Automatic Detection of Cloth Defects based on Laws Texture Filtering

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Abstract: In this paper, the difference between the fabric features of the cloth and the normal part is used to realize the automatic detection of the flaws in the cloth. And the classic Laws texture filtering method and support vector machine (SVM) classifier are used to detect the flaws. The detection mainly includes two steps. The first step is to divide the cloth image into multiple sub-blocks of the same size, each sub-block as a sample, and then calculate the texture features of each sub-block separately, and the second step uses SVM classifier to different the samples of cloths. In the second step, the SVM classifier is used to classify different cloth samples to detect the fabric defects. Experiments show that the proposed algorithm can basically realize the automatic detection function of flaws in the cloth and can effectively identify whether the cloth has flaws.

1. Introduction

In the evaluation criteria of fabric textile quality, whether the fabric contains defects and the length of defects are the most important evaluation indicators. In order to minimize the impact of defects on the fabric, efficient and timely detection of defects is the key to improve fabric quality. At present, in the domestic cloth textile industry, because of the introduction of a large number of artificial subjective factors in the process of testing, the quality of testing is ultimately uncertain. In addition, this method has a large workload, poor reliability, relying on the experience of staff, and causes inefficient work, unable to repeat operations for a long time and other irresistible drawbacks. According to relevant research, the human visual system can only detect about 60% - 75% of the significant defects. Therefore, in order to minimize the impact of human factors in the detection process, the development of automatic detection technology is an important way to improve the reliability of detection results.

The automatic detection methods in China can be divided into two categories: laser broken yarn detection method and image acquisition and processing detection method. The former mainly uses laser to detect whether the yarn fluctuates and whether the laser scanning reflects centrally, so as to judge whether the fabric is defective; the latter mainly uses real-time image acquisition and digital image processing technology to detect defects. Laser yarn breaking detection method has the shortcomings of large power consumption and high missed detection rate, and the real-time cloth image monitoring system is difficult to popularize because of the expensive price of imported equipment and the low detection rate.

Machine vision has been applied in industry abroad for a long time, and has a wide range of application prospects, especially in finished product detection and quality detection. The following high-performance complete sets of equipment have been put into the market for fabric detection: the IQ-TEX system launched by Evs Company of Israel adopts high-definition color line scanning technology and enhanced defect sorting algorithm, which can be exploited concurrently. Fabric defects with accuracy greater than 0.5mm were detected. German Dr. Schenker can detect textiles with multi-image defect analysis technology, which can identify defects below 1mm. Fabriscan system of Swiss Uster Company collects moving cloth images using multiple high-level linear array CCD camera arrays according to cloth width and detects flaws through trained neural network

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models. At the same time, there are Cyclops of Barco, ELSISS of Erhardt Leimer, Germany, SmartView Texture and Surface Detection System of COGNE, USA, etc. However, the imported equipment is expensive, and the maintenance process is cumbersome and inconvenient, so it can not be popularized. There is no self-developed high-efficiency automatic detection system in China, and the automatic detection technology of fabric defects needs to be further studied and improved.

This paper mainly studies how to detect defects in real-time after they appear in the fabric textile process, and proposes an automatic detection algorithm which uses Laws filter to extract features and distinguish and detect defects by SVM classifier.

2. Detection Algorithm

2.1. Laws Texture Filter.

In image processing, using local template to detect different types of texture is a method to generate texture features. Laws [12] proposed a method of texture energy measurement, which measures the change in a fixed size window and calculates the energy of different types of textures with convolution template. The basic idea of this method is to filter the micro-window first, then transform the energy, then rotate the components, and finally classify them.

The template for texture analysis is generated by the following vectors:

Edge $\mathrm{E} = [-1\ -2\ 0\ 2\ 1]$,

Gray level $\mathrm{L} = [1\ 2\ 4\ 2\ 1]$,

Wave $\mathrm{R} = [1\ -2\ 4\ -2\ 1]$,

Spot $\mathrm{s} = [-1\ 0\ 2\ 0\ -1]$.

Vector L is the local mean of weighted center and E is the detection edge. These vectors are used to extract templates with different texture features. For example:

$$\mathrm{EL} = [-1\ -2\ 0\ 2\ 1]^T \mathrm{X} [1\ 2\ 4\ 2\ 1] = \begin{bmatrix} -1 & -2 & -4 & -2 & -1 \\ -2 & -4 & -8 & -4 & -2 \\ 0 & 0 & 0 & 0 & 0 \\ 2 & 4 & 8 & 4 & 2 \\ 1 & 2 & 4 & 2 & 1 \end{bmatrix}$$

Used to measure gray edge.

Sixteen energy maps can be generated by using E, L, R and S. Because some symmetrical templates can be combined with each other, nine templates can be generated: LE/EL, LS, SL, LR, RL, EE, ES/SE, ER/RE, SS, SR/RS and RR. These nine templates can measure textures with different features.

2.2. Support Vector Machine Classification.

Support Vector Machine (SVM) is a commonly used classification and recognition algorithm, which has good generalization ability and has been widely used. The basic idea is to construct an optimal classification function for two types of problems, so that the two types of samples can be separated as far as possible without error, while maintaining the maximum gap between the two categories, which is particularly effective for small samples and high-dimensional classification problems. The different inner product kernel functions of SVM will form different algorithms. The main kernel functions can be divided into the following three categories:

(1)Linear inner product function: $\mathrm{k}(\mathrm{x},\mathrm{y}) = \mathrm{x} \cdot \mathrm{y}$

(2)Polynomial inner product function(Ploy): $\mathrm{k}(\mathrm{x},\mathrm{y}) = [(\mathrm{x} \cdot \mathrm{y}) + 1]^{\mathrm{d}}$

(3)Radial Basis Inner Product Function(Rbf): $\mathrm{k}(\mathrm{x},\mathrm{y}) = \exp\{-|\mathrm{x} - \mathrm{y}|^2/\delta^2\}$

Literature [1] compares the above three kernels. The experiments show that the radial basis function has good performance for most databases. In this paper, different kernels are selected and the statistical results are compared.

2.3. Algorithm Flow Chart.

The flow chart of defect detection algorithm based on Laws texture filtering is as follows:

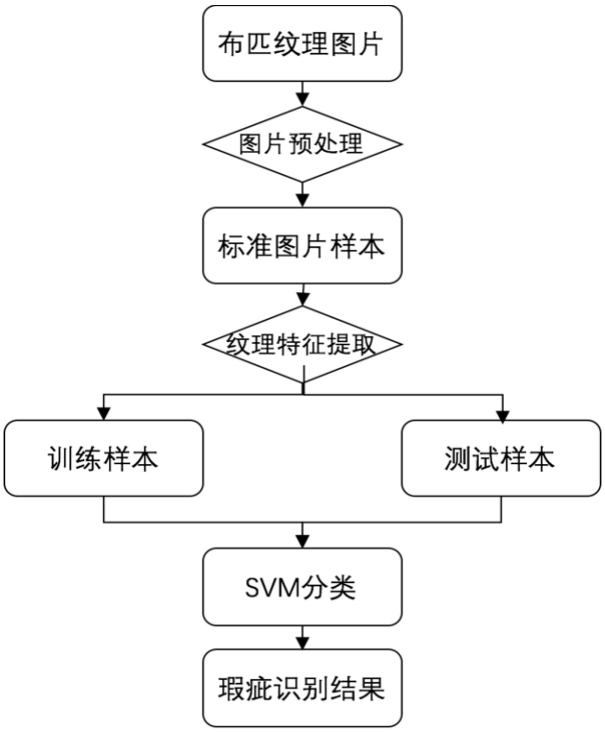

Figure. 1 Flowchart of algorithm

The specific steps are as follows:

1) Acquisition of real-time cloth image

2) gray level of preprocessed image

3) Select a part of the image from the flawless image as a positive sample to calculate texture features and capabilities.

4) Calculate the internal distance between each feature for testing

5) Using data results as input training of SVM classifier to test flaws

3. Experimental design

3.1. Composition of Experimental Data

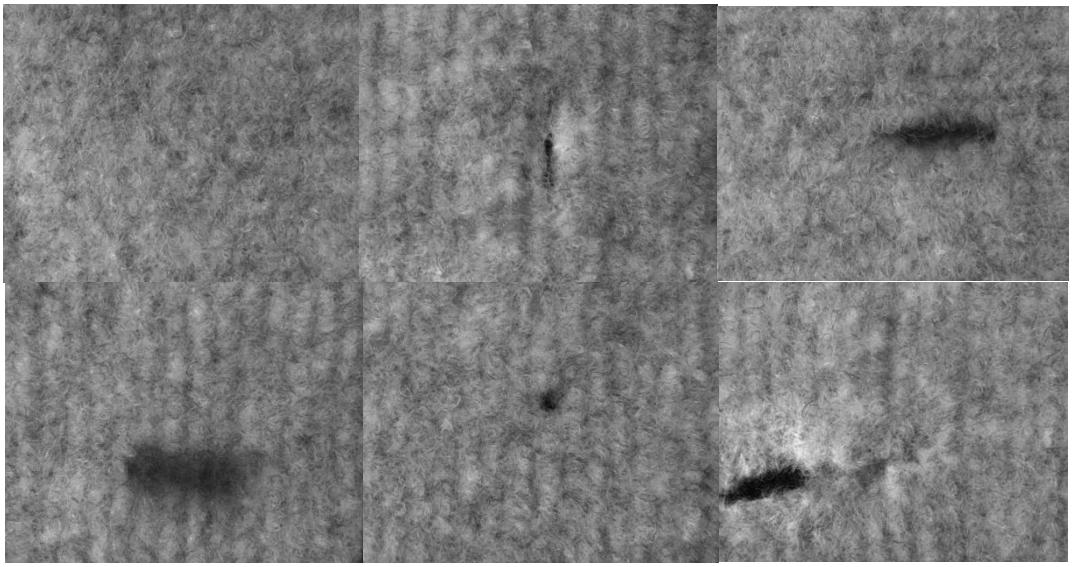

Figure. 2 Original sample

Six images captured in Figure 2 below are taken as original sample images for experiment. One is normal image and the other five are defective images. Each of the first five experimental images is evenly segmented into pixels of the same size. In this case, the size of the pixel block is 16*16,

200 normal pixel blocks and 40 defective pixels are selected. Block is used as training set, and the 6th experimental picture is processed the same way. 63 normal and 34 defective pixel blocks are selected as test set. Because the cutting size of the pixel blocks will affect the test results, four different sizes are used to compare the same samples. The sizes are 16*16, 27*27, 32*32 and 64*64, respectively. Thus, the optimal size of the test results is obtained.

3.2. Recognition Algorithm in This Paper

Firstly, 200 pixel blocks are selected as positive samples from known flawless images, and some flawed pixel blocks are selected as negative samples from flawed images. The texture and feature texture of these regions are calculated to extract the size of texture regions and the corresponding energy function of each texture. Then, the internal distance between each feature is calculated, and the 16*16 pixel blocks are sequentially obtained from the energy image, which are transformed into 1*9 vectors. As the input of SVM, each column represents a sample. The covariance matrix for calculating multidimensional Gauss distribution is transformed into determinant. The energy function corresponding to each texture is calculated. The results are used as input of SVM classifier to train and test the predicted results.

3.3. Comparison of SVM Results with Different Kernel Functions

The main parameters of SVM are penalty factor (c) and kernel function parameter (g). The function of parameter C is to adjust the confidence range and the proportion of experience risk of the learning machine in the determined feature space so as to adjust its generalization ability. For the kernel function parameter g, when G is too small, the test sample will produce "over-learning" phenomenon which does not have any generalization ability. When G is too large, there will be a phenomenon of "under-learning" which divides all samples into one class.

At the same time, the size and size of the selected pixel blocks are different, and the texture information carried is also different. In order to select the optimal size of pixel blocks, this paper compares the selected size of pixel blocks, and compares 16*16, 27*27, 32*32, 64*64 different size of pixel blocks, and experiments on different kernel functions under different size of pixel blocks.

In this paper, by adjusting and comparing, the appropriate nuclear parameters are selected to achieve the optimal recognition effect. The prediction accuracy of different kernel functions with different block sizes is shown in Table 1 below.

Table 1 Predicts the results of SVM using four commonly used kernels (percentages)

Size or Kernel Function	Rbf	Ploy	Gaussian	Auto
16X16	64%	56%	64%	65%
27X27	86%	33%	39%	30%
32X32	86%	53%	41%	35%
64X64	82%	66%	81%	80%

4. Conclusion

In this paper, the traditional Laws texture energy extraction method is used, and SVM with different kernels is used to perform comparative experiments on the same data set of pixel blocks of different sizes. Comparing the results of prediction accuracy, it is assumed that for RBF kernel function, too large or too small sub-pixel block size selection will lead to low accuracy. When sub-pixel block size is 27*27 to 32*32, it will reach a relatively stable level. For Ploy, Gauss and Auto kernels, when the sub-pixel block size is small, the number of defective sub-pixel block samples obtained is large, which leads to the training model. When the size of the sub-pixel block is larger, the texture information contained in each sub-pixel block is more detailed, which makes the training results more fitting, but at the same time, the robustness may be worse because of fewer samples.

Looking up the table, when the size of sub-pixel block is 27*27, the recognition accuracy of defects can reach 86% when using SVM of Rbf kernel function. The Laws texture energy extraction

and SVM junction proposed in this paper have a good research role in fabric recognition and defect detection. At the same time, the parameters of SVM can be further optimized to achieve higher accuracy, which is the main research direction of the author in the future.

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