Research on Fabric Defect Detection Based on Multi-branch Residual Network

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Abstract. Aiming at the problem that traditional object detection models have low recognition accuracy for small and medium-sized defects. Based on the original residual module, this paper adds a new convolution branch that dynamically adjusts the size of the receptive field with the number of network layers, and then replaces the residual module in the Hourglass-54 down-sampling stage, and proposes a new backbone network: Hourglass-MRB. The experimental results show that the Corernet-Saccade model using Hourglass-MRB improves the recognition accuracy of small and medium-sized fabric defects by 5.8% and 5.6%. The overall recognition accuracy of the system reaches 81.5%. Theoretically, the speed of fabric defect detection reaches 110 m/min. This article provides more effective support for advancing the internationalization of textile quality assessment.

1. Introduction

The clothing industry occupies an important position in the global economy, accounting for about 2% of the global GDP. As one of the materials of clothing, fabric defects produced during production or transportation will reduce its value by 45%-65%. Therefore, fabric defect detection is an important part of the entire textile production process.

At present, most of the clothing enterprises in the world mainly adopt manual and traditional machine vision methods for fabric defect detection, and these methods have some disadvantages. There are two main disadvantages of manual detection: (i) Test results are subjective; (ii) the detection efficiency is low, and workers will be tired after working for a long time, which cannot meet the requirements of current enterprises. In recent years, there have been many related defect detection researches. In 2019, Jun-Feng Jing¹ et al. proposed a fabric defect detection method based on CNN transfer learning. This method not only improves the detection effect of fabric defects but also improves the robustness of the algorithm, but it lacks optimization for specific data sets. In 2020, Chen Kang, Zhu Wei et al. first used the deep residual network to extract the feature information of the fabric surface, and added several prediction anchor points to the Faster-RCNN region generation network to improve the detection accuracy. This method is based on the improvement of Faster-RCNN algorithm, the detection speed is low, and the effect of multi-scale defect detection is very poor.

Compared with the convolution neural network, the hourglass network only uses the last layer of convolution as the target feature[2]. The hourglass network combines the low-level and high-level features of the network to maximize the use of image feature information. The hourglass network instead of the traditional convolution neural network to extract the characteristics of fabric defects has indeed achieved very good results, but because each layer of the hourglass network uses a single receptive field to extract features, it lacks a description of the overall and local related information. It
is difficult to identify defects in complex situations such as light and occlusion. In response to this, this paper proposes a new residual hourglass network, which increases the network’s description of the overall information of the key points, and at the same time strengthens the constraint relationship between the whole and the part of the key points, which helps to improve the overall recognition accuracy.

2. Related

2.1. Introduction to the basic residual block
In a range, the deeper the neural network model, the stronger the feature extraction ability, but as the number of layers increases, its training parameters also increase, resulting in the accuracy of the network model becoming stable and then rapidly decrease. The residual block[3] uses identity mapping to create a new network layer, and other layers are directly copied from the shallow model, which can solve the problem of network accuracy degradation. Its structure is shown in Figure 1.

![Figure.1 Structure of Residual Block](image)

The formula of the residual block:

\[ y = F(x; \{w_i\}) + h(x) \]  \hspace{1cm} (1)

x and y are input and output vectors, \( F(x; \{w_i\}) \) represents the residual part. \( F = W\sigma(Wx) \) and \( \sigma \) are Relu nonlinear correction unit, \( w_i \) are convolution calculations, \( h(x) = x \) means identity mapping. Identity mapping does not increase the parameters, so it does not increase the amount of calculation. In the forward propagation process, the identity mapping of the residual block is introduced, so that the n+1 layer contains more information than the nth layer, so as to avoid the problem of gradient disappearance.

2.2. Hourglass Backbone Network
The residual block is the basic unit of the hourglass network. The traditional convolutional neural network uses the last convolutional layer to extract the target features. The hourglass network combines the low-level and high-level features of the network with its unique bottom-up and top-down structure to make the final features more Specific and more effective, so as to maximize the use of image feature information. With the help of the residual error module and the unique structure that retains the feature information of each layer, the hourglass network can predict defects of different sizes with feature maps of different scales, and has a better effect on fabric defect detection. The hourglass network adopts an end-to-end processing method. The operation of down-sampling and then up-sampling makes the entire network in an hourglass style. Figure 2 shows a structure of hourglass network.
In the figure, C1~C4 correspond to C4b~C1b, C5~C7 are feature extraction layers. Cubes of different sizes represent images of different dimensions. The larger the cube, the higher the dimensional of the output image. Take C4b as an example. After C7 is up-sampled, the resolution is doubled. C4a and C4 have the same size. Both resolutions are twice that of C7. C4b is obtained by adding the up-sampled C7 and C4a. In the same way, after the feature layers are superimposed, the feature map of the last layer not only retains the information of all layers, but also maintains the original image size. A heat map representing the probability of key points can be generated through 1x1 convolution.

The hourglass network can be formulated as:

$$x_{n+1} = H(x_n) + F(x_n, W_n)$$

(2)

Where $x_n$ and $x_{n+1}$ are the inputs and outputs of the $n$th unit, $H(x_n)$ is the identity map, $W_n$ is the weight, and $F(x)$ is the residual function. In the convolution process of hourglass network input image, the scale of each layer is reduced to half of the original, and then feature extraction is carried out. Through this method, the network can extract different features at different resolutions.

3. Method

3.1. Design of multi branch residual block

The defects such as knots, broken warp and pulp spots on the fabric surface account for less than 1% of the fabric image, which belongs to Small-size object. The main problems of small target are low resolution, blurred image and less information. Therefore, the ability of feature expression is weak and the recognition is difficult.

The new residual module proposed in this paper is shown in Figure 3. A new convolution branch is added to the original residual module, which is called multi branch residual block (MBR). The new convolution branch increases the receptive field with the deepening of the hourglass network layers, thus increasing the ability of feature extraction and feature extraction for local information.

MBR can be formulated as:

$$y' = F(x, W_1) + J(x, n) + x$$

(3)

$x$ and $y'$ are the input and output of MBR respectively, $n$ is the convolution kernel size and $J(x, n)$ is output of the new convolution branch.

3.2. Hourglass network based on multi branch residual block

This paper uses MBR to replace the residual block in the sub-sampled phase of the original hourglass
network, and designs an hourglass network based on the multi branch residual block, named Hourglass-N. The size of the convolution kernel of the ordinary hourglass network residual block is fixed. With the deepening of the network level, the extracted feature information changes from the whole to the local. If the small fabric surface defect is detected, the extracted feature information is more limited. MBR sets different convolution kernel sizes for each layer of the hourglass network. The specific setting rules are:

\[ n = H_i \times 2 - 1 \]  

(4)

\( H_i \) is the number of layers of the current hourglass network. The left side of the hourglass network performs down-sampling. The feature maps generated from the high-level to the low-level of the network increase from large to small. The size of the new branch convolution kernel \( n \) of MBR increases from small to large, thus it can extract additional feature information at different scales to highlight local details. MBR only replaces the residual block in the down-sampling stage of the original hourglass network, which can retain the current stage information while extracting additional local detailed feature information. If the Hourglass-N network has \( k \) down-sampling layers, \( G(x) \) is the output, and \( x \) is the input, the output of the Hourglass-N network can be obtained from equations 1, 3, and 4 as:

\[ G(x) = \sum_{i} (x + y_i) \]  

(5)

This article refers to the Hourglass-54 backbone network to stack three Hourglass-Ns to form a new backbone network: Hourglass-MBR. The network structure is shown in Figure 4. Due to the structural characteristics of the hourglass network itself, each sub-hourglass network can generate a heat map as a prediction. The input of each stage of the hourglass network is composed of the input of the previous stage of the hourglass network, the feature map and the heat map. In the prediction process, the loss function is defined so that the network combines the context information of the fabric image to better complete the update of the underlying parameters and improve the robustness of the network.

![Diagram of Hourglass-MBR](image)

**Figure 4** Structure of Hourglass-MBR

Normally, the loss value only compares the difference between the final output value of the network and the true value, while the hourglass network needs to calculate the loss value by calculating the key heat map of the estimated fabric defect at each stage of the network and the defect heat map marked in the data set to obtain \( L_i \), then calculate the average of the loss values at each stage to get the final loss value \( L \), the corresponding formula is:

\[ L = \frac{1}{k} \sum_{i=1}^{k} L_i \]  

(6)

\[ L_i = \frac{1}{M} \sum_{j=1}^{M} \left| y_{ij} - \hat{y}_{ij} \right| \]  

(7)

\( k \) is the number of hourglass networks in the network, \( M \) is the number of defects in the fabric image, \( y_{ij} \) and \( \hat{y}_{ij} \) are respectively the estimated heat map and the real heat map of the \( j \)th fabric defect in the same stage.
4. Experiment
This paper uses the fabric data set of Ali Tianchi competition to verify the experiment. The data set contains 20 kinds of defects, 6000 pieces of cloth images with defects and 9612 defect areas. Among them, there are 7428 small and medium size defects, accounting for 77%, 1763 medium size defects, accounting for 18%, 421 large size defects, accounting for 5%. In this experimental platform, cpu is Intel i9 7900X, gpu is NVIDIA RTX Titan *2 and the RAM is 128 GB.

In this experiment, the resolution of the data set was reduced from 2466*1000 to 512*512, and input to the CornerNet-Saccade network. The experiment was trained 46000 times, the batch size was set to 64, the two graphics cards were each 32, and the Hourglass-MRB backbone network was used. The evaluation results of the CornerNet-Saccade training fitting and the original CornerNet-Saccade are shown in Table 1.

| Algorithm                  | Backbone       | Small   | Medium  | Large   | mAP    | Test time |
|----------------------------|----------------|---------|---------|---------|--------|-----------|
| CornerNet-Saccade          | Hourglass-MRB  | 0.355   | 0.768   | 0.892   | 0.815  | 200ms     |
| CornerNet-Saccade          | Hourglass-54   | 0.297   | 0.712   | 0.893   | 0.742  | 170ms     |

The original CornerNet-Saccade algorithm[5] and the improved CornerNet-Saccade algorithm have 29.7% and 35.5% in the recognition accuracy of small-size defects, respectively, increased by 5.8%; the recognition accuracy of medium-size defects has increased from 71.2% to 76.8%, increased of 5.6%. Figure 5 shows the visualization of the original CornerNet-Saccade network and the CornerNet-Saccade network using Hourglass-MRB.

![Figure 5](image)

Figure 5 Recognition effect of two kinds of CornerNet-Saccade

The upper part of Figure 5 is the original CornerNet-Saccade detection effect, and the lower part is the improved detection effect. (a), (b), (c), (d) can be seen that the improved CornerNet-Saccade network is more accurate in identifying and locating defect types. Comparing Figure 5(b), it can be seen that the improved CornerNet-Saccade is more accurate in determining the bbox. Comparing Figure 5(c) and (d), it can be seen that the original CornerNet-Saccade is not accurate enough for defect location, and there is also a missed detection. It can be seen that the improved scheme proposed in this paper is more accurate in judging the boundary box of the defect, and to a certain extent, it reduces the missed detection rate.

5. Conclusions
The Hourglass-MRB proposed in this paper dynamically sets different convolution kernel sizes with different layers to realize the dynamic change of receptive field, which makes the model retain the original information and extract additional local feature information of fabric image. The experimental results show that the improved CornerNet-Saccade sacrifice a small amount of detection efficiency
compared with the original model, but the detection accuracy of small and medium size defects is improved by 5.8% and 5.6% respectively. Under the standard of IOU threshold of 0.75, the average accuracy is improved from 74.2% to 81.5%, and the miss detection rate is reduced.

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