Fabric Defect Detection Based on Regional Growing PCNN

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Abstract—This paper presents an adaptive image segmentation method based on a new Regional Growing Pulse Coupled Neural Network (PCNN) model for detecting fabric defects. In this method, the pixels of analyzed image are mapped on the neurons in a pulse coupled neural network. Improved PCNN model and regional growing theory are combined in the light of the requirements for fabric defect detection. And the mean and variance value of the defect-free images are introduced into this model. The validation tests on the developed algorithm were performed with fabric images from TILDA database and results showed that the proposed method is feasible and efficient for fabric defect detection.

Index Terms—PCNN, regional growing, fabric image, defect detection, image segmentation

I. INTRODUCTION

Defect detection is a vital step for quality assurance in fabric production. At present, defect detection during the manufacturing is still a manual work. This leads to low production efficiency and subjective detection results. Therefore, fabric defect detection is a significant problem in fabric quality control processing, and developing a fast, efficient, reliable and real-time defect detection system becomes inevitable. With the development of computer and digital image processing technology, computer vision has been increasingly applied to detect fabric defects automatically to replace the traditional methods [1, 2]. Image segmentation is the most basic process and essential technology in the computer vision research. And the segmentation results impact on subsequent recognition and understanding directly.

Fabric defects are usually caused by the irregular interwoven between warps and wefts or by the defects and pollution of raw materials. The texture in the defect area is dramatically different with that in the normal fabric surface. It is more intuitive to extract fabric defect texture and shape feature in spatial domain. The common feature extracting methods include gray-level co-occurrence matrix, auto-correlation function, LBP (Local Binary Pattern), the Gauss Markov Random Field (GMRF) model [3-7] and so on. The fabric texture exhibits a high degree of periodicity. So fabric images can also be transformed to other domains using the Fourier transform, the Gabor transform, or the wavelet transform for locating defects in the images [8-10]. However, most of these methods are limited to analyzing certain types of defects or lack flexibility in dealing with changes in fabric structures and background.

The study in this paper discusses the PCNN model in the application of fabric defect detection. In 1990, PCNN is proposed by Eckhorn, which explains the experimentally observed synchronous activity among neural assemblies in the cat cortex [11]. Because this model has the biological basis, it is widely used in image processing [12, 13]. At present, some researchers have made studies about defect detection based on traditional PCNN model. Some discussions about the influence of iteration are made in [14]. Reference [15] improved the PCNN model and a new parameter called the deviation of the contrast (DOC) was introduced to describe the contrast difference between the analyzed image and a defect-free image of the same fabric. The threshold is set by DOC and segmentation results were obtained by iterating the improved PCNN model.

When PCNN is applied to image segmentation, the communication behavior of neurons is totally similar with the regional growing process. So the segmentation algorithm based on PCNN model belongs to the category of regional segmentation. However, most of the algorithms based on traditional PCNN model haven’t exhibited the characteristic of regional segmentation [16]. The fabric defect detection methods based on PCNN model in [14, 15] only belong to threshold segmentation and their segmentation results are very dependent on the iteration. The setting of the optimal iteration is one of key problems in the research of PCNN model.

In 2002, Stewart proposed an improved PCNN model for image segmentation [17]. This model combined PCNN and regional growing theory together and represented the essence of PCNN model completely. However, it is hard to implement this improved model to specific application due to the high time complexity. Up
to now, there is no related literature to introduce the application of this improved model in fabric defect detection.

This paper proposed a new regional growing PCNN model according to the features of fabric image and successfully applied it to fabric defect detection. The time complexity is reduced greatly by the means of lowering the resolution of the detected image, introducing the mean and variance value of defect-free image. And the comparison experiments showed that the proposed method is feasible and efficient for fabric defect detection.

II. THE PCNN MODEL AND ITS APPLICATIONS

A. Introduction of the Basic PCNN Mode

PCNN is a kind of feedback neural network that interconnected by lots of neurons [16]. Some researchers modified the linking field network, and then it became the pulse coupled neural network model. Fig. 1 shows a basic PCNN neuron model. And it can be described by the following five equations:

\[
F_y[n] = e^{-\alpha}F_y[n-1] + L_y + \sum_{i} M_{yi}Y_i[n-1]
\]

(1)

\[
L_y[n] = e^{-\beta}L_y[n-1] + \sum_{i} W_{yi}Y_i[n-1]
\]

(2)

\[
U_y[n] = F_y[n] + \beta L_y[n]
\]

(3)

\[
Y_y[n] = \begin{cases} 
1 & U_y[n] \geq \Theta_y[n-1] \\
0 & U_y[n] < \Theta_y[n-1]
\end{cases}
\]

(4)

\[
\Theta_y[n] = e^{-\alpha} \Theta_y[n-1] + V_y Y_y[n-1]
\]

(5)

The model has three main parts: the receptive fields, the modulation product and the pulse generator. The neuron receives input signals from other neurons and from external sources through the receptive fields. Then the signals are divided into two channels. One is feeding channel, the other is linking channel. In the modulation part the linking input \( L \) is weighted with a parameter \( \beta \) and added a constant bias, then multiplied with the feeding input \( F \). The internal activity \( U \) is the output of the modulation part. The pulse generator compares the internal activity \( U \) with a threshold \( \Theta \). If the internal activity \( U \) is larger, the neuron will emit a pulse. The state of output \( Y \) will transform from zero to one. Emitting a pulse here is called ‘fired’. At last, the pulse generator will adjust the threshold \( \Theta \) according to the state of the neuron. If the neuron has fired, the threshold \( \Theta \) will be increased to a large value to prevent the neuron from emitting at the next time, and then it will decay gradually according to equation (5). When the threshold \( \Theta \) falls below the internal activity \( U \), the pulse will be emitted again. The process will continue until preset conditions are met.

B. PCNN Application in Digital Image Processing

An image is a kind of changed brightness or grayscale information in 2d or higher dimension space. For a two-dimensional image of \( M \times N \), PCNN can have \( M \times N \) input neurons, each corresponding to a pixel in the image and taking its grayscale as an external input. Each neuron has two states: fired or unfired. When a neuron has fired, the pulse will be delivered to adjacent neurons. If adjacent neurons have similar intensity, they will fire together because of the pulse coupled action. So the binary output \( Y \) contains objectives, edges and textures in image processing. This is the theoretical foundation of PCNN for image processing just as image denoising, image segmentation, image edge extraction and so on [16].

Fabric image reflects the surface morphology of fabric texture and has periodically grayscale distribution in the yarn direction. And defect areas usually have different grayscale distribution compared with normal texture. Based on these, the fabric defects are segmented by the different firing time when applying PCNN.

III. THE NEW REGIONAL GROWING PCNN MODEL FOR FABRIC DEFECT DETECTION

The proposed model in this paper is based on Steward’s PCNN model [17] and introduces the statistical information of defect-free images to complete the detection process automatically.

When applying the proposed model to segment the defect images, a single layer two-dimensional network is designed. In the network, the neurons and the pixels are in one to one correspondence. And all the neurons can only fire one time. Once fired, the state can be kept to next time and the neuron will not fire any more.

The final output of proposed model is a binary matrix \( R \) which has the same size as the external input image \( I \). Matrix \( R \) records the state of each neuron in the network. It can be shown in (6).\n
\[
R_y[n] = \begin{cases} 
1 & Y_y[n] = 1 \\
R_y[n-1] & Y_y[n] = 0
\end{cases}
\]

(6)

All the values in matrix \( R \) are initialized to zero. And \( Y_y[n] \) is the grown output at the nth time which is got according to (4). Matrix \( R \) merges all the grown areas from time zero to \( n \) and represents the segmentation results at nth time. Actually, at the early stage of the growing process for each time the output \( Y_y[n] \) recorded the positions of each preparing seed which is shown as follow:

\[
Y_y[n] = \begin{cases} 
1 & F_y[n] \geq \Theta_y[n] \\
0 & F_y[n] < \Theta_y[n]
\end{cases}
\]

(7)

Equation (7) represents the way how the preparing seeds are selected in the proposed model. Here feeding input \( F \) is simplified to the grayscale image \( I \). And \( \Theta \) is the threshold for all neurons. The preparing seeds should be filtered before the growing process. And the filtering condition is described in (8):

\[
D_y > \text{thresh} \_d
\]

(8)
Here $D$ is the variance of each preparing seed and $\text{thresh}_d$ is the reference variance got by the defect-free image.

The proposed model further simplifies the linking input $L$ described as follow:

$$L_y[n] = \sum_y Y_y[n-1]$$  \hspace{1cm} (9)

It sums up the output of the nearest eight neighbors. Only the pixels that have non-zero linking input can be captured by the seeds and merged into a region.

The internal activity $U$ and the grown output $Y$ are described as (3) and (4). And the linking coefficient $\beta$ in (3) is described in (10):

$$\beta_n = \beta_n + \Delta \beta$$  \hspace{1cm} (10)

The linking coefficient $\beta$ is initialized to a value that the seed will capture at least one neighbor neuron and iteratively added by a constant value $\Delta \beta$. The set of neurons captured by a small $\beta$ will be a subset of that captured with a larger one.

In the proposed model the feeding input $F$ is variable and linked with the grown output $Y$ which is described as follow:

$$F_y[n] = F_y[n-1]|Y_y[n-1]|$$  \hspace{1cm} (11)

Once a neuron fired, its feeding input $F$ will be set to zero. This action can be interpreted in this way: After a neuron emitted a pulse, the energy of its feeding input $F$ is used up. From now on, no matter how much the threshold $\Theta$ is, this neuron will not fire. Therefore, all neurons can be treated equally for all times in this model. And it becomes much easier to set the threshold $\Theta$ which is shown in (12):

$$\Theta_y[n] = \begin{cases} 1 & n = 0 \\ \Theta_y[n-1] - \Delta d & \text{others} \end{cases}$$  \hspace{1cm} (12)

Firstly threshold $\Theta$ is initialized to the maximum value of the feeding input $F$. And then $\Theta$ is subtracted by a small constant $\Delta d$. And $\Delta d$ will affect the efficiency of the growing process.

The termination conditions of the growing process for each time in this model are shown in (13) and (14).

$$\beta_n \geq \beta_{\max}$$  \hspace{1cm} (13)

$$|M_{\text{new}} - M_{\text{old}}| \geq S_{\max}$$  \hspace{1cm} (14)

Above $\beta_{\max}$ and $S_{\max}$ are set in advance. And $M_{\text{old}}$ is the mean intensity value of the captured pixels at old linking coefficient $\beta$. And $M_{\text{new}}$ is the mean intensity value at the added $\beta$. Any condition is met the growing process at the current time is over.

The proposed model introduced a termination condition for the whole growing process according to the mean value of the defect-free sample image. It is shown as follow:

$$\Theta_y[n] < \text{thresh}_m$$  \hspace{1cm} (15)

Here $\text{thresh}_m$ is the reference mean value got by the defect-free image. When the threshold $\Theta$ falls below reference mean value $\text{thresh}_m$, the whole growing process accomplished.

The proposed model in this paper is developed aimed at the characteristics of fabric defect detection. They can be summarized as follows:

(a) The proposed model associates output $Y$ with the feeding input $F$. It makes the firing behavior of the neuron easy to be understood and all the neurons to be treated equally.

(b) The proposed model introduced a binary output matrix $R$ to replace the multi-value matrix $P$ [17]. The matrix $R$ at any time represented the segmentation results of fabric defect image.

(c) The proposed model improved the way that the seeds are selected. Several seeds could be selected at one time. And the variance of defect-free image is introduced into the model to make the segmentation results more accurate.

(d) The proposed model introduced the mean value of the defect-free image to terminate the total growing process. That makes the running time greatly reduced.

IV. FABRIC DEFECT DETECTION ALGORITHM BASED ON THE PROPOSED MODEL

The defect detection algorithm based on the proposed model in this paper includes three parts: preprocessing, seeds selection and growing process of the seeds. Among them, preprocessing is only executed one time in all the algorithm and other two parts will be executed once at each time. The flowchart for the algorithm is shown in Fig. 2.

A. Preprocessing

The preprocessing in this paper consists of three steps: image resolution adjustment, image normalization and mean filtering. Firstly, the resolution of detected image is reduced to the extent that the differences between the defect area and the normal could be distinguished. The image with high resolution will take more processing time and high resolution affects the detected results by the algorithm in this paper. Secondly, the low resolution image is normalized and the highest grayscale value is set to one, and the lowest is set to zero. Finally, mean filtering is applied to the normalized image. Mean filtering can not only filter the typical random noise, but also decrease the sharp change of image intensity. Fig. 3 shows the segmentation results before and after the filtering operation. And it can be seen that the segmented area is more complete due to the smoothing of the filter.

B. Automatic Selection of the Seeds

Seeds selection is the most important step in fabric defect detection algorithm in this paper which impacts on the final segmentation results seriously.

Generally, the grayscale value in defect area is different with that in normal texture which is shown in Fig. 4. The grayscale value in defect area is lower in Fig. 4(a) while in Fig. 4(c) it is higher than that in normal area. In this paper seeds are selected according to the grayscale value from high to low. If the grayscale value in defect area is lower, the detected image should be reversed.
The seeds selected by (7) are preparing seeds in which there may be some error seeds. All neurons (fired or unfired) have the same threshold. For the neurons ever fired, the feeding input \( F \) is set to zero, so these neurons cannot be selected and not be captured by the seeds any more.

Due to non-uniform illumination or uneven distribution of fabric texture, the distribution of pixels in normal areas usually seems similar as in defect areas sometimes. This can be seen in the three rectangles shown in Fig. 4(b). Rectangle 1 is a part of the defect area and the other rectangles belong to the normal texture. When selecting seeds, the pixels in normal texture (in rectangle 2 and 3) may be chose by mistake. In order to assure the accuracy of the final segmentation, it is necessary to filter the preparing seeds before the growing process.

It can be found from Fig. 5 which is generated through calculating the variance of each pixel in Fig. 4(a) and (c) that the variance value in the defect area is obviously higher than that in the normal area. Therefore, the steps for seeds selection are as follows, first select the preparing seeds according to (7), and then calculate the variance value of each preparing seed, finally judge the seed by (8).

The neurons corresponding to error seeds which are eliminated will still be captured by correct seeds in the next growing process due to their high feeding input value. So for each growing process the feeding input \( F \) should be updated twice according to (11). One is the time for selecting the preparing seeds, and the other is after the growing process at the current time.

### C. Growing of the Seeds

The whole growing process is divided into different times. This paper defined the operation that updating the linking input \( L \), the internal activity \( U \) and the output \( Y \) in sequence according to (9) (3) and (4) as a basic capturing process. For each linking coefficient \( \beta \), the basic capturing process will be iterated many times until there are none pixels captured by the seeds or the value of output \( Y \) don’t change any more. And the growing process at each time is composed of above processes under several linking coefficient \( \beta \).

The growing process of the seeds is described in detail as shown in Fig. 6. The defect grayscale image is shown in Fig. 6(a) which is also the feeding input \( F \) in the proposed algorithm in this paper. It can be seen from Fig. 6(a) that the grayscale value in defect area is higher than that in normal image and the pixels with dark background are the selected seeds for the first time. The threshold \( \Theta \) is initialized to 0.99 first. The output \( Y \) is shown in Fig. 6(b) generated by (10) and it records the position of selected seeds. The updated feeding input \( F \) by (11) is shown in Fig. 6(c). Then the basic capturing process starts with an initial linking coefficient \( \beta \). First the linking input \( L \) is calculated according to (9) shown in Fig. 6(d) and the neighborhood is \( 3 \times 3 \). Then the internal activity \( U \) is
The neurons of which the feeding input $F$ is 0.8 in Fig. 6(a). Therefore, with the increase of linking coefficient $\beta$ at each time and the decrease of threshold $\Theta$ by (12) at different time, the neurons adjacent to the seeds and having similar feeding input in Fig. 6(a) can be captured and merged into a region shown in Fig. 6(g). After the growing process at current time finished the feeding input $F$ should be updated for the next time which is shown in Fig. 6(h).

The termination conditions of the growing process for each time are decided by (13) and (14). When the linking coefficient $\beta$ surpasses $\beta_{\text{max}}$ or the difference of mean intensity value between the grown areas of different $\beta$ surpasses $S_{\text{max}}$, the growing process at current time is over. The setting of $\beta_{\text{max}}$ and $S_{\text{max}}$ impacts on the final segmentation result seriously. Through above growing processes, it can be seen that the larger $\beta_{\text{max}}$ is, the larger the grown area is. And the parameter $S_{\text{max}}$ restraints the growing process of the seeds but makes the grown area smoother. The segmentation results corresponding to different parameters are shown in Fig. 7 and they match the above descriptions.

Due to different grayscale value between the defect area and normal texture in defect image, this paper introduces the mean value of defect-free image to automatically control the whole regional growing process. It can be seen from (12) that with the increase of the time, threshold $\Theta$ decreases gradually. If the threshold $\Theta$ is less than the mean value which is shown in (15), the whole algorithm in this paper is over. The binary matrix $R$ generated by (6) is the last segmentation result.

V. EXPERIMENTAL RESULTS

In the process of production, there are three major categories of fabric defects: point defect, line defect and surface defect. This paper performed experiments mainly on the TILDA database and compared the segmentation
results by proposed algorithm in this paper with the other two methods. One is the segmentation method based on traditional PCNN model [18] and the other based on unsupervised multi-channel Gabor filter [10]. All the algorithms are implemented in Intel I3 530 CPU with 2G system memory using MATLAB and experimental results are shown in Fig. 8.

In Fig. 8, (a1) to (k1) are original defect images and include most of fabric defect types. These images have non-even intensity distribution due to non-uniform illumination. The grayscale value on the left of the image shown in Fig. 8 (c1) is higher than that on the right. And in other defect images the right part has higher grayscale value. Fig. 8 (a2) to (k2) are segmentation results by the
The segmentation results by different defect detection algorithms: (a1~k1) Original defect images; (a2~k2) The result images by the proposed method in this paper; (a3~k3) The result images by traditional PCNN method; (a4~k4) The result images by unsupervised multi-channel Gabor filter method.

TABLE I.
THE PROCESSING TIME OF THE PROPOSED ALGORITHM IN THIS PAPER (SECONDS)

<table>
<thead>
<tr>
<th>Defect image</th>
<th>a1</th>
<th>b1</th>
<th>c1</th>
<th>d1</th>
<th>e1</th>
<th>f1</th>
<th>g1</th>
<th>h1</th>
<th>i1</th>
<th>j1</th>
<th>k1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Processing time</td>
<td>0.182</td>
<td>0.386</td>
<td>0.289</td>
<td>0.455</td>
<td>0.469</td>
<td>0.865</td>
<td>0.860</td>
<td>0.397</td>
<td>0.391</td>
<td>0.751</td>
<td>0.687</td>
</tr>
</tbody>
</table>

TABLE II.
COMPARISON OF THE PERFORMANCE EVALUATION OF THE THREE METHODS

<table>
<thead>
<tr>
<th>Segmentation methods</th>
<th>Defect images</th>
<th>The method in this paper</th>
<th>Traditional PCNN</th>
<th>Gabor filter</th>
</tr>
</thead>
<tbody>
<tr>
<td>J</td>
<td>a1</td>
<td>0.2989</td>
<td>0.3678</td>
<td>0.8046</td>
</tr>
<tr>
<td></td>
<td>b1</td>
<td>0.4463</td>
<td>0.4494</td>
<td>0.9008</td>
</tr>
<tr>
<td></td>
<td>c1</td>
<td>0.5798</td>
<td>4.4862</td>
<td>0.7983</td>
</tr>
<tr>
<td></td>
<td>d1</td>
<td>0.4526</td>
<td>4.4821</td>
<td>0.9492</td>
</tr>
<tr>
<td></td>
<td>e1</td>
<td>0.5385</td>
<td>2.1190</td>
<td>0.9580</td>
</tr>
<tr>
<td></td>
<td>f1</td>
<td>0.6131</td>
<td>3.3090</td>
<td>1.4099</td>
</tr>
<tr>
<td></td>
<td>g1</td>
<td>0.5455</td>
<td>2.1354</td>
<td>1.1850</td>
</tr>
<tr>
<td></td>
<td>h1</td>
<td>0.5250</td>
<td>7.6309</td>
<td>5.9346</td>
</tr>
<tr>
<td></td>
<td>i1</td>
<td>0.1736</td>
<td>3.6048</td>
<td>0.9640</td>
</tr>
<tr>
<td></td>
<td>j1</td>
<td>0.5442</td>
<td>1.6229</td>
<td>1.1252</td>
</tr>
</tbody>
</table>

It can be seen from Fig. 8 that when the difference of the grayscale value between defect area and normal texture in defect image is large, all three methods have good segmentation results just as shown in Fig. (a) and (b). But if the difference is not obvious shown in other defect images, only the algorithm proposed in this paper can detect the defects accurately, and other two methods usually have under-segmentation or over-segmentation results.

In order to quantitatively evaluate the performance of the proposed method of this paper, we used a parameter $J$ to measure the quality of image segmentation.

\[
J = \frac{S_r}{S_s} 
\]  

(16)

Here $S_r$ is the pixel number of defect area marked manually in the defect image, and $S_s$ is the pixel number proposed method in this paper and they consist of the grown areas at different times without any post-processing. The results based on traditional PCNN model are shown in Fig. 8 (a3) to (k3). And Fig. 8 (a4) to (k4) are the results by the method of unsupervised multi-channel Gabor filter method. The Gabor filter bank includes three scales and six orientations.
by failure detection and fault detection. The parameter $J$ quantitative described the accuracy of the defect detection algorithm. If the value of $J$ is higher than one, it indicates that the results are over-segmentation. And if $J$ is lower than one but close to one, it indicates the results are under-segmentation. The optimal segmentation results appear when the value of $J$ is close to zero. Table 2 presents the performance parameter of the three segmentation methods for the same defective images in Fig. 8. It can be concluded from digital analysis that the performance measure $J$ of the proposed method in this paper is superior to those of the other two methods. Table 1 lists the processing time of each image in Fig. 8 by the proposed method in this paper. It can be seen that the time complexity is reduced greatly.

VI. Conclusions

This paper presents a new method for fabric defect detection. In this method, improved PCNN model and regional growing theory are combined together in the light of the requirements for fabric defect detection. The mean and variance value of the defect-free images are also introduced into this model. Results showed that the proposed method is feasible and efficient for defect detection. Because the proposed algorithm is based on neural network and the setting of the parameters is simple, it is easy to hardware implementation and provides favorable conditions for real-time defect detection. The later work will further improve and perfect the proposed model for fabric defect detection and makes this model more accurate and general.

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References


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