Defect Detection for Wet-laid Fiberglass Mat Based on An Automatic Iterative Otsu Method

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ABSTRACT

Real-time defect detection in industrial products is a challenging problem. Image segmentation is an extremely important step in defect detection. Threshold is one of the most commonly used methods in image segmentation, which can segment objects from image background. As a classic thresholding method, Otsu can obtain satisfactory threshold value when the difference between object and image background is obvious. However, when the proportion of the object is small, Otsu method has a poor segmentation effect. In this paper, we propose a defect detection method based on Otsu method to tackle the problem of automatic defect detection of wet-laid fiberglass mat. After the pre-processed image is segmented by the Otsu method, we remove the isolated pixels in the image and mark the remaining image areas. The marked image area will be processed as a new image. Then we repeat the above operation until the defect location is accurately determined. The proposed automatic iterative Otsu method can continuously reduce the size of the image to be processed, increase the proportion of defect area and improve the image segmentation effect of Otsu method. The experimental results show that our method can largely eliminate the image noise, determine the defect location and achieve high robustness and computational efficiency in automatic defect detection.

CCS CONCEPTS

• **Computer systems organization** →**Embedded systems;** *Redundancy;* Robotics; • **Networks** →Network reliability;

KEYWORDS

defect detection, image segmentation, Otsu method, wet-laid fiberglass mat

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1 INTRODUCTION

Wet-laid fiberglass mat, a kind of building material, is made of cut glass fiber, whose manufacturing process is similar to paper making. Due to its corrosion resistance, fire resistance and water resistance, fiberglass mat is widely used in building materials industry, such as asphalt, glass fiber reinforced plastic, floor, etc. Some defects will occur in the wet-laid fiberglass mat production process. Those defects will seriously affect the quality of wet-laid fiberglass mat and reduce company profits. At present, the defect detection of wet-laid fiberglass mat depends on artificial vision detection. Manual detection is not only inefficient but also has high labour intensity and high costs. At the same time, the detection effect depends on the work experience and work status of workers. Therefore, artificial defect detection is not objective and stable. Defect detection based on machine vision is non-contact, objective and efficient, which can improve the productivity and quality management, and has been widely used in industry[6, 15, 17, 19]. Therefore, automatic defect detection is one of the most attractive researches in computer vision.

As a quality control method, automatic defect detection has been widely used in many walks of life, such as agriculture[1], manufacturing industry[6, 19] and construction industry[7]. Automatic Defect detection based on machine vision system includes image acquisition, image processing and defect detection. Image processing is an important step in defect detection, which includes steps of image segmentation, feature extraction, and defects classification[9]. Among them, image segmentation is the most crucial step. As an image segmentation method, thresholding technique is a common method[20] because of its fast processing speed, small storage space and easy in manipulation. The basic idea of thresholding technique is to select an optimal gray-level threshold value to separate the object from the image background. Thresholding techniques can be classified into two categories: global thresholding and local thresholding[23]. For the former, a single value is chosen to segment an image into two classes: object and the background. For the latter, multiple threshold values need to be selected according to the localized gray-level information, it can deal with the uneven image changes but the process is complicated and slow.

Threshold technique has been a research subject and many works have been published in the past decades. For example, S.Arora et al.[20] proposed a fast statistical recursive multilevel thresholding method, which segment an image into multiple levels using its mean and variance. Cuevas et al.[2] used the method based on the mixture of Gaussian functions to select the threshold and the parameters are calculated using three nature inspired algorithms (Particle Swarm Optimization, Artificial Bee Colony Optimization and Differential

Evolution). Xie et al.[18] proposed a fast threshold segmentation method which used polynomial to fit the curve of gray histogram and takes the characteristic of gray histogramąŕs valley into consideration in Otsu method, and this method has a satisfactory image segmentation with a low computing time. In addition, various kinds of defect detection threshold techniques have been proposed in the literatures[11, 22, 24]. Most threshold methods are only applicable to specific application scenarios, however, there is no general method for defect detection.

Sezgin[13] conducted a survey in threshold technology and suggested that Otsu[10] method is simple and efficient and is one of the most commonly used methods to select a threshold value. Otsu method is a global thresholding technique, which selects a threshold value by the maximum between-class variance or the minimum within-class variance of the image histogram. When the difference between object and background is obvious, Otsu method can achieve better segmentation effect. However, a downside of Otsu method is that once the proportion of the object changes, the threshold value will be affected, which affects the effect of Otsu method. According to the study of Lee et al.[8], when the object proportion is 30%, the image segmentation effect is the best. When the proportion falls below 10%, the segmentation effect drops sharply.

According to the characteristics of fiberglass mat images, and combining with the downside of Otsu method and improved Otsu methods in the application, we propose an automatic iterative Otsu method for fiberglass mat defect detection. The contributions of this research are summarized as follow: (1) An improved Otsu method is proposed to select the optimal threshold value by iterative method. In each iteration, the image is segmented, morphologically processed and the new image region is marked. By continuously increasing the object proportion, the accuracy of each step threshold is improved. It can solve the problem that Otsu method has a poor segmentation effect when object proportion is small. (2) The proposed method has fewer iterations and less time complexity, and can meet the real-time requirements of actual production. Therefore, it can be extended to other industrial detection fields. (3) The proposed method can determine the location of the defects. The pre-processing method can reduce the image noise and is suitable for images with a lot of noise.

2 OTSU METHOD AND THE IMPROVED OTSU METHODS

We briefly introduced the Otsu method and a variety of improved Otsu methods.

2.1 The Otsu method

The Otsu method aims to automatically find optimal threshold value for image segmentation. The gray-level value of the image is divided into two categories, foreground and the background. At the optimal threshold, the variance between the foreground and the background is the maximum, and the difference between the foreground and the background is also the most obvious. Therefore, Otsu method can reduce the possibility of misclassification.

The pixels of a given image can be represented with a gray level range from 1 to L. The number of pixels at level i is denoted by n_i, and the total number of pixels is denoted by n. The probability of occurrence of the gray level i is defined as follows:

$$p_i = \frac{n_i}{n}, p_i \geq 0, \sum_{i=1}^{L} p_i = 1 \tag{1}$$

Now, the pixels of the image will be divided into two categories, foreground part and background part. The range of foreground pixels is 1-T and the range of background pixels is T-L, where T is the threshold value. And q_i(i=[0,1]) represent the probability of foreground and background.

$$q_0(T) = \sum_{i=1}^{T} p_i \tag{2}$$

and

$$q_1(T) = \sum_{i=T+1}^{L} p_i \tag{3}$$

The average grey value of foreground and background pixels is defined as follows:

$$u_0(T) = \sum_{i=1}^{T} i * \frac{p_i}{q_0(T)} \tag{4}$$

and

$$u_1(T) = \sum_{i=T+1}^{L} i * \frac{p_i}{q_1(T)} \tag{5}$$

The variances of foreground and background can be computed as:

$$\sigma_0^2(T) = \sum_{i=1}^{T} [i - \mu_0(T)]^2 \frac{P(i)}{q_0(T)} \tag{6}$$

and

$$\sigma_1^2(T) = \sum_{i=T+1}^{K} [i - \mu_1(T)]^2 \frac{P(i)}{q_1(T)} \tag{7}$$

So, the optimal threshold value can be determined as:

$$T = arg \max \sigma_w^2(T) \tag{8}$$

where

$$\sigma_w^2(T) = q_0(T)\sigma_0^2(T) + q_1(T)\sigma_1^2(T) \tag{9}$$

2.2 Improved Otsu methods

Otsu method can achieve better results when the object and background image are significantly different or the image gray-level histogram has two distinctly different peaks. However, Otsu method will not get the optimal result when the image grays-level histogram has more than two peaks or one of the background and foreground has a large variance. Over the years, researchers have proposed many methods to improve the Otsu method. Zhu et al.[25] improved the Otsu method by proposing a fast 2d Otsu method. The 2d Otsu method utilizes the gray-level information of each pixel and its spatial correlation information within the neighborhood. Compared with the otsu method, the noise resistance of this method is improved. However, the 2d Otsu method increases algorithm complexity and runtime. The improved 2d Otsu methods can be found in literatures[14, 21], but time complexity of the algorithm is still high. In 2010, Na Wang et al.[16] proposed an improved 3d Otsu thresholding method. Although the segmentation speed of this algorithm is faster than 3d Otsu method, it still cannot meet the requirements of real-time detection. M.Huang et al.[5] proposed an improved Otsu method by narrowing the selection range of threshold and searching the minimum variance ratio. The new improved algorithm has high segmentation precision and fast computation speed. However, the fiberglass image contains a lot of noise, and these noises have a great influence on the effect of this method. In 2012, Fan and Lei[4] proposed a modified valley-emphasis method for automatic thresholding(NVE). In 2015, X.Yuan et al.[3] proposed an improved Otsu method using the weighted object variance(WOV) for defect detection, and the WOV method provides better segmentation results. In 2016, Jiming Sa et al.[12] proposed an Otsu method which based on Sobel Operator(SO). Their experimental results achieved a good segmentation performance.

3 PROPOSED METHOD

3.1 Image pre-processing

According to the characteristics of wet-laid fiberglass mat defects, they can be classified into nine types, namely wrinkle, fiber block, loss of long fiber, adhesive block, bulge, foreign fiber, impurity, fiber group and hole. The representative images of the above nine defects are shown in Fig.1.

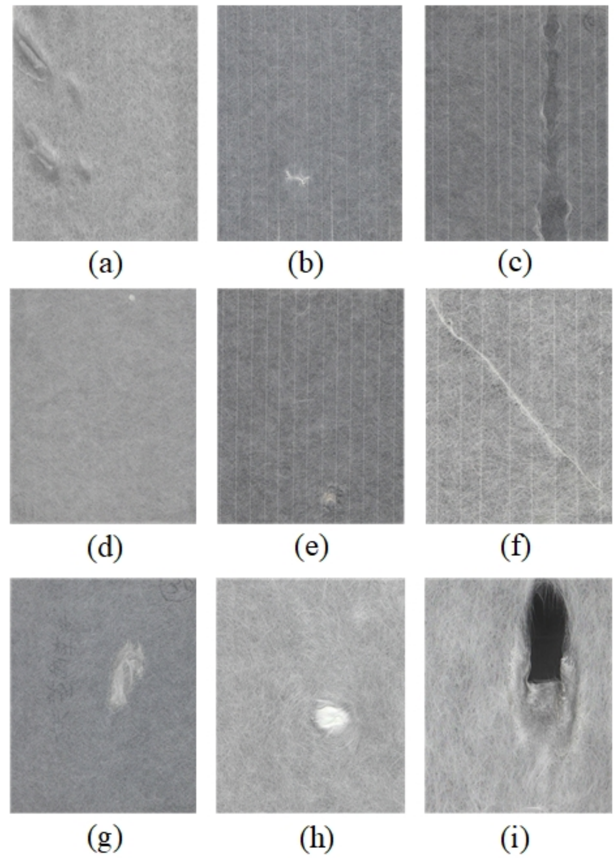


Figure 1: Wet-laid fiberglass mat defects image. (a)wrinkle; (b)fiber block; (c)loss of long fiber; (d)adhesive block; (e)bulge; (f)foreign fiber; (g)impurity; (h)fiber group; (i)hole;

In actual production, the acquisition of image will inevitably produce some noise, so the image must be preprocessed to reduce interference. The effect of pre-processing will affect the effect of image segmentation. Therefore, image pre-processing is an important step in image processing. The pre-processing techniques covered in this paper include smoothing filtering, morphological processing and defect enhancement.

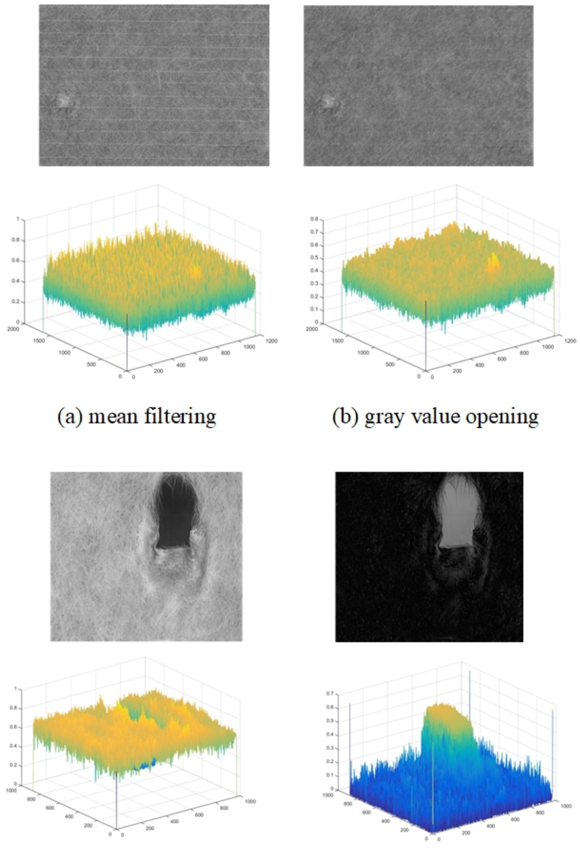
In this paper, the image noise mainly comes from the target noise and the noise produced by the camera. Median filtering algorithm has better filtering effect and faster filtering speed for wet-laid fiberglass mat image. Therefore, this paper uses median filtering algorithm for smoothing filtering. There are a lot of useless isolated points in the fiberglass mat image and they will be removed by the morphological method. To reduce interference, some long vertical fiber will be removed by using a non-vertical structure element during the corrosion. Fig.2 shows the effect of the corrosion process. From the image, the lines have been blurred and the defect areas still exist. Compared with the 3-D gray histogram in fig.2(a), the defect area in the 3-D gray histogram in fig.2(b) is more obvious.

The background texture of the fiberglass mat is complex and contains a lot of noise. Filtering and morphological processing have limited denoising effect, so to reduce the difficulty of image recognition, we enhance defect area through background removal and contrast enhancement. Background removal can remove a lot of noise interference in the background. Contrast enhancement can enhance the gray level difference between the object and the background in the image, which is convenient for distinguishing between foreground and background.

The gray-level value range of fiberglass mat image background is narrow, so we remove background by mode. At the same time, it is necessary to ensure that the image background and foreground have the same symbols, so the process is showed as:

$$g = |g - M(g)| \tag{10}$$

g is the gray value matrix, and M(g) is the most frequent number in gray matrix. As the Fig.2 (c) and (d) shows, after processed by formula (7), the background area is removed. The original dark defect area will be brighter than the background area.



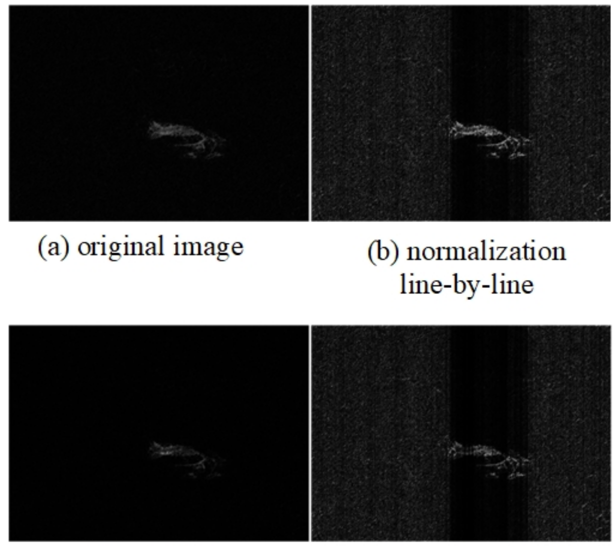
(a) mean filtering (b) gray value opening

(c) original image (d) background removal

Figure 2: Image pre-processing

In the field of image processing, contrast enhancement algorithms can be roughly divided into two categories: histogram adjustment and gray level transformation. Histogram adjustment is not suitable for this paper, so we use the gray level transformation method. Gray-level transformation algorithm uses the idea of normalization and inverse normalization transformation to enhance gray-level image. This process requires a kernel function. The slope of the tangent function increases with the increase of gray value and is sensitive to parameter changes. Therefore, this paper uses the tangent function as a kernel function to normalize the gray value to $[0, \alpha * \pi/2]$, where α is the adjustment factor, which is used to control the change rate of high gray value partial contrast.

To make the defect information more complete, this paper uses the normalization method to process the pixels of the image line-by-line. As shown in Fig.3, line-by-line normalization enhances the defect and retains more image information. Although this method also retains more background information, the connectivity of these background points have been destroyed, and it is easy to filter them out.



(a) original image (b) normalization line-by-line

(c) global normalization (d) two kinds of normalized difference

Figure 3: Comparison of normalizaiton effect

Algorithm 1 Defect Enhancement Algorithm

Input: Gray image g
Output: Gray image with enhanced defect
1: Subtract the background using g=$|g - M(g)|$
2: for each line of the images do
3: Normalize the vector into $[0, \alpha * \pi/2]$ by Min-Max Normalization
4: end for
5: for each pixel of the images do
6: Apply tangent function to it
7: end for
8: for each line of the images do
9: Normalize the vector into [0, 255] by Min-Max Normalization
10: end for

Defect enhancement process is shown in Algorithm 1. Step 1 is background removal. Contrast enhancement content can be divided into three parts: normalized preprocessing, kernel function transformation, and inverse normalization processing, corresponding to steps 2 to 4, steps 5 to 7, and steps 8 to 10, respectively. Normalization process normalizes the pixel values in the gray level image to $[0, \alpha * \pi/2]$. The kernel function transform is to treat each pixel in the image with a tangent function and distribute its pixel values according to the tangent function curve. The inverse normalization process is to re-stretch the transformed pixel value to [0, 255].

3.2 Automatic iterative Otsu method

As shown in Fig.4(a), after image preprocessing, the connectivity of the background area disappears and the connectivity of the defect area remains. The image is processed by Otsu and its threshold T is obtained. Then, the image is segmented according to the threshold T, and there are many isolated bright spots in the segmented image. We set a suitable value S_T to remove the isolated points when the isolated point area is less than S_T. As shown in Fig.4(b), an image containing the object and a small amount of noise is obtained. As show in Fig.4(c), we get the edge position of this image and mark it with a red line in the gray level image. The marked area is the new area to be processed. The above operations are iterated until the preset termination conditions are reached. The proposed method can remove isolated interference points and continuously increase the proportion of target areas, thus improving the accuracy of Otsu method at each step. Finally, the defect is accurately identified and its location is determined. The whole process is showed as Algorithm 2.

In step 1, the input image is preprocessed to reduce noise interference. Step 2 indicates that S represents the image area and t represents the number of iterations. Step 3 is the end condition of the iteration, including two parts. ΔS refers to the reduction of image area after each iteration and ε is a smaller value. When the ΔS is less than the small value ε, it means that the area of the image is not reduced, and the iteration ends. t refers to the iterations and the iteration will end when t is greater than the set maximum $t_{\max}$. In step 4, the image will be processed by morphological processing and contrast enhancement, then the image is segmented by the Otsu method. In step 5, an area threshold S_T is set. In the binarized image, points with an area less than S_T are removed, so the residual noise points in the background are removed. In step 6, the object and remaining noise point areas are marked and the marked area will be process as a new study area. In step7 and step8, S, ΔS and t is updated.

Algorithm 2 Automatic Iterative Otsu method

Input: Image g
Output: Image with marked defective regions
1: Pre-process g by methods in section 3.1
2: S = the size of g, $\Delta S = S$, the number of iterations is t
3: while $\Delta S \geq \varepsilon$ and $t \leq t_{max}$ do
4: Process g using morphology, contrast enhancement and Otsu
5: Delete those regions of which the size $\leq S_T$
6: Extract the minimum enclosing rectangle as the new g
7: $\Delta S = S -$ the size of g
8: S= the size of g, t=t+1
9: end while

.

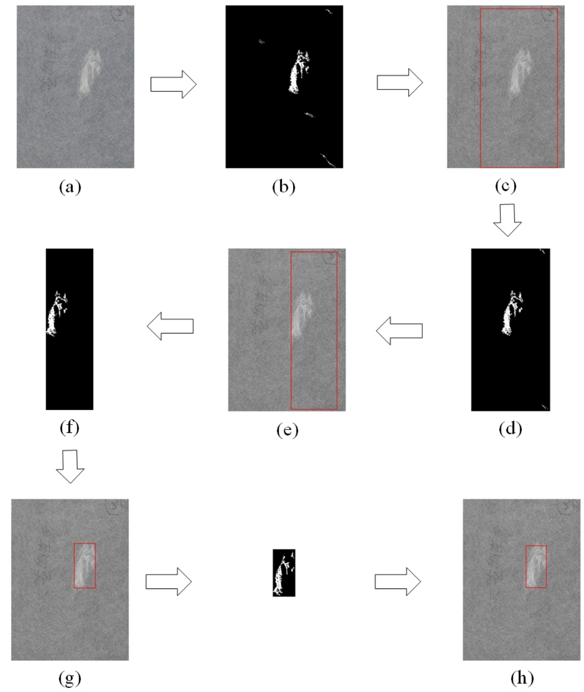


Figure 4: Automatic iterative Otsu method for processing Fig.1(g)

4 EXPERIMENTAL RESULTS AND ANALYSIS

The core idea of the proposed method is to eliminate non-connected area, reduce the size of the image to be processed to increase the proportion of the object, and thus improve the segmentation accuracy of Otsu method. Finally, the position of the defect area will be determined. Experiments are conducted in a computer using MATLAB R2016a, with Intel Core 2.50GHZ CPU and 7.81 memory.

Take Fig.1(g) as an example, Fig.4 shows the entire processing of the image. In this process, S_T is set to 300, and there are four iterations. As shown in the red line area, a new area will be obtained after each iteration, and the other areas of the image will not be involved in the next iteration. The proportion of the new area after each iteration is shown in Table 1. As the iteration progresses, the red line area constantly approach to the defect area until the end of the iteration. In the above process, the area to be processed decreases continuously, which means that the proportion of the object is increasing. Finally, the defect area is determined.

In order to prove the effectiveness of the automatic iterative Otsu method, we carried out experiments to compare Otsu method, NVE method, WOV mehtod, SO method and the proposed method in this paper. Among these method, NVE method, WOV methos and SO method are the improved Otsu methods proposed in the past few years, and have achieved good results. Nine different types of image sets were used to test the segmentation results. We choose the

Table 1: Data change table for impurity image processing

number of iterations	1	2	3	4
proportion of the area to be treated	0.6409	0.3774	0.0494	0.0446
Otsu threshold	44	50	58	75

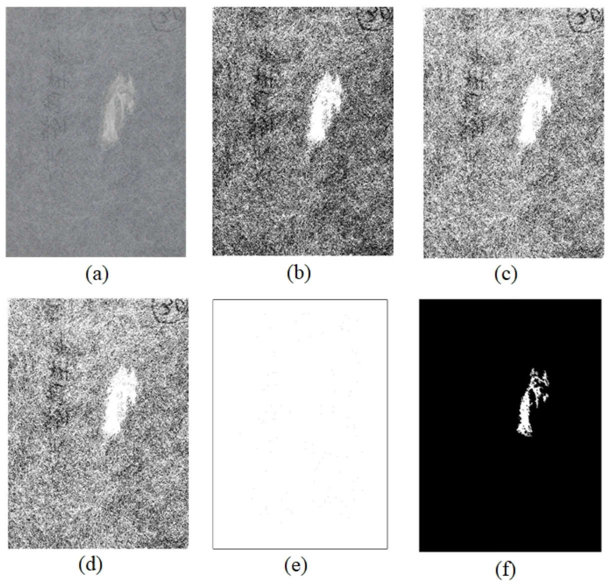


Figure 5: Segmentation results of different method. (a)original image; (b)Otsu method; (c)NEV method; (d) WOV method; (e) SO method; (f) proposed mehtod;

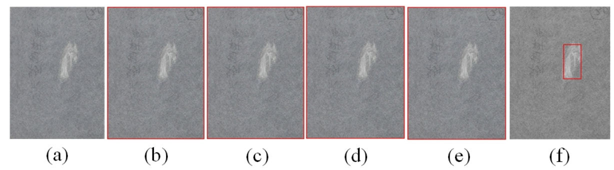


Figure 6: Defect detection results. (a) original image; (b) Otsu method; (c) NVE mehtod; (d) WOV mehtod; (e) SO method; (f) the proposed method

processing results of Fig.1(g) to display. As shown in Fig.5, Otsu method does not achieve a satisfactory segmentation effect. The NVE and WOV methods have similar effects on fiberglass mat image segmentation and are better than the effect of Otsu method. The threshold value selected by the SO method is small, and the fiberglass mat image segmentation effect is poor. However, the proposed method in this paper achieves satisfactory results for the segmentation of fiberglass mat images. As shown in Fig.5(f), object and image background are clearly segmented and most of the noise points in the image are removed.

Further analysis of the results shown in Fig.5, we found that the reason for the poor performance of the NVE, WOV and SO methods is the particularity of the wet-laid fiberglass mat image. The process of collecting wet-laid fiberglass mat images will inevitably produce some noise. More importantly, the glass fibers in the wet-laid fiberglass mat are disorderly ordered, which will greatly interfere with the segmentation of the image. NVE method and WOV method has better effect on image segmentation with less noise, but the two methods are not suitable for segmentation of wet-laid fiberglass mat images. The SO method is based on edge detection and is most affected by noise, so the segmentation effect on the wet-laid fiberglass mat image is the worst. The reason why the proposed method can get better results is that we propose an effective preprocessing method, and the noise is processed in each step of the iteration.

As shown in Fig.6, the proposed method can determine the location of the defect area, and other methods cannot determine the defect location. In each iteration, the proposed method removes the isolated points and marks the remaining connection area. In the next iteration, the marked area will be treated as a new area. The area to be processed is shrinking and the defect location is finally determined. Using the proposed method in this paper, all of the defect positions in Fig.1 were successfully determined. The number of iterations of the nine images and the object ratio data are shown in Table 2.

Finally, we compare the time complexity of the five methods mentioned earlier. As shown in Table 3, the time complexity of the five methods is O(m*n), where m and n represent the length and width of the image. However, SO method involves convolution operation, and its operation time is relatively long. Compared with Otsu method and other improved Otsu method, the proposed method does not increase the time complexity. Therefore, the automatic iterative Otsu method can meet the requirement of real-time detection and get good detection results. Overall, the proposed method has a good segmentation effect and can determine the position of defects, which is suitable for the defect detection of fiberglass mat.

Table 3: Time complexity of different methods

Methods	Time complexity
Otsu method	$O(m*n)$
NVE method	$O(m*n)$
WOV method	$O(m*n)$
SO mehtod	$O(m*n)$
Proposed method	$O(m*n)$

Table 2: Data table of automatic iterative Otsu method processing image

Image number	a	b	c	d	e	f	g	h	i
number of iterations	3	5	3	3	3	3	4	3	3
Proportion of the final region	0.3244	0.0068	0.1603	0.001	0.0015	0.7978	0.0446	0.0223	0.1802

5 CONCLUSION

This paper proposed an automatic iterative Otsu method for the wet-laid fiberglass mat defect detection. Due to the particularity of the wet-laid fiberglass mat image, there is a lot of noise in the image and which have a great influence on the image segmentation effect. According to the characteristics of wet-laid fiberglass mat image, we adopt a series of preprocessing methods to reduce noise interference. The preprocessing methods include median filtering, background removal, morphological processing and contrast enhancement techniques. The experimental results demonstrate that the preprocessing methods can reduce image noise and achieve good denoising effect.

We adopt the iterative method to process the preprocessed image. In each iteration step, we remove the isolated points in the image to reduce the image area and increase the object proportion. The experimental results show that the proposed method can improve the segmentation accuracy of the Otsu method. At the same time, we mark the position of the target area in each iteration and finally determine the location of the defect.

Compared with Otsu method, NEV method, WOV method and SO method, the proposed method obtains better segmentation results and can determine the location of defects. Meanwhile, compared with the conventional manual detection, the proposed method can improve the efficiency, reduce the cost and improve the quality management. In conclusion, the automatic iteration Otsu method is a more effective approach to wet-laid fiberglass mat defect detection and can meet the actual production demand. Although the proposed method can improve the image segmentation accuracy of the Otsu method and determine the defect position, it does not classify defects. However, defect classification plays an important role in improving product quality. In the future, more works will be devoted to the classification of defects.

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