PSO and Gabor.

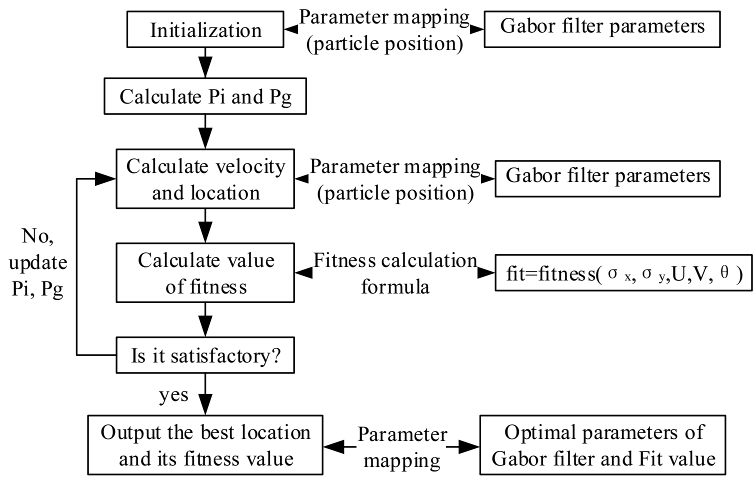


Fig. 2. PSO flow chart

3 The Proposed Method

The method can be roughly divided into three parts: obtaining the optimal parameters (Part1), judging the defects (Part2) and locating the defects (Part3). And all parts share some basic buildings as the image blocking, and calculation and comparison with similarity. In Fig. 3 illustrates the testing procedure. Part1 is implemented by Algorithm 1, 2 and 3, Part2 is implemented by Algorithm 3 and 4, Part3 is implemented by Algorithm 5.

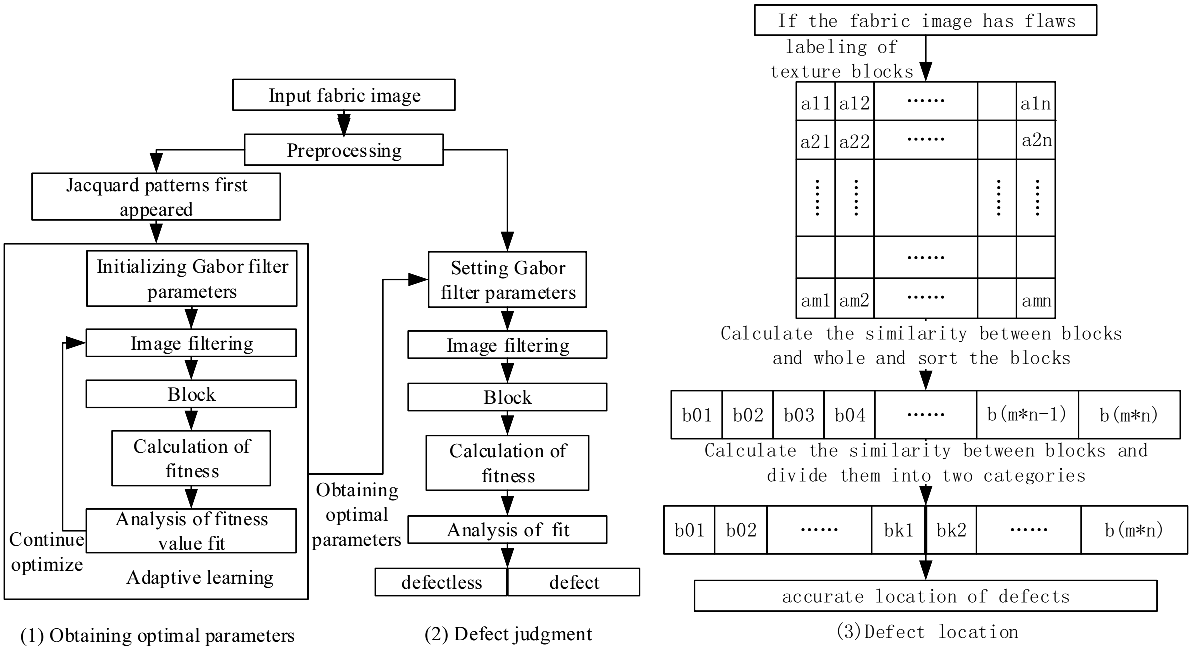


Fig. 3. Flow chart of fabric defect detection

There are certain assumptions for this method due to the limitation of similarity part. The assumption is that the defect area is less than 50% of a given fabric image.

Algorithm 1. PSO

Input: grayscale image *I*, the parameters *X* of Gabor.

Output: the optimal value of fitness, the optimal parameters of Gabor.

1. for each particle *i*
2. Initialize velocity *Vi* and position *Xi* for partical *i*
3. Evaluate partical *i* and set *Pi* = Xi
4. end for
5. *Pg* = min{*Pi*}
6. while not stop
7. for *t* = 1 : tmax
8. Updata the velocity and position of partical *i*
9. $v_i^{t+1} = wv_i^t + c_1 rand()(Pi_i - x_i^t) + c_2 rand()(Pg - x_i^t)$ and $x_i^{t+1} = x_i^t + v_i^{t+1}$ ($t = 0,1\cdots$)
10. Evaluate partical *i* by Algorithm 2
11. if fitness(*Xi*) < fitness(*Pi*)
12. *Pi* = *Xi*;
13. if fitness(*Pi*) < fitness(*Pg*)
14. *Pg* = *Pi*;
15. end for
16. end while
17. Print *Pg*

Algorithm 2. fitness

Input: grayscale image *I*, the block size S_h and S_v of *I*, the particles *X* of PSO (the parameters of Gabor).

Output: the fitness value of each particle (the parameters of Gabor).

1. Feature *F* extraction by Gabor filtering.
2. Blocking the image *I* and feature *F* with the size S_h and S_v.
3. Calculated the similarity matrix M_S of this by using Algorithm 3, which combining image *I* and feature *F*
4. The value of fitness is min(M_S)/max(M_S).

Algorithm 3. the similarity function
Input: grayscale image I, feature F, the block size S_h and S_v of I or F.
Output: the similarity matrix M_S.

1. Divide the value of image I and feature F into 16 levels.
2. The gray histogram *HistI* of image I and energy histogram *HistF* of feature F with each block are obtained.
3. for i = 1 : m
4. for j = 1 : n
5. Calculate M_{Sij}, which obtained by the value between $HistI_i$, $HistF_i$ and $HistI_j$, $HistF_j$
6. end
7. end

Algorithm 4. Defect judgment
Input: grayscale image I, the block size S_h and S_v of I or F, the optimal parameters of Gabor
Output: whether this is defect or not

1. Feature F extraction by Gabor filtering with the optimal parameters.
2. Blocking the image I and feature F with the size S_h and S_v.
3. Calculated the similarity matrix M_S of this by using Algorithm 3, which combining image I and feature F.
4. The value of fitness *fit* is min(M_s)/max(M_s).
5. Determine if a defect is present by the value of *fit*, and if it is, execute Algorithm 5, or end the run

Algorithm 5. Defect location
Input: grayscale image I, feature F, the block size S_h and S_v of I or F.
Output: the location of defects.

1. The similarity between each block and the whole is calculated like Algorithm 3 and sorted according to the similarity.
2. Calculate the features of each block, which including the mean and variance of the grayscale image, and the mean and variance of the feature.
3. FCM clustering was carried out for each block feature.
4. The similarity of step.2 and the clustering results of step.3 are used to compare and screen out suspected blocks containing defects.
5. Accurately locate the size and location of defects by FCM algorithm.

In the algorithm experiment, the block size is determined by the pixel size of the pattern of the mini-jacquard fabric and the possible defective pixel size: there are two or more mini-jacquard pattern cycles. If there are any defects in the fabric, the percentage of defective parts should be less than half of the total. The difference of similarity is low when the block size is too large or too small. In view of whether the block size is reasonable or not directly affects the calculation results of similarity, the block size is calculated by the similarity function. The value of similarity, Algorithm 3, is calculated by histogram similarity, which is determined by the pixel value of the preprocessed image and the probability histogram of the filtered energy value. In order to reduce the computational complexity, the gray image and the energy image are compressed to 16 levels and then the corresponding probability histogram is calculated. If the similarity calculated from gray probability histogram and energy probability histogram are S_1 and S_2, then the similarity $S = (S_1 + S_2)/2$.

In this paper, the FCM algorithm is used to classify the texture images of fabrics with defects. The parameters of the FCM algorithm are as follows: The number of clusters: $C = 2$, the weighted index: $m = 1.08$, and the maximum number of iterations: $t_{\max} = 200$.

4 Results and Analysis

Since there are fewer defects and a small area in industrial production, it is assumed that if there are defects in the fabric to be tested, the defect area is up to one fourth of the area of the image to be tested. The collected images were classified and counted according to GB/T 17759-2009 Textile Fabric Defect Detection Method. 160 images of fabrics were selected, of which 120 were defected (60 were jacquard fabrics and 60 were plain fabrics), and 40 were defectless (20 were jacquard fabrics and 20 were plain fabrics) [26]. In the experiment, the non-gray image is mapped to gray image, and then the image size is 256*256, and the block size is 30*30, texture information boundary does not participate in the operation because it contains more noise. In order to verify the validity of the method, an experimental test is carried out. The processor of the experimental machine is Intel Core i7, the CPU is 2.40GHz, the running memory is 4.00GB, the operating system is Windows 10, and the compiling environment is MATLAB R2014a.

The PSO optimization process (simulation) and results in Fig. 4 are shown in Fig. 5. *Z* is the degree of adaptiveity of the calculation. when the actual PSO is optimized, the optimization parameters are the all parameters of the Gabor filter, after optimization, the filtered texture image does not mark the defect, and can not be used as a result. The final texture image is re-classified and the classification results are displayed as binary images, as shown in Fig. 4.

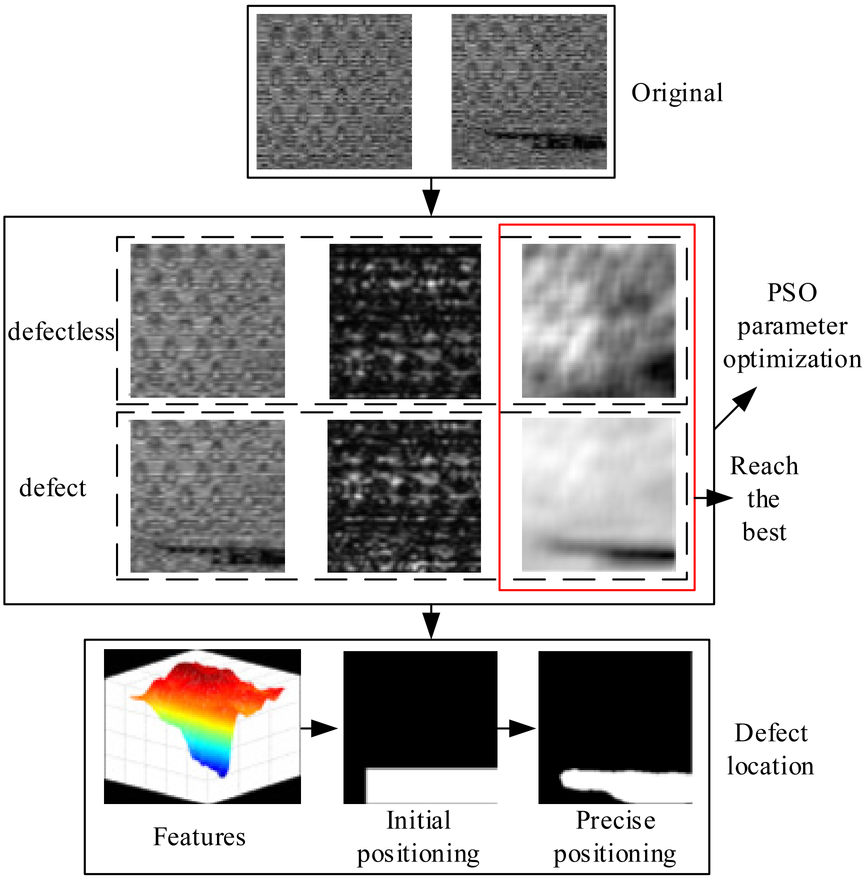
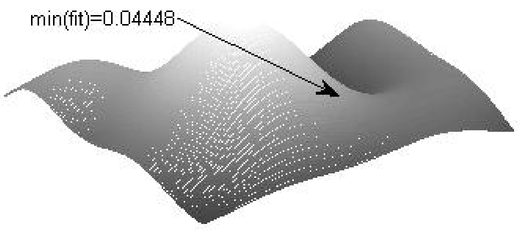
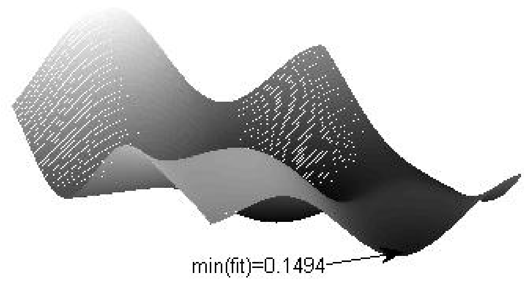


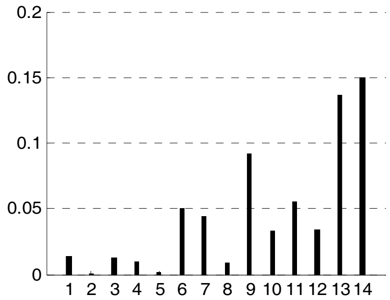
Fig. 4. Process and results of fabric defect detection



(a) fabric with defects



(b) fabric without defects



(c) the value of Fit of partially detected images
Number (1-12) are fabrics with defects; number (13, 14) are fabrics without defects

Fig. 5. Operation (Simulation) and results of PSO

In contrast experiments, three different methods are used to calculate texture maps or saliency maps of fabric images. The methods proposed in literature [13] (method 1), in literature [18] (method 2) and in this paper (method 3). Method 1 is a defect detection method which combines global and local significance for small jacquard fabric, Method 2 is a defect detection method using global texture information for plain fabrics. It has a learning process and needs to provide defectless images, Method 3 is a method for detecting defects in combination with global and local texture information, which can be used for defect detection of jacquard fabrics and plain fabrics.

The experimental results show that the three algorithms are outstanding in the detection of fabric defects. As shown in Fig. 6, when the plain fabric is tested for defects, all three methods can locate the defect, and the method 2 works best, When the jacquard fabric is tested for cockroaches, methods 1 and 3 can locate the cockroaches, and method 3 works better. When the feature is acquired for different sizes of pictures as shown in Table 1, the larger the single pixel is, the longer the calculation time is; the time when the texture information is acquired in the same pixel value state is shorter than the time when the significant image is acquired. As shown in Table 2 (image size: 256*256), comparing the time-consuming results of the same fabric images, the learning time of the methods is as follows: method 1 has no learning process, and the learning speed of method 2 is 37.8s, which is slower than that of method 3, which is 7.352s, detection time: Among the three detection methods, the longest time consumed by method 1 is 0.829s, the shortest time consumed by method 2 is 0.102s, and the time consumed by method 3 is 0.568s. If the total sample size is n, the unqualified number is d, the wrong number is k, which defect free fabric is identified as defective fabric, and the number of missed checks is b, which defective fabrics are identified as defectless fabrics, then the overall accuracy rate is $(d-k)/(d-k+b)$, the missed checks rate is $b/(d-k+b)$, and the missed checks rate is $k/(n-d+k-b)$. As shown in Table 3, the comprehensive accuracy of method 1 in plain fabric defect detection is 88.1%, and that in mini-jacquard fabric defect detection is 93.3%, the comprehensive accuracy of Method 2 in plain fabric defect detection was 95.2%, and that in mini-jacquard fabric was 89.3%, because the fabrics without defect were used for learning, the comprehensive accuracy rate was high, the false detection rate and the missing detection rate were low. The comprehensive accuracy rate of method 3 in the detection of enamel of plain fabrics was 93.2%, and the comprehensive accuracy rate of cockroach detection of mini-jacquard fabrics was 94.2%.

(a1) original drawings of defective fabrics　(b1) test results of method 1　(c1) detection results of method 2　(d1) detection results of method 3

(a2) original drawings of defective fabrics　(b2) test results of method 1　(c2) detection results of method 2　(d2) detection results of method 3

(a3) original drawings of defective fabrics　(b3) test results of method 1　(c3) detection results of method 2　(d3) detection results of method 3

Fig. 6. Test results of different flaws

Table 1. Time-consuming to obtain significant/texture features

The image pixel	significant(s)	texture features(s)
64*64	0.03	0.02
128*128	0.19	0.05
256*256	0.76	0.14
512*512	0.79	0.17

Table 2. Time-consuming operation of each algorithm

	Method 1	Method 2	Method 3
Learning/optimization(s)	0	37. 8	7.352
Detection(s)	0. 829	0.102	0.568

Table 3. Results of each method

		Method 1	Method 2	Method 3
Plain	Defect positive	0.87±0	0.95±0.001	0.93±0.003
	Defectless positive	0.89±0	1.00±0	0.90±0.007
	Overall accuracy	0.881	0.952	0.932
	Fault detection	0.153	0	0.112
	Miss rate	0.119	0.048	0.068
Jacquard	Defect positive	0.93±0	0.88±0.02	0.94±0.01
	Defectless positive	0.92±0	1.00±0	0.93±0.008
	Overall accuracy	0.933	0.893	0.942
	Fault detection	0.092	0	0.079
	Miss rate	0.067	0.107	0.058

Method 1 has a general detection effect in the detection of enamel of plain fabrics, and the detection effect is good in the detection of crepe of mini-jacquard fabric, but the overall running time is longer. Method 2 has a good detection effect in the detection of enamel of plain fabrics, and has a general effect in the detection of crepe of small jacquard fabrics, and the running time is short, but it is necessary to provide a defectless fabric image. Method 3 has a general detection effect in the detection of enamel of plain fabrics, and the detection effect is good in the detection of crepe of mini-jacquard fabric, and the running time is shorter. In summary, the method proposed in this paper can be used for fabric defect detection. And in the detection of mini-jacquard fabric, the method is slightly better than other methods.

5 Conclusion

In this paper, an adaptive real-time detection method is proposed to obtain effective texture features of fabrics by optimizing filter parameters to ensure the accuracy of defect location without providing defect-free fabric images for learning and reducing filtering times, which improves the adverse effects brought by manual intervention and ensures the timeliness of defect location. In the final accurate defect location, the criterion based on similarity is introduced, and the primary positioning is changed to the secondary positioning to enhance the interaction between the whole and the local, and the accuracy of defect location is improved. Experimental results show that the proposed algorithm has better accuracy, real-time performance and stability than other small jacquard fabric defect detection methods under the condition of no standard fabric reference learning.

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