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Fabric Defect Detection Algorithm for Dense Road and Sparse Road

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Abstract. In order to improve the results of fabric defect detection with less obvious features such as dense road and sparse road, a Gaussian hybrid clustering algorithm is proposed. Firstly, the image is preprocessed by means of mean filter, and then a Gabor filter and Gaussian mixture clustering algorithm are used to identify the defects of the image to be detected. The experimental results show that compared with other defect detection methods, the method is effective in detecting the defects of fabrics such as dense road and sparse fabric, and has some practical value in defect detection.

1. Introduction

Fabric defects affect the quality of fabrics to a great extent in the process of fabric production. To improve the quality of fabrics, the number of fabrics defects must be reduced. At present, many textile factories in our country still use manual detection method to detect fabric defects. Most of the fabric production lines work in a harsh working environment. Repeated manual labor for a long time is inefficient and the rate of missing detection is high. In particular, the detection results are easily affected by the subjective factors of the testing personnel, resulting in missed detection and false inspection. In order to improve the detection accuracy and efficiency, many scholars at home and abroad have actively explored the design and construction of fabric defect automatic detection algorithm and hardware platform, making it possible to detect fabric defects automatically. There are many kinds of fabric defects with different characteristics. Some researchers have proposed a variety of defect detection algorithms, such as statistical, spectrum-based and model-based fabric defect detection algorithms. These algorithms have been effectively studied and significant results have been achieved. MAK K L, KUMARA, TSAIIS, etc [2], take advantage of Gabor function in time-frequency two-domain multi-resolution and multi-scale analysis, use multi-level matching Gabor function filter to detect fabric defects, solve the redundancy problem of filtering results, but are vulnerable to noise. JING JF and so on [4] proposed the defect detection method which combines the wavelet transform and the neural network, can effectively extract the details of the defect features, but the real-time performance is poor and the calculation is large. BUHG et al [5] successfully identifies fabrics defects by combining fractal dimension with support vector machine, but there are few kinds of defects detected. Kim SC, Susan S, etc [6], use Gaussian mixture model to model the most suitable class for each pixel, which has high accuracy for fabric defect classification, but the training process is too complex and dependent on the model. Considering the advantages and disadvantages of the above algorithms, a fabric defect detection



method based on Gaussian mixture clustering and Gabor filter is proposed in this paper. The algorithm first uses mean filter to preprocess, then uses Gabor filter and Gaussian mixture clustering to detect the detected image, and finally identifies the defect image. For example, after morphological post-processing, the experimental results show that the method is better than Gabor detection or Gaussian mixture clustering algorithm for the detection of specific types of defects, such as sparse, dense and so on. The detection results are clearer, and the probability of misjudgment for other types of defects is low.

2. detection methods

Firstly, an optimal parameter training model of Gabor filter based on CoDE is constructed to train the optimal parameters of Gabor filter for the sample image without defect and the sample image with circuitry and sparse defect, and then the image to be detected is pre-processed to eliminate the illumination and image acquisition in the process of image acquisition. Random noise caused by equipment and other reasons can also effectively suppress the influence of background texture information on defect detection; then, Gabor filter model and Gaussian mixture clustering model are used to judge whether there are defects in the image to be detected, and the images with defects are subtracted by Gaussian mixture clustering model twice. Finally, the defect image is obtained by morphological processing of the defect image. The specific flow chart is as follows:

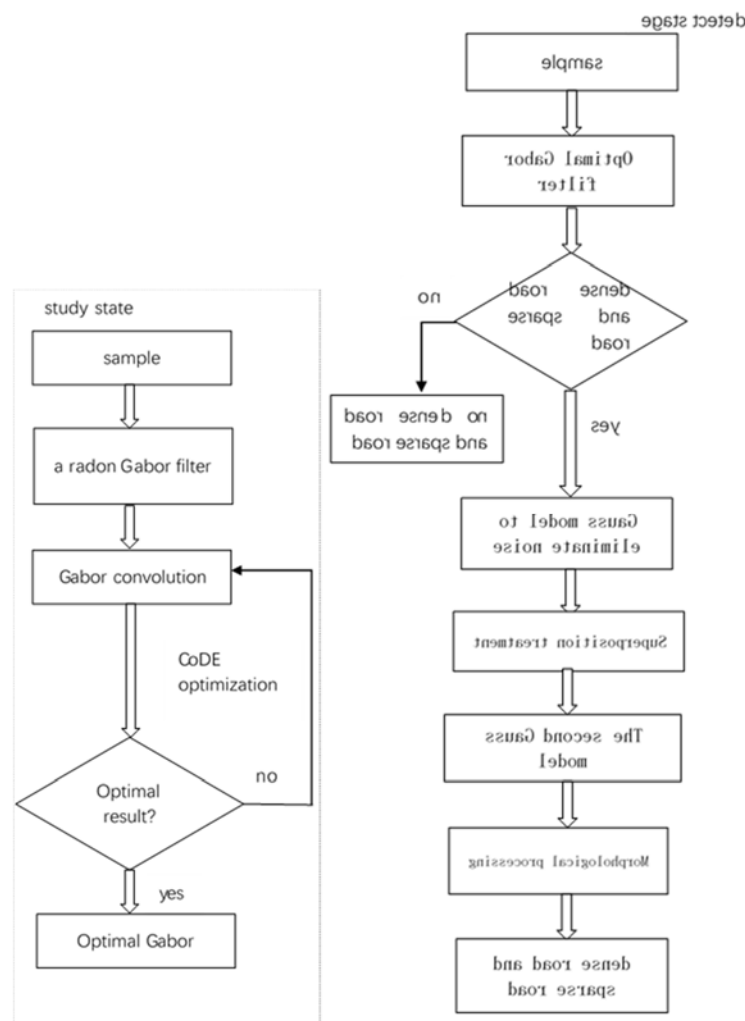


Figure 1. Morphological processing of the defect image

2.1. Gabor wave filter

The two-dimensional Gabor transform function [9] is a directional composite sinusoidal grating modulated by two dimensional Gauss function. The formula in the spatial domain is as follows:

$$f(x, y) = \frac{1}{2\sigma_x\sigma_y} \exp \left[-\frac{1}{2} \left(\frac{x'^2}{\sigma_x^2} + \frac{y'^2}{\sigma_y^2} \right) \right] * \exp(2\pi j f_0 x') \quad (1)$$

Where F_0 represents the central frequency of the sinusoidal grating limited by span. The smoothing parameter sigma X and sigma Y represent the shape factor of the Gauss surface. In other words, they determine the larger or smaller selectivity of filters in the spatial domain. When the sigma x equals to the sigma y, the surface of Gauss is a circle. Normally, the parameter θ can also be expressed as θ , so the shape of the Gaussian surface can be adjusted by changing the coefficient θ . (x, y) is rotated by theta (x, y):

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \quad (2)$$

Half peak bandwidth B is another important term for specifying Gabor filters:

$$B = \log_2 \frac{\sigma_x f_0 \pi + \sqrt{\frac{\ln 2}{2}}}{\sigma_x f_0 \pi - \sqrt{\frac{\ln 2}{2}}} \quad (3)$$

According to Daugman [9], the half peak bandwidth along the preferred direction is about 1-1.5 eight degrees. Because value sigma x should not be directly specified, it is determined by frequency bandwidth, B, B and sigma X are inversely proportional. Therefore, Gabor filter is widely used in texture analysis as a band-pass filter because of its small bandwidth in spatial and frequency range.

The structure of shuttle fabrics is made up of weft and warp yarns, so fabric defects are usually vertical and horizontal. Therefore, the selection of parameter theta can only consider 0 or. Mehrotra [10] elaborates that a fictitious Gabor filter can be used to detect edges perpendicular to Gabor filter parameter theta. Therefore, this paper uses the combination of real Gabor filter and virtual Gabor filter to detect secret and sparse defects, so as to ensure the best detection results.

2.1.1 Composite differential evolution algorithm (CoDE). Differential evolution (DE) is a simple and effective evolutionary algorithm for global optimization of continuous search domains. In the past decade, various DE variants have been developed to solve real-world optimization problems, such as signal processing, data mining, chemical engineering, etc. In these DE variants, composite DE (CoDE) is a powerful composite DE, and its computation is far less complex than other algorithms. In CoDE, three selected test vector generation strategies and three control parameters are randomly combined to generate a tracking vector. The three tracking vector generation strategies are "rand/1/bin", "rand/2/bin" and "current to rand/1". The three control parameters are [F=1.0, Cr=0.1], [F=1.0, Cr=0.9] and [F=0.8, Cr=0.2]. These policies and parameter settings have their unique advantages and can complement each other. This characteristic of CoDE performs well in solving unimodal and multimodal problems.

2.1.2 Gabor Optimal parameter design of filter. Since the proposed optimization objective function contains many local optimal solutions, it is a complex optimization problem to obtain the optimal Gabor filter by adjusting the filter response of the template image. Considering the superior performance of CoDE in solving multimodal problems [11], we choose CoDE as the optimization algorithm. Next we will explain the optimization process in detail.

A Gabor transform function has four parameters: f_0 , θ , σ_x , σ_y and theta, three of which need to be optimized: f_0 , θ , σ_y . For the parameter theta, it is set to 0 degrees and 90 degrees. The center frequency f_0 , the frequency bandwidth B and the shape factor lambda constitute the decision vector in the

optimization process. The best Gabor filter consists of maximizing the parameters of the objective function J. It should be noted that J is used for horizontal and vertical optimization of Gabor filters.

The specific optimization process is as follows:

(1) Form of representation: the first step in the optimization process is to encode the solution into a decision vector. For fabric defect detection, decision vectors have 3 dimensions: F0, B and lambda. The aim is to find the optimal combination of F0, B and lambda according to the objective function.

(2) Population initialization: In order to initialize the population, we randomly assign real numbers within a specific range to each dimension of the chromosome. The two variables (B and lambda) are continuous, while the other (F0) is discrete. To apply CoDE to our problem, we initialize chromosomes with real numbers, and then round off the dimensions representing F0 when evaluating populations based on objective functions.

(3) Mutation, crossover and selection: after initialization, groups need mutation and crossover operations. In our problem, CoDE is used as an optimization algorithm, which has three selection strategies and three parameter settings to generate test vectors. The three track vector generation strategy is "RAND / 1 / bin", "RAND / 2 / bin" and "Current-to-rand / 1". The three control parameters are set to [F=1.0, Cr=0.1], [F=1.0, Cr=0.9] and [F=0.8, Cr=0.2]. In each generation, three candidate test vectors Ui1, Ui2 and Ui3 are obtained for the individual Xi in the current population by using three test vector generation strategies. Each test vector generation strategy has a set of control parameters randomly selected from the three parameters. We evaluated the three test vectors according to the objective function and selected the best test vectors (denoted as Ui) from Ui1, Ui2 and Ui3. If it is superior, it will enter the next generation of Xi. The evolution process will not stop until the predefined standards are met.

2.2. Gauss mixture clustering model

Gaussian Mixture Model (GMM) is usually referred to as GMM. Gaussian distribution is used as a parametric model, and the Expectation Maximization (EM) algorithm is used for training. In the Gaussian mixture model (GMM), we can regard the data as generated from several Gaussian distributions. The Mixture Model itself can also be arbitrarily complex. By increasing the number of models, we can approximate any continuous probability density distribution arbitrarily.

$$p(x|\mu_i, \sigma_i, \pi_i) = \sum_{i=1}^3 \pi_i \frac{1}{\sqrt{2\pi}\sigma_i} \exp\left(-\frac{(x-\mu_i)^2}{2\sigma_i^2}\right) \quad (4)$$

So we can calculate the probability of all defects and noise.

Gaussian mixture clustering model usually considers that the data is from K different Gaussian distribution function combination, such as formula (13) in the use of GMM clustering should first set the K value. In this paper, because there are only fabric defect parts in the fabric sample, defect-free parts, the false detection part, so the K value of 3 is more appropriate.

$$p(x) = \sum_{i=1}^K \pi_k N(x; \mu_i, \sigma_i) \quad (5)$$

However, for the parameters of N (x), it is necessary to use EM algorithm for unsupervised training.

Step E: for observation point Xi, the probability generated by the K component is formula (14):

$$\gamma(x_i, k) = \pi_k^{(t)} \frac{N(x_i; \mu_k^{(t)}, \sigma_k^{(t)})}{\sum_{j=1}^k \pi_j^{(t)} N(x_i; \mu_j^{(t)}, \sigma_j^{(t)})} \quad (6)$$

Step M: Xi can be seen as a sum of parts, in which the part produced by the k-th component is naturally gamma (xi, k) xi, so it can be considered that the k-th component produces the following data:

$$\gamma(x_i, k)x_i, i = 1, 2, \dots, N \quad (7)$$

Since each Component is a standard Gaussian distribution, it is easy to find the parameters corresponding to the maximum likelihood distribution. Thus, the parameters are updated and the next iteration is repeated in step E until the algorithm converges, and the exact location of noise and defects is distinguished.

2.3. Morphological processing

Background correction of segmented fabric images is done by mathematical morphology. This method is simple and efficient, and its basic idea is to measure and extract the corresponding shape of the image by using the structural elements with a certain shape to achieve the purpose of image analysis and recognition. In this algorithm, we use a linear structure element whose length is 15 and the angle is π . After etching the defect image, we do open and close operations to eliminate the isolated noise. Finally, the background color is reversed.

3. Experiment and result analysis

3.1. Comparison and analysis with classical algorithms

In order to verify the effectiveness of the defect detection algorithm proposed in this paper, 60 warp-knitted fabric images were collected. According to GB/T 17759-2009, the collected images were classified and counted. Twenty pairs of defect samples were selected for analysis. All the samples are 8-bit gray images of 512 pixels X512 pixels. The experiment adopts the platform of MATLAB2016b to carry out the simulation of defect detection.

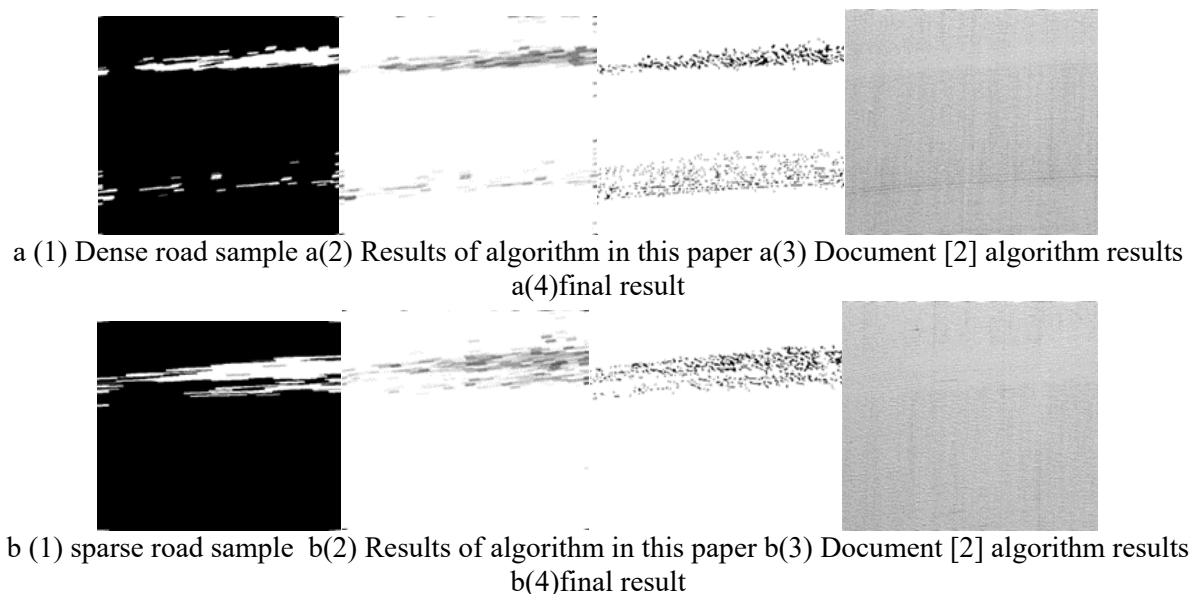


Figure 2. Simulation of defect detection

From graphs a, and b, we can see that compared with the classical algorithm in reference [2], the proposed algorithm can more accurately identify the location of defects, and is less affected by noise.

3.2. Comparison of detection results between Gabor model and algorithm

Table 1. Accuracy comparison of Gabor models

Detection model (%)	Precision	sensitivity	Specificity	Accuracy
Model of this paper	94.4	92.3	94.5	93.4
Model in document [1]	82.6	78	83.5	80.8
Model in document [2]	79.3	80.2	79.1	79.7
Model in document [3]	87.4	83.5	87.9	85.7

Compared with the classical algorithm, this algorithm has higher precision, sensitivity, specificity and accuracy in the learning process of the model. In the use phase of the algorithm, the accuracy of flawless samples and flawed samples is much higher than other classical algorithms, and the time required is shorter. It can be considered that the algorithm is far superior to other algorithms in detecting defects such as secret paths and dilute roads.

4. Conclusion

This paper mainly focuses on the detection methods of warp knitted Road, dilute road and so on. The CoDE algorithm is used to train the optimal parameters of Gabor filter for quintic warp-knitted fabric images, and the unsupervised Gaussian hybrid clustering model is used to remove the interference of isolated defects. Compared with the classical algorithm, it can more effectively and accurately distinguish the dense and sparse defects of warp-knitted fabrics, and accurately restore the dense and sparse defects of warp-knitted fabrics. Experimental results demonstrate the effectiveness, stability and robustness of the proposed algorithm. Similarly, the algorithm in this paper can only have a good test result for the shortcomings of the secret road and the sparse road, and has limitations. We hope to continue to optimize the algorithm in the future learning, and can classify more types of defects.

Acknowledgements

Introduction to the first author: deju Li (1964-), male, professor, The main research directions are image processing and pattern recognition. E-mail: lidejun@wtu.edu.cn.

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