FABRIC YARN DETECTION BASED ON IMPROVED FAST R-CNN MODEL

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Reception: 16/11/2022 **Acceptance**: 09/01/2023 **Publication**: 06/03/2023

Suggested citation:

X., Haiyan (2023). **Fabric yarn detection based on improved fast R-CNN model**. *3C TIC. Cuadernos de desarrollo aplicados a las TIC, 12(1)*, 287-306. https://doi.org/10.17993/3ctic.2023.121.287-306

ABSTRACT

With the rapid development of modern computer technology, and gradually combined with the textile industry, the application of modern computer technology in the field of textile is increasingly extensive, which makes textile production gradually move towards the road of automation development. This paper proposes an automatic detection method of simple weave fabric density based on computer image vision. Computer vision and digital image processing technology are used to analyze and identify the simple weave fabric's warp and weft yarn information and calculate the fabric density. To avoid the phenomenon of warp and weft yarn skew, a method of fabric skew correction based on the Radon transform is proposed. The optimal decomposition order of these four fabrics is k = 2, k = 5, and k = 3. The decomposition series is k. It is found that the relative error of both warp and weft density is about 1.00%. Most of the data obtained by the method of correlation coefficient curve to determine the optimal decomposition series are consistent with the results of the energy curve method. The relative error of the density test results of No. 3 fabric, No. 6 fabric, and No. 7 fabric is higher than 10%, and the relative error of No. 3 fabric is the highest, reaching 66%. This shows serious errors in these three fabrics' warp and weft density. To solve the problems of simple weave fabric density detection, the corresponding algorithm is used to solve the problems. Finally, good results are obtained, which verifies the feasibility of this method. It is significant to realize the automatic measurement of fabric density in textile factories.

KEYWORDS

Fabric yarn; Fast R-CNN algorithm; Visual inspection; Image processing; Wavelet decomposition.

https://doi.org/10.17993/3ctic.2023.121.287-306

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https://doi.org/10.17993/3ctic.2023.121.287-306

1. INTRODUCTION

With the rapid development of modern computer technology, and gradually combined with the textile industry, the application of modern computer technology in the field of textile is increasingly extensive, which makes textile production gradually move towards the road of automation development. The structure parameters such as fabric texture, density, and color yarn arrangement are important in detecting and controlling textile quality. Currently, most factories and enterprises in the textile industry mainly rely on manual sample analysis and detection of fabric texture with the aid of fabric lenses, which is subjective, time-consuming, labor-intensive, and prone to errors. Therefore, the use of computer image processing technology to effectively replace manual to achieve intelligent fabric density detection, improve industrial production efficiency, achieve automation, and intelligent production of textile products is of great significance.

In recent years, the rapid development of computers has made computer vision technology into people's field of vision and has been much attention. Under our research and exploration, computer vision continues to develop and progress, and image processing technology has been widely used. Especially in textile testing, computer vision technology is also used, which makes the textile industry more intelligent and efficient. Shukla et al. Collected the transmission image and reflection image of fabric sample by optical principle, calculated the autocorrelation value of each row and column of the image with the autocorrelation function after preprocessing, and processed and analyzed the transmission image and reflection image respectively to obtain the relevant information of fabric texture parameters [1]. Finally, the fabric structure is determined by the length and weft of each row, and the fabric structure is determined by scanning the length and weft of each row[2]. Raj et al. Reduced the gray image level through histogram equalization, then constructed the gray level co-occurrence matrix according to the pixel spacing and angle changes, calculated its eigenvalue, and obtained the fabric density parameter through its periodic calculation [3]. Used autocorrelation function to determine the position, density, and weave point position of fabric warp and weft yarn. Later, the data of the organization point area was input into the neural network to output the fabric structure, which was trained repeatedly. Finally, the fabric structure was identified by a neural network [4]. Wu and Cao used the gray projection method to get the gray projection curve in the warp and weft direction of the fabric image[5,6]. The warp and weft yarns were separated according to the position and quantity of the gray projection curve peak and valley, and the fabric warp and weft density was calculated. Trafton et al. First calculated the weft density of twill and satin fabrics was by the gray projection method and then calculated the warp density of twill and satin fabrics was through the relationship between the density of twill and satin fabrics and the fabric texture. Later, the study found that fabric warp and weft yarn inclination was easy to occur when image processing was used to detect the density of fabric warp and weft [7-9]. Monfared and XZ et al. Proposed using Hough transform to obtain the fabric tilt angle, then making a gray projection on the fabric along the tilt direction, and finally judging

https://doi.org/10.17993/3ctic.2023.121.287-306

the yarn gap according to the wave crest of the projection curve to calculate the fabric warp and weft density [10,11].

Qin uses MATLAB language to carry out a series of preprocessing for woven fabric images, then carry out wavelet decomposition and reconstruction to separate and extract the information of warp and weft yarn, and then carry out binarization and smoothing processing to obtain the distribution image of warp and weft yarn. Finally, the warp and weft density of the woven fabric is obtained through program calculation [12-15]. Shi et al. Carried out multi-layer wavelet decomposition on woven fabric image through wavelet transform, reconstructed single-layer signal and calculated average brightness value of warp and weft yarn direction image, and finally calculated warp and weft density according to periodic change of brightness signal [16,17]. Combined image processing technology with time-frequency transform theory, transformed woven image from the time domain to frequency domain through Fourier transform, selected characteristic region to filter and separate single group of warp and weft yarn images. Finally, the adaptive threshold method was used to locate yarn, count the number of warp and weft yarn, and calculate woven fabric's warp and weft density [18-20]. Obtained the frequency spectrum of the fabric through a two-dimensional fast Fourier transform and calculated the fabric warp and weft density through the correlation between the characteristic change of the frequency spectrum and the fabric warp and weft density [21]. Using the Halcon algorithm library and machine vision technology, Niu processed the fabric image by Fourier transform, analyzed it by Gabor transform, and finally calculated the fabric warp and weft density through wavelet transform results [22]. Barreto and Shi use Fourier transform and wavelet transforms to process fabric images, analyze spectrum characteristics, process interference information, and then transform them into spatial domain through inverse transformation. Finally, fabric warp and weft density can be calculated by spatial domain detection or correlation between frequency spectrum features and warp and weft yarn density [23,24]. Le obtains the power spectrum of woven fabric image by Fourier transform, then processes the threshold value and calculates the fabric warp and weft density by using the relationship between the spatial domain and frequency domain. Secondly, it uses wavelet transform to separate the warp and weft sub-images of woven fabric. After processing, the ideal warp and weft yarn density information is obtained. Finally, a computer program automatically calculates the fabric warp and weft density. Others use the wavelet transform to reconstruct the fabric spatial domain image according to the spectrum characteristics of the fabric image to detect the fabric warp and weft density [26,27]. Some also use the deep learning method to train many samples to obtain stable automatic detection of fabric density after Fourier transform or wavelet transform processing of fabric [28].

To sum up, there have been a lot of research and achievements in the automatic detection of fabric warp and weft density, but there are still some problems that have not been solved perfectly, and so far, it has not been well applied to actual industrial production. This paper proposes a warp and weft yarn detection method based on the improved fast R-CNN algorithm, which is of great significance to realize the automation and intelligent production of textile products.

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2. IMPROVED FAST R-CNN ALGORITHM

The current deep learning algorithm uses a convolutional neural network to recognize yarn features, and when the number of training samples of the network is enough, its recognition accuracy and robustness are better than the traditional image processing technology, so it has a good application prospect.

2.1. BASIC STRUCTURE AND CHARACTERISTICS OF CONVOLUTION NEURAL NETWORK

A convolutional neural network (CNN) is a feedforward neural network with a depth structure. It can complete the local sampling and image-sharing task using a neural network. Since the convolutional neural networks can collect the spatial and channel information of feature graphs simultaneously, it is mostly used in the backbone network of the algorithm to achieve feature extraction tasks[29-30]. CNN structure is generally divided into the following layers: convolution, pooling, activation, and full connection layer. The algorithm's core is to adaptively and update the convolution kernel parameters iteratively through the computer's automatic learning, so the convolution layer's calculation is particularly important. The main purpose of the convolution layer is to extract features of different receptive fields by convolution kernels of various sizes.

CNN differs from the common neural network in that the neurons in the previous layer are only partially connected with the current layer. This connection structure greatly reduces the number of branches in the network. A convolution kernel is a local region. Let the convolution kernel go through the whole characteristic graph.

Weight sharing means that a single parameter controls multiple connections without considering the position relationship of input data. A convolution kernel with fixed internal weight parameters is used to process the whole graph by a convolution operation. The convolution kernel is equivalent to the weight of the traditional network. Each neuron of the traditional network has different weights, but the same set of convolution kernels is used in feature processing, so the parameters of the convolution neural network are shared.

Pooling is an important downsampling operation. Its principle is to do some simple operations on the neurons in the convolution layer through the local correlation and take the results as the input values of the neurons in the pooling layer. This operation not only reduces the amount of calculation but also retains valuable information. Common pooling operations include maximum pooling and average pooling. We can select different pooling techniques according to the actual situation to prevent model overfitting and improve network robustness.

The full connectivity layer (FC) is located at the end of the network hierarchy. Its function is to connect the feature maps of the previous layer output and map all the features distributed in the front layer network to the output sample space to reduce the influence of the target location on classification accuracy. The full connection layer can

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be completed in the actual network by convolution, and all feature expressions can be mapped to one output value by a convolution operation.

2.2. R-CNN SERIES ALGORITHM

In the development of deep learning, R-CNN is the first industrial-level target recognition and detection algorithm, which has become an important research direction in the target recognition and detection field. Fast R-CNN, fast R-CNN, and other algorithms are based on R-CNN, aiming at the shortcomings of the previous generation of algorithms for continuous optimization expansion research. Through training and calculation, the R-CNN algorithm filters the targets in the candidate region, filters out the invalid feature regions and then completes the corresponding classification according to the task requirements. Compared with the one-stage target recognition and detection algorithm, the recognition error rate and miss recognition rate of the series of algorithms are relatively low, but the recognition speed is relatively slow. We can choose different algorithms for different target recognition and detection requirements in practical applications.

It overcomes the limitation of traditional machine learning methods. The biggest contribution of the Alex net network is the introduction of the activation function of the modified linear unit (re Lu). The introduction of the re Lu activation function can not only effectively prevent the overfitting phenomenon but also shorten the training period due to the reduction of calculation.

The target classification method of the R-CNN algorithm is to use SVM to classify the extracted features and then use the non-maximum suppression algorithm (NMS) to evaluate the feature area. The high-score region is identified as the target area, and the overlapping, redundant area is removed to obtain the region with the highest possibility of the target. An important factor that affects the performance of the target recognition and detection model is whether the object can be located accurately. Because the inaccuracy of the target candidate frame region will cause the overlap area error, it is necessary to modify and regress the candidate frame and then generate the final prediction frame.

The fast R-CNN algorithm is an efficient target recognition and detection algorithm based on the R-CNN algorithm and uses a deep neural network. Because of the shortcomings R-CNN algorithm, the fast R-CNN algorithm has made corresponding improvements. The fast algorithm uses the output of the intermediate convolution layer of the vgg-16 network.

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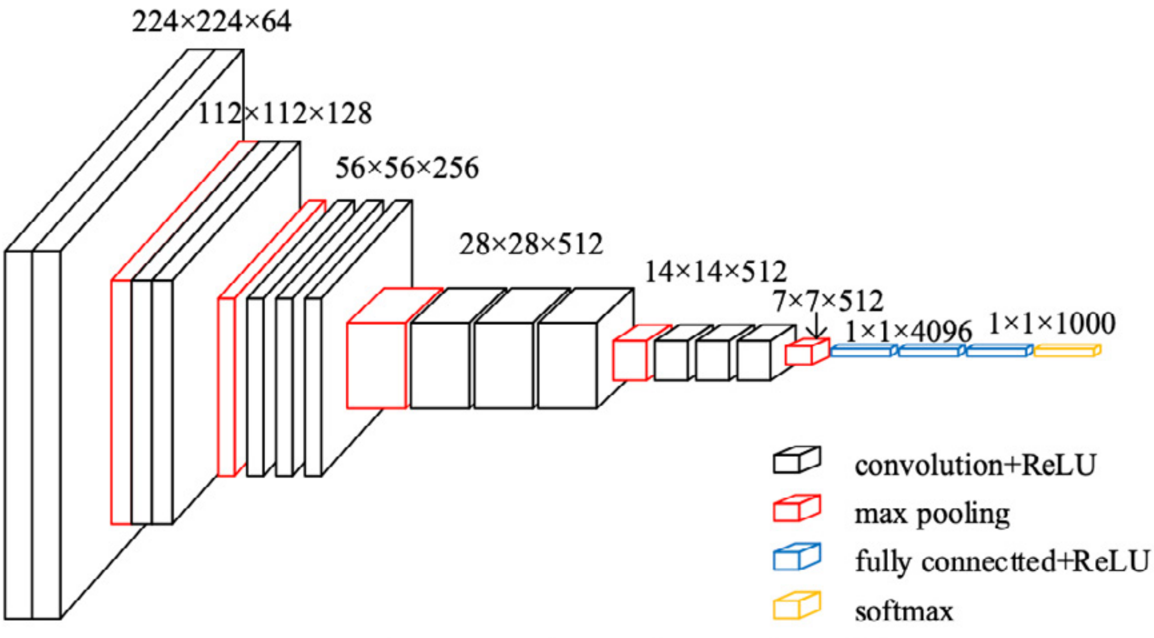

Figure 1. Structure of vgg-16 network model

The fast R-CNN algorithm can complete the task of feature extraction, detection frame regression, and classification at the same time. The efficiency of this algorithm is far higher than that of other algorithms of the R-CNN series. The fast R-CNN algorithm does not need distributed training and testing. Firstly, it proposes a series of anchors with preset sizes through the regional recommendation network (RPN), then adjusts the anchor's size several times through the training network and outputs the final target detection regression box. Since this paper will optimize the fast R-CNN algorithm, the principle of the algorithm is analyzed in detail from three aspects: network architecture, RPN structure, and algorithm loss function.

$$L(\{p_i\}\{t_j\})=\frac{1}{N_{cls}}\sum L_{cls}(p_i,p_i^*)+\lambda\frac{1}{N_{reg}}\sum_i p_i^* L_{reg}(t_i,t_i^*) \tag{1}$$

2.3. YOLO ALGORITHM

Yolo (you only look once) is a target recognition and detection framework based on suggestion region. Yolo algorithm is different from the two-stage recognition and detection idea. Yolo algorithm first divides the given image into S×S cells, which cell is responsible for detecting the center of each target. Compared with the two-stage detection algorithm, S×S cells are equivalent to the target region of interest, so there is no need to generate candidate regions through the network similar to RP, and the detection task can be completed in one step.

$$C_j^i = pr(\text{ object }) * IOU_{pred}^{truth} \tag{2}$$

Next, the C conditional category probabilities are predicted by the segmented grid, and the redundant boundary boxes are removed by non-maximum suppression (NMS) to get the best result

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$$pr\left(class_i / object\right) = \frac{pr\left(class_i \times object\right)}{pr(object)} \tag{3}$$

$$pr\left(class_i / object\right) * pr(object) * IOU_{prad}^{truth} = pr\left(class_i \cdot object\right) * IOU_{prrd}^{truth} \tag{4}$$

Yolo is a simple and fast end-to-end algorithm, but the accuracy of Yolo recognition and detection is not high, and the object positioning is not accurate enough. It is not good enough for small targets and dense target recognition and detection.

Table 1. Comparison of advantages and disadvantages of target recognition algorithm

Algorithm name	advantage	shortcoming
R-CNN	1. CNN is proposed to extract features 2. Map on Pascal VOC increased from 35.1% to 53.7%	1. The training process is divided into stages, and the recognition speed is slow 2. Consumes disk space
Fast R-CNN	1. Using the full winder network, the ROI pooling, all feature maps can be predicted only once 2. The problem of image distortion and redundant computation is reduced	1. The method of extracting candidate regions is computationally expensive and repetitive 2. The end-to-end training is not implemented
Faster R-CNN	1. Propose RPN network 2. Real end-to-end detection model 3. Recognition accuracy and speed have been greatly improved	1. ROI pooling operation results in precision loss 2
YOLOv3	1. Faster speed 2. End to end model	1. There is the deviation in the accuracy of object position recognition 2. Low recall rate

3. SIMPLE WEAVE FABRIC DENSITY DETECTION BASED ON WAVELET TRANSFORM

Wavelet transform is the inheritance and development of the traditional Fourier transform. Wavelet transform has good adaptability for time-frequency windows. Different from Fourier transform, the window size cannot change with the change in frequency. Wavelet can be used for multi-scale analysis, feature extraction, and analysis of the object's high-frequency and low-frequency information, a new image processing method. This study uses the wavelet transform to detect simple weave fabric images' warp and weft density.

3.1. WAVELET TRANSFORM

Compared with the Fourier transform, the wavelet transform has better time-frequency window characteristics, which has attracted many experts and scholars to study. In the past ten or twenty years, wavelet transform has developed rapidly and widely in many scientific and technological fields. Wavelet transform decomposes the signal into a series of wavelets by scaling and shifting the original wavelet. Compared with Fourier transform, the wavelet transform overcomes its three shortcomings: first, Fourier coefficients cannot change with frequency, but wavelet coefficients can; Two wavelet transforms can well reflect the signal frequency change with time; Wavelet transform - Fourier transform can solve the problem of variable window size. Wavelet transforms mainly include continuous wavelet transform and discrete wavelet transform.

$$C_\Psi = \int_{-\infty}^{+\infty} \frac{|\Psi'(\mathrm{x})|^2}{\mathrm{x}} dx < \infty \tag{5}$$

$$W_f(k,t) = \langle f(x), \Psi_{k,t}(x) \rangle = \frac{1}{\sqrt{k}} \int_R f(x) \Psi^* \left(\frac{x-t}{k} \right) dx \tag{6}$$

Where k is the decomposition series, and t is the displacement Ψ(x) length. The basic wavelet function can be obtained Ψ(x) based on the wavelet transform. The wavelet sequence function after displacement and decomposition is as follows:

$$\Psi_{k,t}(x) = \frac{1}{\sqrt{k}} \Psi\left(\frac{x-t}{k} \right), k, t \in R; k > 0 \tag{7}$$

When the decomposition series K and the displacement length T are continuous variables, the above wavelet transform process is called continuous wavelet transform (CWT). There is another form of discrete wavelet transform (DWT). In many cases, the decomposition series K and the displacement length t need to be discretized by the power series.

$$W_f(m,n) = \langle f(x), \Psi_{m,n}(x) \rangle = \frac{1}{\sqrt{k_0^m}} \int_R f(x) \Psi^* \left(\frac{x-nt_0}{k_0^m} \right) dx \tag{8}$$

The discrete wavelet sequence function is as follows:

$$\Psi_{m,n}(x) = \frac{1}{\sqrt{k_0^m}} \Psi\left(\frac{x-nt_0}{k_0^m} \right) \tag{9}$$

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3.2. WAVELET TRANSFORM OF SIMPLE WEAVE FABRIC

The fabric image can be decomposed into approximate and detailed image information by one-dimensional wavelet transform on two-dimensional images, low-frequency, and high-frequency parts. Then the high-frequency part can continue to be decomposed into a group of high-frequency and low-frequency components, and the low-frequency part can be further decomposed into another group of high-frequency and low-frequency components. Finally, a two-dimensional image is decomposed into four parts by wavelet transform. Compared with one-dimensional wavelet transform, two-dimensional wavelet transform decomposes the high-frequency information component more carefully along the horizontal and vertical directions and further decomposes the high-frequency part into horizontal detail component, vertical detail component, and diagonal detail component. Therefore, four parts can be obtained after the first level decomposition: approximate detail component, horizontal detail component, vertical detail component, and diagonal detail component. In theory, the decomposition process can be continued for a long time.

After the multi-scale decomposition of fabric images, wavelet transform can reconstruct and output approximate and detailed image information according to the demand. Wavelet has good decomposition and reconstruction ability, so it can obtain clear and complete fabric structure information and detail information without losing important information and eliminating interference information.

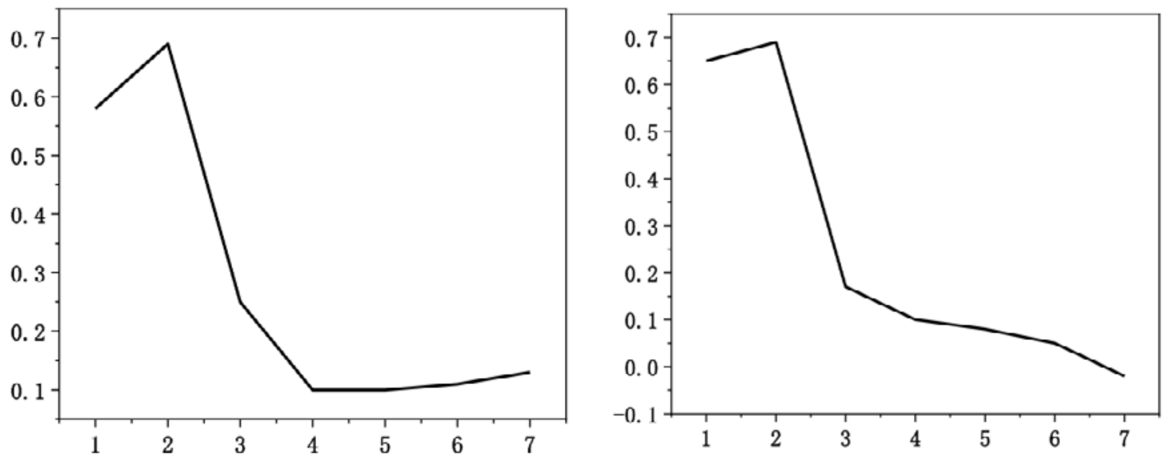
The principle of automatic detection of fabric warp and weft density is that the horizontal high-frequency detail component and vertical high-frequency detail component, which match the height of warp and weft yarn, are obtained by wavelet decomposition and reconstruction, and the number of warp and weft threads is calculated to obtain the fabric warp and weft density. The horizontal high-frequency detail component and vertical high-frequency detail component obtained by different scales are completely different. The matching degree of detail component and yarn number is also completely different. Therefore, the decomposition scale of wavelet decomposition directly affects the horizontal and vertical detail component information obtained and the accuracy of the fabric warp and weft density information reflected by the image. To obtain the most complete warp and weft yarn information to obtain the warp and weft yarn number information matching the image height, the wavelet decomposition scale has directly impacted the fabric's accuracy. Knowing which scale is processed is necessary to obtain the reconstructed detail image, which is highly matched with the fabric image details. We call this wavelet decomposition scale the optimal decomposition series. Therefore, the research on determining the optimal decomposition series is of great significance for the automatic calculation and detection of warp and weft density.

3.3. DETERMINATION OF OPTIMAL WAVELET DECOMPOSITION SERIES OF FABRIC IMAGE

The correlation coefficient is used to study the degree of linear correlation between two variables. The curve of the correlation coefficient can reflect the correlation between two variables, but it is unclear about the degree of correlation, so it is a kind of uncertain relationship. To determine the optimal wavelet decomposition series by the method of correlation coefficient curve is to compare the correlation degree between the fabric image reconstructed by wavelet decomposition and the fabric image before decomposition and reconstruction, and calculate the correlation coefficient of the two images, and take the decomposition series corresponding to the maximum correlation coefficient as the optimal decomposition series. Then the fabric is decomposed into high-frequency details and series to get the optimal fabric density. The concept of the correlation coefficient is that assuming that there are two matrices of the same dimensions, A and B, the correlation coefficient of a and B is calculated as follows:

$$r = \frac{\sum_m \sum_n \left(A_{mn} - \bar{A}\right)\left(B_{mn} - \bar{B}\right)}{\sqrt{\left(\sum_m \sum_n \left(A_{mn} - \bar{A}\right)^2\right)\left(\sum_m \sum_n \left(B_{mn} - \bar{B}\right)^2\right)}} \tag{10}$$

Where m and N represent the rows and columns of the matrix, respectively.



(a) (b)

Figure 2. Sample correlation coefficient curve

From the correlation coefficient curve in the above figure, it can be seen that the correlation coefficient curve of each sample fabric has a maximum peak value, which indicates that the reconstructed image obtained by wavelet decomposition and reconstruction under the corresponding decomposition series is most similar to that before fabric image processing, Therefore, the maximum peak value of correlation coefficient curve is selected as the optimal decomposition series of wavelet decomposition and reconstruction. From the curve in the figure above, the maximum correlation coefficients of fabrics 1, 2, 3, and 4 are 2, 2, 5, and 3, respectively, which means that the optimal decomposition order of the four fabrics obtained by the method of correlation coefficient curve is k = 2, k = 2, k = 5, k = 3, that is, for fabric 1 at decomposition scale 2, for fabric 2 at decomposition scale 2, for fabric 3 at decomposition scale 5When the decomposition scale of fabric 4 is 3, the horizontal

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and vertical high-frequency detail components matching the number of warp and weft yarns can be obtained by wavelet decomposition and reconstruction respectively.

In the study of determining the optimal decomposition order by the correlation coefficient, it is found that the results obtained by some fabrics are not very ideal. In the process of a large number of experimental studies, the optimal decomposition order determined by the maximum correlation coefficient is still inaccurate. For example, in the treatment of fabric 3 above, the maximum correlation coefficient is 5. After processing, the matching degree between the detail component and the warp and weft yarn of the fabric is not large, so a more stable and accurate method to determine the optimal decomposition order is studied. Solving the optimal decomposition series is to obtain the optimal detail components after decomposition and reconstruction. Through the in-depth study and analysis of all the component information obtained from many experiments, it is found that there is a certain relationship between the optimal wavelet decomposition series and the information of all components obtained after decomposition and reconstruction.

In this paper, the concept of energy curve is introduced to determine the optimal decomposition series of wavelet decomposition and reconstruction. The energy values among the approximate, vertical, horizontal, and diagonal components obtained by wavelet decomposition and reconstruction are calculated using the energy calculation function energy. The program operation formula is: [a, h, V, D] = wenergy2 (C, s). A is the approximate low-frequency component of the image after decomposition and reconstruction, h is the horizontal high-frequency detail component after decomposition and reconstruction, V is the vertical high-frequency detail component after decomposition and reconstruction, and D is the diagonal high-frequency detail component after decomposition and reconstruction. The energy curve is used to determine the optimal wavelet decomposition series. The wavelet coefficient square is used for each component after decomposition and reconstruction by the energy function, and then the energy of each component is obtained by summation, and then the energy proportion of each component is calculated by normalization. Finally, the relative gradient change of energy is calculated, and the energy curve is drawn to observe the change of the energy curve. The lowest peak value of the energy curve is taken as the optimal decomposition order of the wavelet, and the fabric image is processed by wavelet transform.

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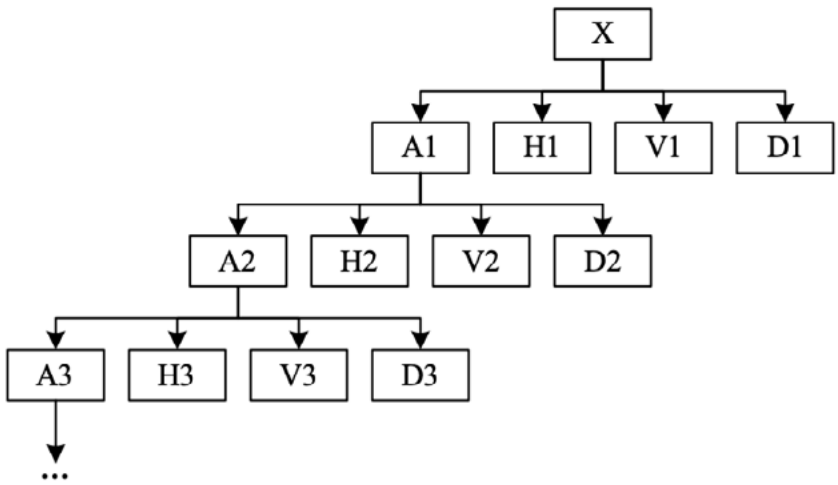

Figure 3. Wavelet decomposition tree

The two-dimensional signal x (fabric image) is decomposed into four components: A1, H1, V1, and D1, after the first-order wavelet decomposition. The second-order decomposition further decomposes A1 into four components, namely A2, H2, V2, and D2. The third-order decomposition decomposes A2 into four components: A3, H3, V3, and D3. The subsequent decomposition is carried out according to this law, and the whole wavelet decomposition process is like branching out. Therefore, the decomposition process and the resulting components can be represented in a tree view.

From the above wavelet decomposition tree, we can know that all the components obtained from the two-dimensional image after K (k is a natural number greater than 0) level decomposition include approximate image component AK, horizontal detail component H1, H2, HK, vertical detail component V1, V2, VK, and diagonal detail component D1, D2, Dk. If each component of the output after decomposition and reconstruction is regarded as a matrix, then the information contained in the component is stored in the matrix data. Assuming that there are n data in each matrix, each component is written into a matrix in the form of:

$$A_{\mathrm{k}} = \left[a_{k1} \quad a_{k2} \quad a_{k3} \quad \dots \quad a_{kn}\right] \tag{11}$$

$$H_{\mathrm{k}} = \left[h_{k1} \quad h_{k2} \quad h_{k3} \quad \dots \quad h_{kn}\right] \tag{12}$$

$$V_{\mathrm{k}} = \left[v_{k1} \quad v_{k2} \quad v_{k3} \quad \dots \quad v_{kn}\right] \tag{13}$$

$$D_{\mathrm{k}} = \left[d_{k1} \quad d_{k2} \quad d_{k3} \quad \dots \quad d_{kn}\right] \tag{14}$$

4. SIMPLE WEAVE FABRIC DENSITY TEST RESULTS AND ANALYSIS

Simple fabric is the original fabric, which is also called basic fabric. It includes plain weave, twill weave, and satin weave. All fabrics can not be separated from warp and

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weft. This paper's fabric density detection method can monitor all fabrics containing warp and weft. However, there is a problem of high relative error in the density monitoring of individual fabrics. To get a better result of fabric design, we need to use the computer to calculate the fabric density automatically.

4.1. CALCULATION OF WARP AND WEFT DENSITY OF SIMPLE WEAVE FABRIC PROCESSED BY COMPUTER

From the analysis in the previous section, it can be seen that clear warp and weft density yarns are arranged. The black horizontal line represents the yarn, and the white horizontal line represents the gap between the yarn and the yarn. Therefore, the warp and weft density of the simple woven fabric is required. The number of warp and weft yarns can be obtained by calculating the number of black transverse lines in the vertical and horizontal directions. Then the warp and weft yarn density is calculated. The vertical detail component diagram of fabric represents the arrangement of warp yarn, alternately arranged between warp and blank space. In the image, the alternate arrangement of black pixels and white pixels is shown; The horizontal detail component of the fabric represents the weft arrangement of the fabric.

Similarly, the alternate arrangement of the weft and the blank space means that the black pixels and white pixels in the vertical direction of the image are arranged alternately. Therefore, black and white pixels alternate once, representing a yarn. To calculate the number of yarns in the detail image, we can get it by calculating the number of consecutive black pixels in the image.

Taking the vertical detail component of fabric as an example, the unit length of fabric is set as 10cm, the unit of fabric density is the national standard unit "root / 10cm", and the image width of fabric is d (unit is a pixel). Counting the total number of consecutive black pixels in a row of vertical detail component maps, the yarn number SJ in the horizontal direction can be obtained. The total number of continuous black pixels SJ is divided by the width of fabric image D. According to the parameters of the CCD industrial camera, the camera's resolution can be obtained. Through the resolution, the number of pixels per centimeter P (in pixels/cm) can be obtained. Finally, the warp density converted into a standard unit can be obtained by multiplying MJ and P and multiplying by unit length 10. The calculation formula of fabric warp density PJ is as follows:

$$M_j = S_j \div d \tag{15}$$

$$P_j = M_j \times p \times 10 \tag{16}$$

If the contour curve is marked as $f(\rho)$, and all the peak positions of the drop curve are recorded as $\rho_i, i = 0, \cdots, M-1$ and M are the total number of peaks, the weft density formula of the fabric is expressed as:

$$D_{weft} = \frac{r \times (M-1)}{2.54 \times (\rho_{M-1} - \rho_0)} \tag{17}$$

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In the formula, r is the resolution of the image, and the unit of weft density D_{weft} is/cm.

After the same preprocessing process, the correlation coefficient curve and energy curve are used to determine the optimal wavelet decomposition series and the optimal decomposition series is used to decompose and reconstruct the sample fabric image. After reconstruction, the vertical and horizontal detail components are optimized, and the fabric warp and weft density detected by the two methods are calculated.

Table 2. shows the measurement results of the optimal decomposition series determined by the correlation coefficient curve

Fabric number	Warp density (PCS / 10cm)			
	for the first time	The second time	third time	average value
1	351.20	355.58	350.12	352.30
2	769.48	771.72	775.19	772.13
3	104.11	107.93	103.14	105.06
4	308.56	311.69	310.56	310.27
5	215.24	210.70	213.09	213.01
6	241.82	236.17	240.12	239.37
7	527.67	535.18	538.30	537.05
8	407.66	401.97	407.68	405.77
9	682.00	681.43	675.13	679.52
10	637.11	640.15	634.85	637.11

No. 1 is a woven fabric, No. 2 is a knitted fabric, and No. 3 is knitted fabric; No. 4 is non-woven fabric, No. 5 is three-way fabric, No. 6 is multi-directional fabric, No. 7 is composite fabric, No. 8 is a twill fabric, No. 9 is plain fabric, and No. 10 is checkered fabric. In manual testing, we use a direct method to measusimple weave fabric's warp and weft densric. Use fabric density. The number of yarns in 5cm length is measured by analyzing the mirror, and the warp (weft) yarn density is obtained by multiplying the number of yarns by 2. Each piece of fabric is measured three times, and the average value of the three values is taken as the final measurement result of warp and weft density.

4.2. ANALYSIS OF EXPERIMENTAL RESULTS

For the convenience of measuring the fabric density and weft, we will use the method of measuring the fabric density and going direct. The accuracy and reliability of the two methods are analyzed to verify the feasibility of the computer automatic detection method for the warp and weft density of simple woven fabrics.

https://doi.org/10.17993/3ctic.2023.121.287-306

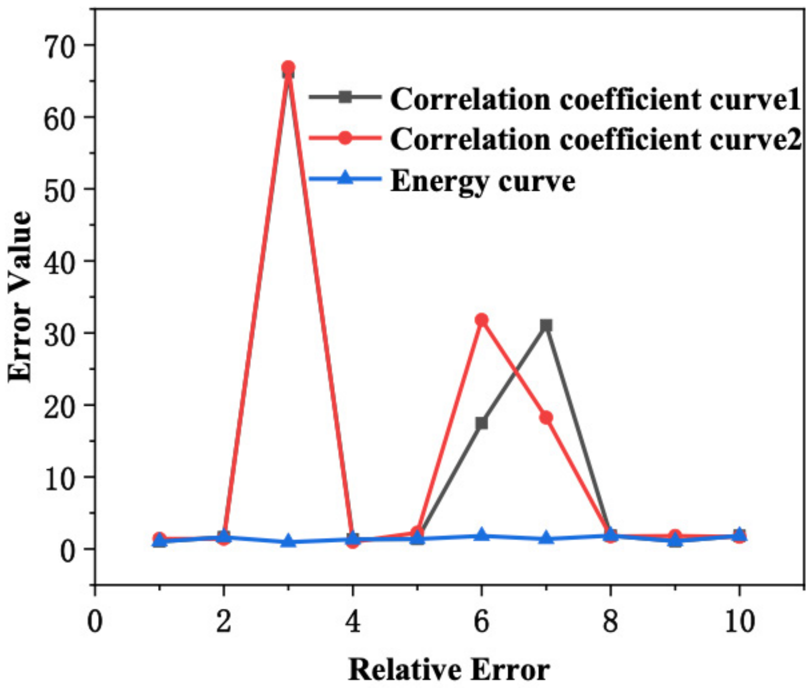

Figure 4. Relative error results

The results show that the relative error of warp and weft density of simple weave fabric is about 1.00% by using the method of energy curve to determine the optimal decomposition series. It is found that the relative error of both warp and weft density is about 1.00%The results show that this method is feasible. However, most of the data results of the correlation coefficient curve method for determining the optimal decomposition series are consistent with the results of the energy curve method. The relative error of the density test results of No. 3 fabric, No. 6 fabric, and No. 7 fabric is higher than 10%, and the relative error of No. 3 fabric is the highest, reaching 66%. This shows a serious error in these three fabrics' warp and weft density. That is to say, the decomposition order determined by the three fabrics' correlation coefficient curves is not the fabric's optimal decomposition series. Therefore, the fabric warp and weft density results calculated by the vertical and horizontal detail components obtained by the wavelet decomposition and reconstruction of the fabric by using this decomposition series will be so different from the real density of the fabric. This group of experimental results also further shows that when using wavelet decomposition and reconstruction methods to detect the fabric warp and weft density, the determination of the optimal wavelet decomposition series is very important. The results of different series decomposition and the real warp and weft density of fabric may be greatly different. Such a large deviation will also greatly impact the subsequent production of fabrics. Compared with the correlation coefficient curve, the accuracy of the energy curve method is better. However, in the experiment, it is also found that the processing error of simple weave fabric with large warp and weft density or complex pattern and color of the fabric itself may be large, which needs further research and improvement.

https://doi.org/10.17993/3ctic.2023.121.287-306

5. CONCLUSION

This paper aims to use computer vision and digital image processing technology to replace manual identification and automate simple weave fabric production detection. This research combines textile knowledge, computer technology, and image processing technology and achieves the integration of subject knowledge, which is of great significance for bringing innovative results. To solve the problems existing in the previous research on the automatic detection of fabric warp and weft density, this paper puts forward the corresponding algorithm. The main research contents and innovations are as follows

1. The method in this paper combines the correlation coefficient curve method to determine the optimal decomposition order of fabrics, which are respectively k=2, k=2, k=5, k=3. When the decomposition scale of fabric 1 is 2, the decomposition scale of fabric 2 is 2, the decomposition scale of fabric 3 is 5, and the decomposition scale of fabric 4 is 3. Therefore, this method can effectively avoid warp and weft skew.
2. Only the fabric density detection method in this paper is used. The relative error of the warp and weft density of the simple woven fabric detected is 1%, which is consistent with the curve with the most decomposition sequence, indicating that the relative error detected by the fabric density detection method in this paper is the smallest and the accuracy is the highest.
3. In this paper, the fabric density detection method decomposes and reconstructs the horizontal, vertical, and high-frequency detail components and approximate detail components of the fabric image. Most of the data from the optimal decomposition sequence determined by the correlation coefficient curve method are consistent with the results obtained by the energy curve method. However, there is a problem of high relative error in the density monitoring of individual fabrics.

DATA AVAILABILITY

The data used to support the findings of this study are available from the corresponding author upon request.

CONFLICT OF INTEREST

The authors declare that the research was conducted without any commercial or financial relationships that could be construed as a potential conflict of interest.

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