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Research on crack detection applications of improved PCNN algorithm in moi nondestructive test method☆

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ABSTRACT

On the basis of the Faraday Magneto-optical Effect (FMoE) method, that the polarized light would rotate its polarizing direction when there is the magnetic in its moving direction, a NDT method based on Magnetic optic imaging (MOI) is proposed to detect and identify the crack. In order to identify the crack, the pulsed-couple neural network (PCNN) model based this method is developed and improved to select the threshold dynamically. The output image of the PCNN model is pulsed image and this kind of image is processed by the magnetic domain spots filter. This kind of filter is based on the connection law which can detect the crack in the pulsed image. The detecting system could be used to identify the crack accurate by the above two steps, which would be confirmed by the results.

1. Introduction

Nondestructive test (NDT) had been accepted and used by more and more researchers and technicians [1–4], especially in crack detection and measurement for industry and aerospace area [5]. Electromagnetic nondestructive test is becoming widely popular due to its high accuracy and high efficiency [6]. Pulsed eddy current test (PECT) and magnetic optical imaging (MOI) method, for instance, are new ways to detect the crack and measure the defects. Furthermore, MOI provides a convenient method and reliable guarantee to obtain the crack defect information by observe the magnetic flux distributions.

For the small cracks detection, the MOI method has some potential advantages over other molds and has been researched frequently. Deng et al. [7] proposed a statistics method based on the MOI method for the aircraft defect detection, and the MOI detection is also used for crack classification in [8], and the skewness function of MOI can be used to study whether the crack is existence. Cheng et al. [9] presented a method to detect the iron crack based on the MOI system, the filter method and edge extract method are used to enhance the image viewed. Diraison et al. [10] did some MOI researches about the characterization of subsurface defects in aeronautical riveted lap joints using a multifrequency imaging setting. Bosse et al. [11] presented a high resolution approach to quantitatively estimate the depth of defects buried in planar metallic structures. These studies of MOI to detect the defects mostly aim at the image enhancing and make the crack image more discriminating. However, as the detecting system improved, for some iron material, the magnetic domain have much impact on the crack recognition [12]. So it needs a method to extract the crack from the MOI image that includes the magnetic domain spots. In order to deal with this problem, it usually needs to segment the MOI image, so that the threshold value researching is important. Tian et al. [13] proposed a method to reduce the influences of magnetic domain spots, but this method is not applicable for some other materials due to the empirical selection of threshold from the researcher. On the other hand, the magnetic domain spots in MOI image has the similar behavior with the crack image. What's more, for different material, the behavior is different. So it needs a method to select the threshold depends on the MOI image, so that it can separate the image well. Cheng et al. [14] proposed a model to research the threshold. This method holds the self-adaptive ability, but it did not consider the information of the nearby pixels. As the magnetic field in the specimen is continuous, the crack information about each pixel has a closed relationship. In order to improve the accuracy of crack detection, this relationship should be taken into consideration. In [15], a skewness parameter was utilized to optimize the threshold. In this algorithm,

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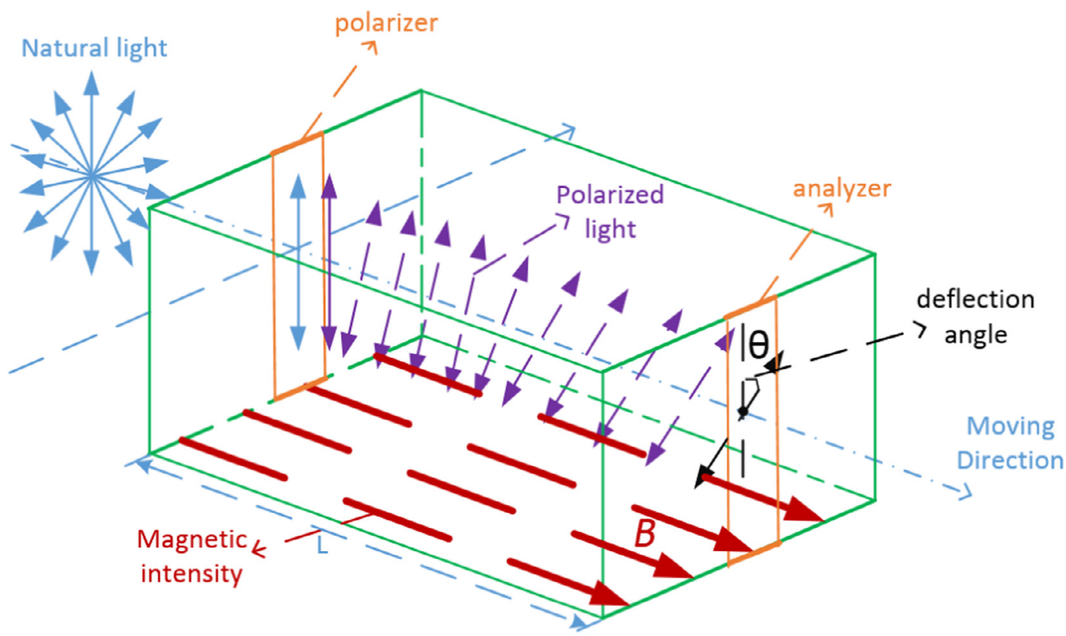

Fig. 1. Faraday magnetic rotation theory.

it should scan the threshold for many times and count the amount of the black pixels, but this process is also time-consuming. On the other hand, the optimization threshold would be influenced by the magnetic domain spots and some other aspects, such as the experimental environment.

For this reason, this paper presents a method to deal with the above problems. Because the view of the magnetic domain spots in the image is similar with the crack, the traditional process method is hard to distinguish them. This method provided in this paper uses the improved PCNN model to select the threshold dynamically and output a pulsed image, this image is processed by the magnetic domain spots filter, which is based on the connection law. On the other hand, PCNN method is some what the statistics algorithm in image process, which would take the pixels that around the research target pixel into consideration. For there are so many neurons should be processed, the statistics method is useful, and the statistics method has used in many research field just like [16]. PCNN method has been applied in many image researching. Wang et al. [17] proposes a PCNN method for multi-focus image fusion, which does not decompose the input source images and need not employ more PCNN or other algorithms such as DWT. Gu et al. [18] uses a unit-linking PCNN for image segmentation. In medical science field, PCNN method also be used to fuse the medical image [19]. PCNN method is one of the neuron net computing method, which uses the state values of the nearby neurons to confirm the state value of current processing neuron. Using the state value parameter, PCNN can easily select the threshold. This neuron net computing method make full use of information of all nearby neurons. As it holds the feedback channel, PCNN is suitable for processing the MOI image which is sensitive to the light. Like some other learning machine algorithm, such as extreme learning machine [20–23], PCNN algorithm can suit for the MOI image that detected in different experimental condition.

The rest of this paper is organized as follows: Section 2 describes the basic theory and method of the MOI technique. Section 3 introduces the experiment setup and the specimen. And the proposed method is presented in Section 4. The next Section 5 is the results of the method and some discussions are done in this section. Finally the conclusions are given.

2. The fundamental of MOI

Faraday magnetic rotation effect (FMRE) is the basic theory of the MOI detection method [24]. The light would be transformed into the polarized light by a polarizer. If there is the magnetic field in the interaction area, its polarizing direction will change. So the light signal that detected by the system contains the crack information. Fig. 1 shows the theory of the Faraday magnetic rotation effect.

For different interaction material, the rotation angle is different. Furthermore, the FMER also indicates that the rotation angle would become bigger if the magnetic field is bigger and the interaction time is more longer. The mathematic representation is shown as below [25]:

$$\theta = \mathrm{VBL}, \tag{1}$$

where θ is the rotation angle, V expresses the Verdet constant of the medium, B denotes magnetic field strength in the moving direction of polarized light, and L represents the distance that the polarized light travels through the medium. When going through another polarizer, the brightness of the light signal would become weak.

In order to make crack image more clearer in the MOI image, the rotation angle should be more bigger. When set up the experimental system, the interaction area is the magnetic-optical glass, because its Verdet constant is big. Fig. 2 shows the model of the detection system. From Fig. 2, it can be known that the reflected light would be detected by the CCD sensor. So in order to make the signal more clearly, a mirror is placed under the glass. Then the light would interact with the magnetic for two times. Hence, the rotation angle can be determined by the following equation:

$$\theta = 2\mathrm{VBH}, \tag{2}$$

where H is the thickness of the magneto-optical glass.

The CCD sensor is used to measure the brightness of the polarized light. If there exists the crack in the detecting area, the light would be weak, or the light would be bright. So the image can be processed to obtain the crack information.

Actually, it is difficult to directly exact the real crack information in the MOI image, due to the existence of the magnetic

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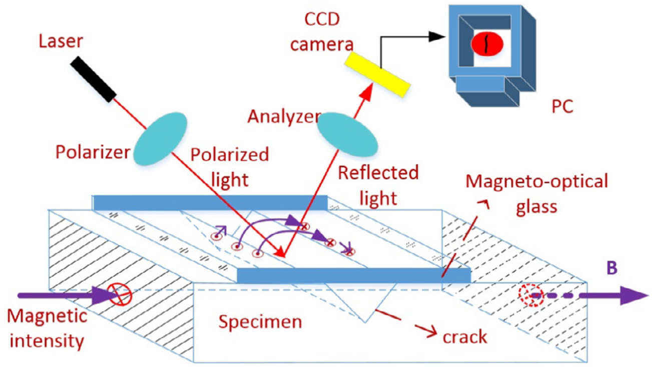

Fig. 2. The MOI detection system schematic.

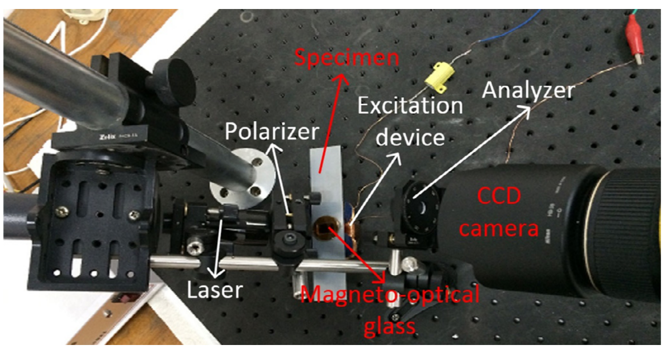

Fig. 3. The MOI detection experiment system.

domain spots [26]. When processing the MOI image, the interference of the magnetic domain spots can not be ignored. In our research, the specimen material is iron and this kind of material would induce many magnetic domain spots. When adding the exciting signal, the magnetic domain spots are discrete spots. The pixel value of the spots is very similar with that of crack. Because of these reasons, it is hard to distinguish them. Furthermore, the spots shape is always different when the specimen is different. On the other hand, the shape of the crack is often different and has no feature. Then the MOI image is hard for the machine learning method to process. Thus, it needs a special method to process the MOI image to identify the crack from the magnetic domain spots.

3. Experiment setup

The detection system is based on the electromagnetic optical to detect the crack of the specimen. This system contains the light source device to apply the laser light, light path system to produce the needed polarized light, electromagnetic excitation system to apply the electromagnetic power in the specimen and the image processing system which includes a CCD camera and a PC. Fig. 3 shows the whole detection system.

From Fig. 3, it can be seen that the light path processing system is constituted by polarizer, magneto-optical glass and analyzer. Furthermore, as it utilizes the reflected light as the detected signal, in order to enhance the reflected light, a thin mirror is used under the magneto-optical glass.

For the specimen in the experiment, it is the sheet iron with an irregular crack, which is shown in Fig. 4. The data comes from this crack with 1mm width and 0.2mm deep.

4. Detecting method based on the PCNN

In this paper research, the crack information is included in the light. The CCD sensor is used to measure the brightness of the light

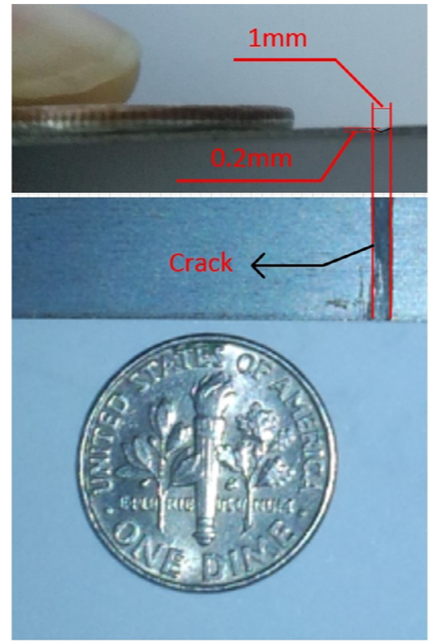

Fig. 4. The specimen and the crack.

and a MOI image can be obtained. In the image, there exist the crack image and magnetic domain spots. In order to extract the crack from the MOI image, it should segment the crack and spots. In this section, an improved PCNN method is used to search the threshold to segment MOI image, and a special filter is introduced to extract the crack from the segmentation MOI image.

4.1. PCNN based method

Fig. 5 shows the unit-linking model if PCNN, where M_{kl} and W_{kl} denote the synaptic gain strengths, $Y_{kl}[n]$ represents the output pulse, α^F and α^L are the time constants and I_j is the image input for the jth pixel.

It is widely known that the third-generation artificial neural network, the pulsed-couple neural network (PCNN), have the very important biological backgrounds. It has incomparable superiority over other current methods when applied in image processing because of the characteristics of global coupling and pulsed synchronization of neurons [27]. Its normal model is published based on the original model of Eckhorn and Johnson [28,29]. In the normal model, a neuron is composed of three parts: the dendritic tree, the linking, and the pulsed generator which is shown in Figure 5. It can be expressed by the following equations:

$$F_{ij}[n] = e^{\alpha_F \cdot \delta_n} \cdot F_{ij}[n-1] + S_{ij} + V_F \cdot \sum M_{ijkl} Y_{kl}[n-1], \tag{3}$$

$$L_{ij}[n] = e^{\alpha_L \cdot \delta_n} \cdot L_{ij}[n-1] + V_L \cdot \sum W_{ijkl} Y_{kl}[n-1], \tag{4}$$

$$U_{ij}[n] = F_{ij}[n] \cdot (1 + \beta \cdot L_{ij}[n]), \tag{5}$$

$$Y_{ij}[n] = \begin{cases} 1 & U_{ij}[n] > \theta_{ij}[n-1], \\ 0 & others, \end{cases} \tag{6}$$

$$\theta_{ij}[n] = e^{\alpha_T \cdot \sigma_n} \theta_{ij}[n-1] + V_T Y_{ij}[n], \tag{7}$$

From Eqs. (3)–(7), it can be found that there exist many parameters that should be selected in this model. $F_{ij}[n]$ and $L_{ij}[n]$ are the inputs which contain the source pixel and its near pixel information. Combining the two elements, the $U_{ij}[n]$ can be obtained and

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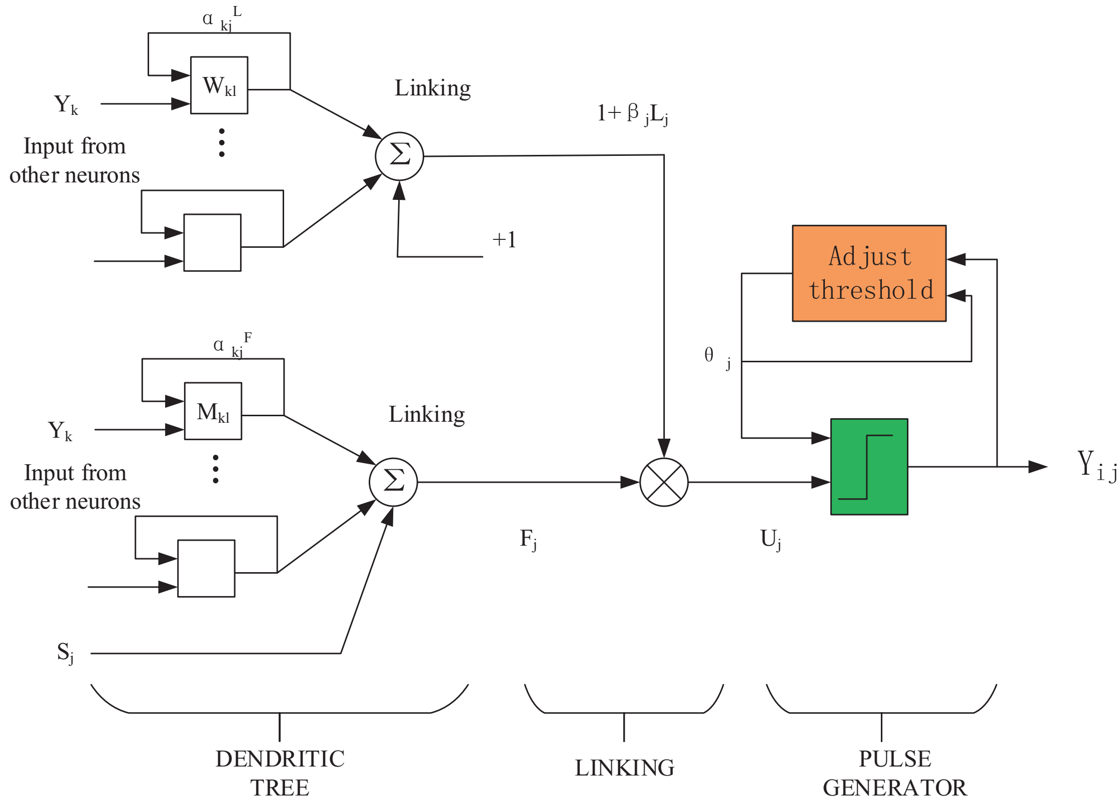

Fig. 5. Unit-linking model of PCNN.

this element is one of the important parameter that determines whether the pixel should be fired or not. The main important parameters in (5) and (7) are β and $e^{\alpha_T \cdot \sigma_n}$ because they determine the connection intensity of the neurons and the changing way of the threshold. Since the parameters that should be selected are so many, it should be simplified in such a place.

In the magnetic optic image process, it often detects the existence of crack, so (3) and (4) can be rewritten as follows

$$F_{ij}[n] = S_{ij} + V_F \cdot \sum M_{ijkl} Y_{kl}[n-1], \tag{8}$$

$$L_{ij}[n] = V_L \cdot \sum W_{ijkl} Y_{kl}[n-1]. \tag{9}$$

In order to change the threshold for every iteration, substituting (8) and (9) into (5), it can be obtained (10)

$$U_{ij}[n]=(S_{ij} + V_F \cdot \sum M_{ijkl} Y_{kl}[n-1])(1+\beta(V_L \cdot \sum W_{ijkl} Y_{kl}[n-1])). \tag{10}$$

As the crack detection progress, it is just to determine whether the pixel is the part of the crack by comparing the situation of the activation of surrounding neurons. For every iteration, it uses the whole fired pixel value as the bases of the threshold. Hence, it can utilize the information of the whole fired pixel and the nearby pixel of the research object in the magnetic optic image process. In (10), it can apply the component $\beta \Sigma S_{ij} Y_{ij}$ to determine the threshold.

In the processing of magnetic optic image, the most important content is to detect the crack of the specimen, although that the shape of the crack is always different. It should be mentioned that it can hardly use the pattern recognition method to detect the crack. On the other hand, in the magnetic optic image processing, it often uses the gray image and searches a threshold to detect the defects. But in many times, the images are different even for detecting the same specimen. So it needs a method to find a good threshold for every magnetic optic image. The PCNN model method is a good way to do this. It is based on the biological vision which can be applied to do the image segmentation. For the referred PCNN model above, it is hard to process the magnetic optic image. Then it proposes a improved PCNN method to search the threshold which is shown in Fig. 6. The decay parameter $e^{\alpha_T \cdot \sigma_n}$ in (7) is changed to a decay constant λ. Meanwhile, the connection way of the neuron is changed that only depends on the connection strength β. In Fig. 6, the Y_{kl} is the fired signal inputs from other neurons, and the S_{ij} is the current image point and the expression are shows in the following

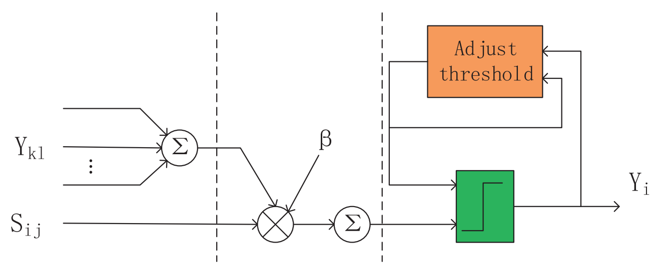

Fig. 6. The improved PCNN model.

$$U = \beta \sum Y \cdot S_{kl}, \tag{11}$$

$$\theta = \lambda \sum Y \cdot S_{ij}, \tag{12}$$

$$Y_{ij} = \begin{cases} 1 & U_{ij} > \theta_{ij}, \\ 0 & \text{others}, \end{cases} \tag{13}$$

where Y_{ij} represents the pulse output for the *ijth* image pixel, S_{kl} denote the input image pixel. There exists the 3×3 matrix of the

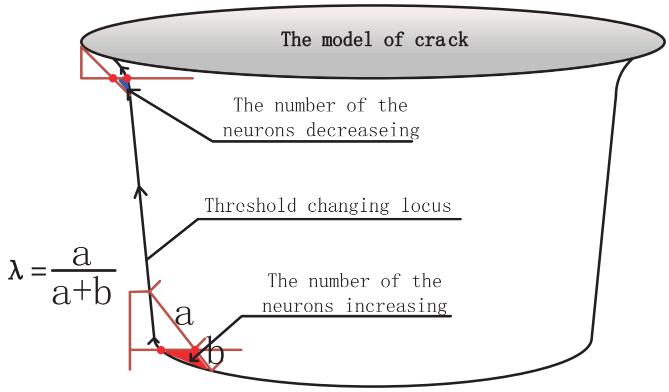

Fig. 7. The crack appearance model.

S_{kl}. θ is the dynamic threshold which is based on the whole image inputs S_{ij}.

Eq. (11) depicts the local information of the target pixel and it determines whether the target pixel be fired or not combine with the parameter θ. The parameter β controls the synaptic gain strengths or weights for the nearest 8 neurons. In the research, it is usually a constant, to conform to the law of the signal transmission. The synaptic gain strength would be great when the two neurons are close to each other. Otherwise, it would be small when they are far away relative. Eq. (14) denotes one way to set the β.

$$\beta = \begin{pmatrix} 0.75 & 0.9 & 0.75 \\ 0.9 & 0 & 0.9 \\ 0.75 & 0.9 & 0.75 \end{pmatrix}. \tag{14}$$

By using this kind of β, it can reduce influences of the bed pixels. In the process, the bed pixel is the small value pixel and one of the nearest is big. Hence, the β can filter the salt noise that exists in the magnetic optic image. λ controls the dynamic threshold growing speed. This model makes threshold increase from small to large. As the parameter λ controlling, the threshold could stop growing after some cycles. Fig. 7 shows the appearance model of the crack. It can be seen that the threshold would increase when the fired neurons number is increasing. On the other hand, the threshold would do not increase, because the fired neurons number would increase slowly and then become unchanged. That is, most of the crack information can be detected by this threshold. This is the good threshold. Considering the shape of crack in the image as a parabola, as shown in Fig. 8, it can simulate the changing process with the following regulations:

$$y = ax^2 + c, x \in [0, m], \tag{15}$$

$$x = \sqrt{\frac{y-c}{a}}, \tag{16}$$

where a and c are the coefficients of the model, m denotes the upper limit of x. The initial threshold is set as the T_1 and calculated as follows:

$$T_1 = \lambda \cdot \frac{\int_0^m y dx}{m}, \tag{17}$$

where λ is the attenuation parameter. Hence, the changing law of the threshold is controlled by the following equations:

$$T_n = \frac{\lambda}{m - \sqrt{\frac{T_{n-1}}{a}}} \left\{ \int_{\sqrt{\frac{T_{n-1}}{a}}}^{m} (ax^2 + c) dx \right\}, \tag{18}$$

$$T_n = \lambda \cdot \left[\frac{a}{3} \left(m^2 + m\sqrt{\frac{T_{n-1}}{a}} + \frac{T_{n-1}}{a} \right) + c \right]. \tag{19}$$

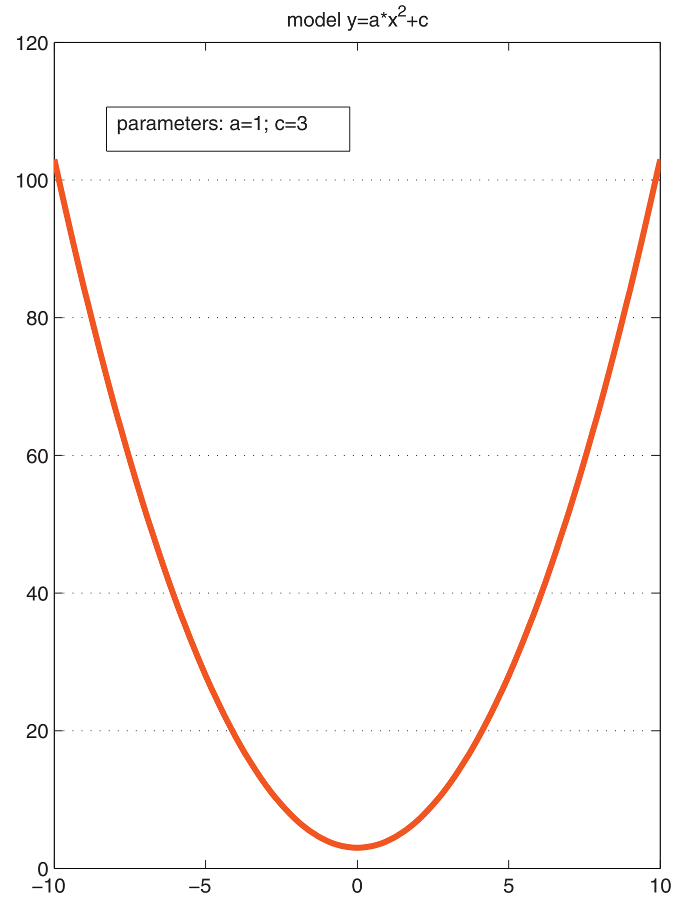

Fig. 8. The crack mathematic model.

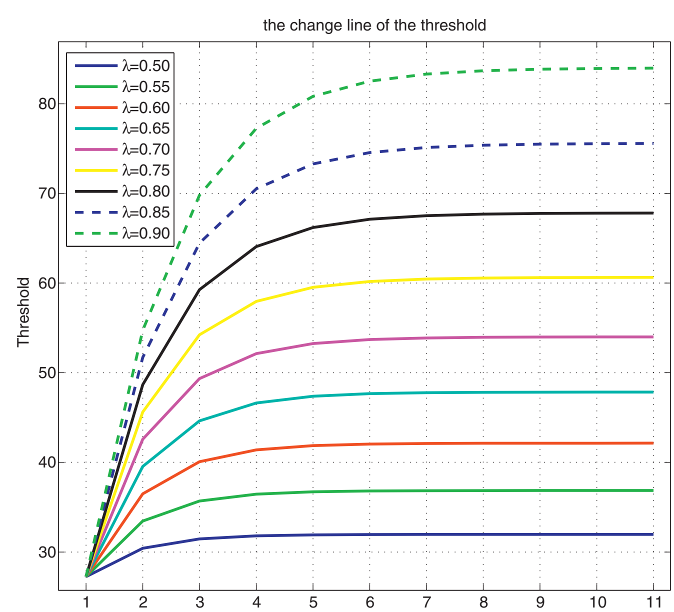

Fig. 9. The changing trend of threshold for different λ.

Fig. 9 shows the simulation results, where $a = 1$, $c = 3$ and $m = 10$. It presents that, for different parameter λ, the changing trend of threshold is different when it is stable. On the other hand, the parameter λ is too small, it cannot be obtained the whole information of the crack. In order to get the best threshold, the parameter λ is selected in the range from 0.7 to 0.8.

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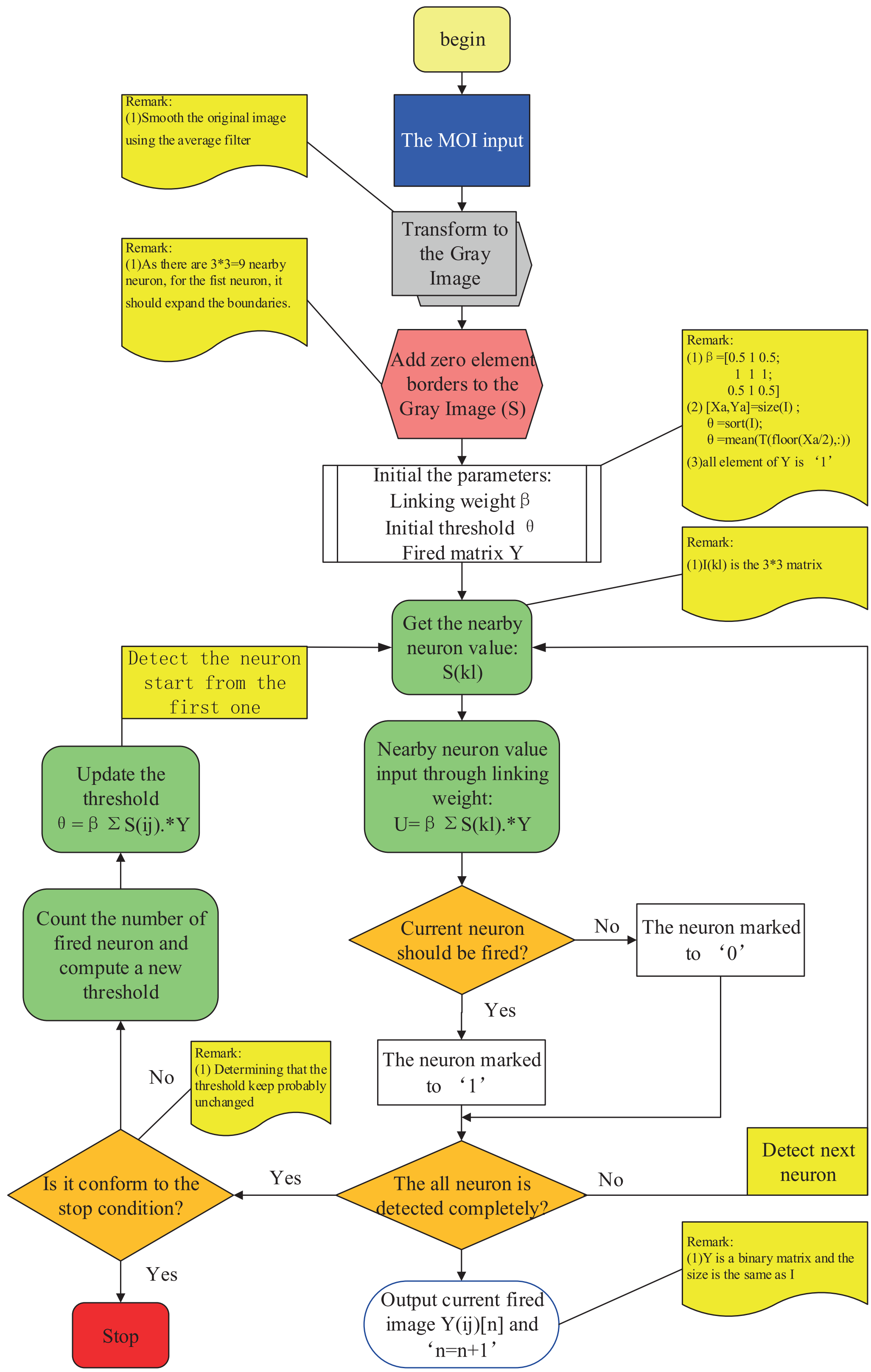

Fig. 10. Flow chart and instructions.

By this method, the pulsed image of the results can be used to detect the crack. The flow chart and part of instructions are shown in Fig. 10. From Fig. 10, it can be known that the PCNN model method is divided into three parts: the magnetic optic image smooth and parameters initial part; the inner iteration part and the outer iteration part. Specifically, the inner iteration part is to iterate through all the neurons and judge if the neuron should be fired. It uses the information of the globe neuron outputs and the nearby 8 neuron outputs. The outer iteration aims to change the threshold for a new inner iteration. It computes a new

0	1	1	0	0	1	0	0
0	0	1	0	1	1	1	0
1	1	1	0	0	0	0	1
1	1	0	1	1	1	1	0
0	0	0	1	1	0	1	0

Fig. 11. The schematic diagram of pulsed image.

0	1	1	0	0	3	0	0
0	0	1	0	3	3	3	0
1	1	1	0	0	0	0	4
1	1	0	2	2	2	2	0
0	0	0	2	2	0	2	0

Fig. 12. The schematic diagram that connection method.

threshold based on the fired neurons. The detail of the PCNN process is introduced in the following:

1. Get the nearby neurons of the target neuron from the image, and then compute the value U, which shows the contribution to the current neuron.
2. Compare the U and θ, if $U \geq \theta$, let the state value of neuron be 1, otherwise, let the value be 0;
3. Then move to next neuron. If all of the neurons of the image are scanned, jump to (4), or jump to (1) and process the next neuron;
4. If the computed threshold conforms to the stop condition, then stop the iteration and stop the program. Otherwise, compute the new threshold. This value is computed by the current output state matrix Y and the image gray value S:

$$\text{Threshold} = \sum_{i=1,j=1}^{i=m,j=n} (Y_{ij} * S_{ij}),$$

where m and n are the row number and column number, respectively. Then update the PCNN threshold θ and jump to (1).

It should be mentioned that the image should be smoothed when transforming into gray image. In the MOI image, the gray values of two nearby neurons are always different. In the PCNN process, for each iteration, the threshold would be computed and updated, and the stop condition depends on the threshold. That is to say the threshold is dynamically changing value, and this characteristic is helpful for the different MOI image processing. In order to make the scanning process more smoothly and make the threshold more accurate, the image should be smoothed. It is helpful for the PCNN method to find the good threshold fast.

4.2. Magnetic domain spots filtering

The pulsed image that is obtained above is a binary image. In order to present the processing process, it uses the data matrix which is shown in Fig. 11 to simulate the image. By analyzing the image, it considers that the crack is connected and its area is bigger than the spots. On the other hand, the distribution of the magnetic domain spots is discrete. So these features can be utilized to extract the crack. The filter is designed based on the following assumptions:

Assumption one: The area of the crack is bigger than the magnetic domain spots.

Assumption two: The connection area is greater than a single magnetic domain spot.

Then, the pulsed image will be taken into the connection process program and the process is as below: if one pixel is not zero and its left side, right side, up side and down side is also not zero, then all pixels should belong to the same connection area and for each area assign a number, as shown in Fig. 12.

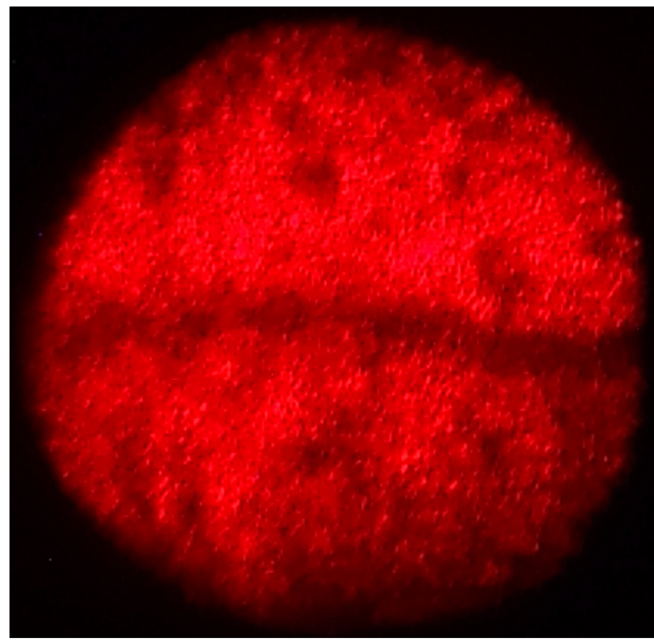

Fig. 13. The magnetic optic image.

By using the filter, it can be known that the crack and the magnetic domain spots have its own number. For each numbered object, the area of it would be calculated. Then, it can extract the crack from the MOI image, based on the above assumptions.

5. Results and discussion

In this paper, it presents a method based on the MOI method to detect the defects. Fig. 13 shows the MOI image measured by the CCD sensor. It can be known that there exists a crack in the middle of the image. However, there exist many magnetic domain spots around crack. In order to segment them by the algorithm, it should be transformed into gray image, as shown in Fig. 14.

The PCNN model based method is used to obtain a binary image with $\beta = [0.5, 1, 0.5; 1, 1, 1; 0.5, 1, 0.5]$ and $\lambda = 0.7$. Fig. 15 shows the output image of the PCNN model for every loop until it stops. For every loop, the threshold of the output image is shown in Fig. 16. Moreover, it can be found that the threshold can become stable from Figs. 9 to 16.

Fig. 15 presents that the crack becomes clearer with the cycle-index increasing. In order to make crack more identifiable, the magnetic domain spot filtering based on the connection law is applied to filter the interference that is displayed in Fig. 17. By processing by the filtering method, it can make the crack more clearly and it can help identifying the crack for the machine. As the

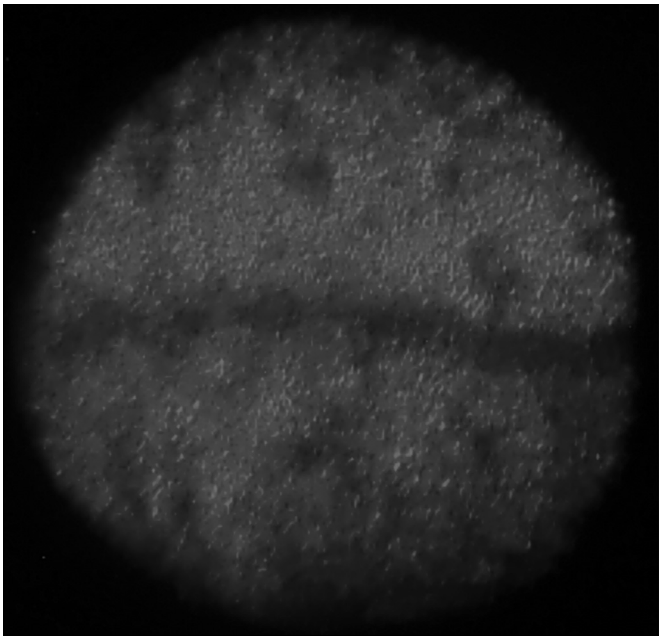

Fig. 14. The gray image.

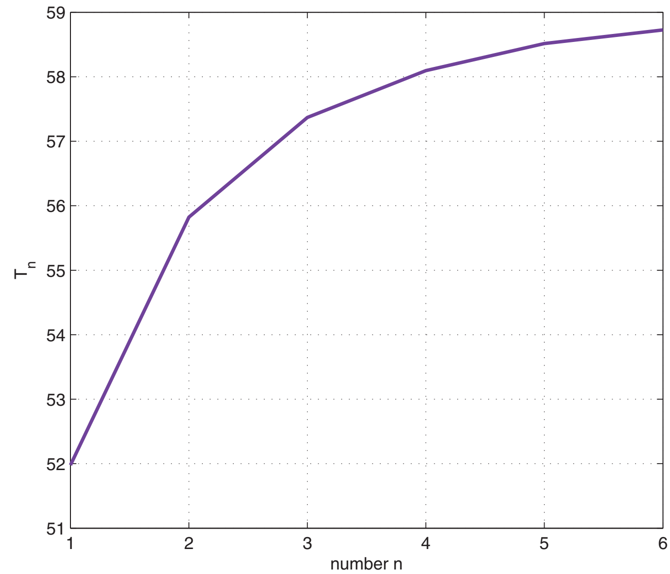

Fig. 16. The threshold for every output result.

process of the threshold researching going on, the suspected crack information are extracted. When the threshold begin to change heavily, it presents that the threshold is among the real crack. When the threshold becomes smooth in Fig. 16, the real crack is scanned mainly over. And then, this point is the good threshold that could separate the image well. Hence, the results certainly contain the real crack, and the results can demonstrate the effectiveness of the proposed method.

Another specimen that has the crack size of 1mm wide and 0.2mm deep is detected. Fig. 18 shows the magnetic optic image and its gray image.

Fig. 19 shows that the output result becomes more and more clear along with the implementation of the program. As shown in Figs. 20 and 21, the detection result can be found when the threshold becomes unchange. Fig. 21 shows that the PCNN model based method can search the threshold dynamically to different magnetic optic image. For the smaller crack, this method could detect the detection well. From the results above, it can be known that for different MOI image, the PCNN method can research a good threshold. By the threshold, the output image holds the characteristics of separating the crack and influences. It uses the information of the image and the fire state image to compute the threshold. This

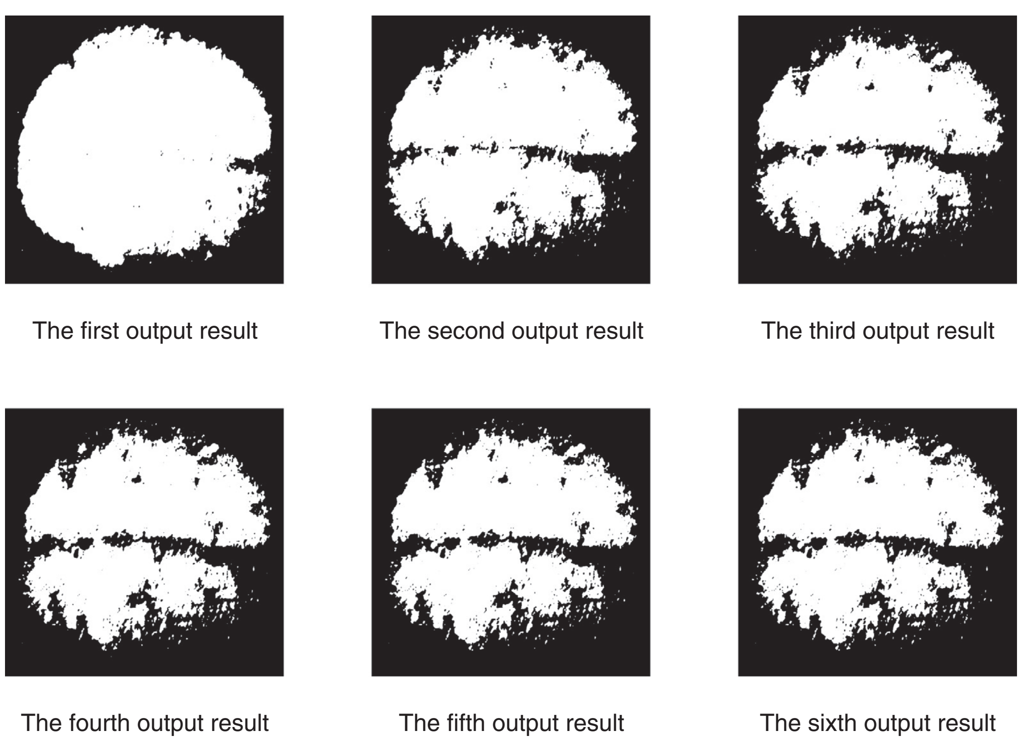

Fig. 15. The output of the PCNN method.

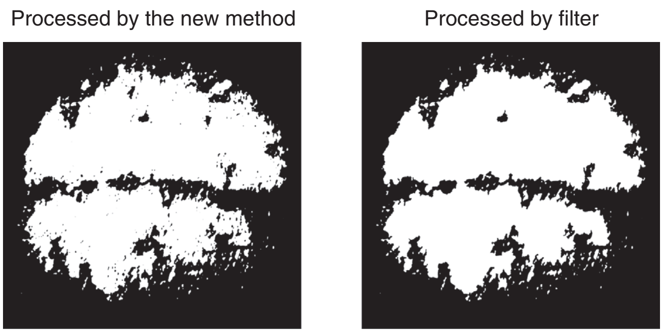

Fig. 17. The comparison between before and after processing.

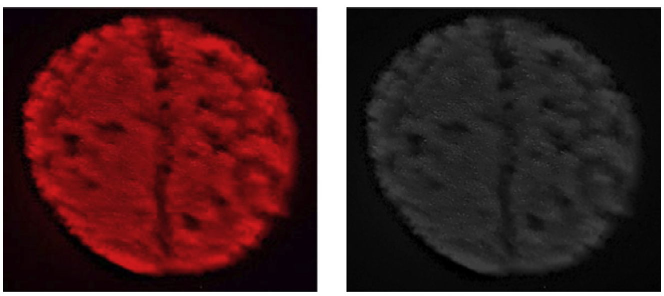

Fig. 18. The image of the second crack.

process can reduce the influences of the nature light and outer experimental environment.

Remarks. From the results, it can be known that the crack is displayed on the image by using the proposed filter. The noises and influences are reduced, such as the magnetic domain spots and bad brightness light dots. Fig. 22 shows some results processed by other filters. It shows that the influences are not reduced. Some of these methods just enhance the edge of the crack. It is disadvantageous for machine to identify the crack intelligent. Otherwise, the proposed method could reach the objective well.

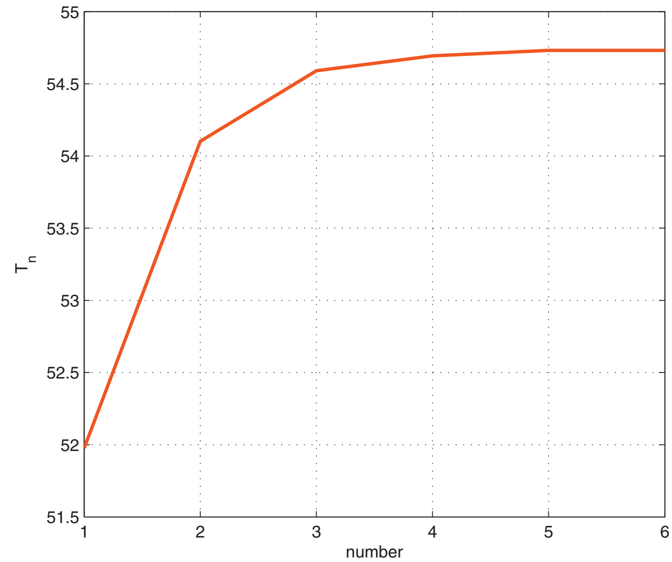

Fig. 20. The threshold for every output result.

Hence, the advantages of the proposed algorithm can be illustrated:

1. This method doesn't depend on the materials properties of specimen. Although that the MOI image is always unconstant, especially the shape and the distribution of the magnetic domain spots, the proposed method just depends on the detected image, it expands the scope to use the method.
2. The ability of crack identifying is strong. The good threshold can be selected by the proposed algorithm. It can be helpful to dectect the real crack included in the image.
3. It does not need so much time. The object of the algorithm processed is the state of each pixel. And this state just contains two number, 0 and 1. So it does not need so much time to process the huge image.

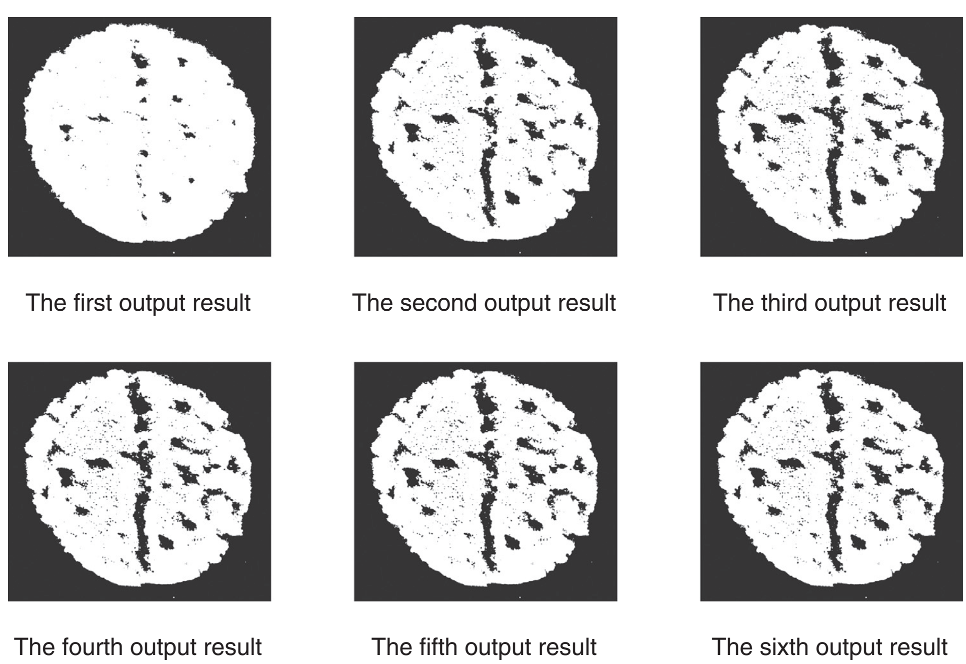

Fig. 19. The outputs of the PCNN model.

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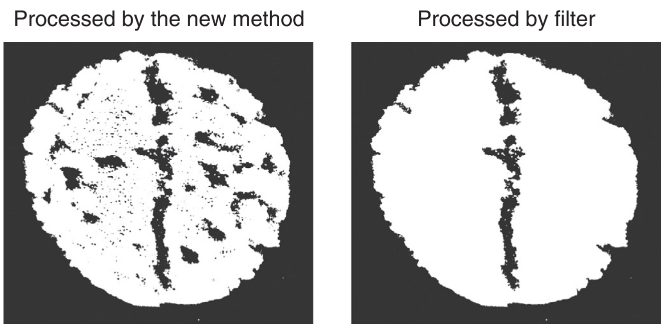

Fig. 21. The result of the crack detection.

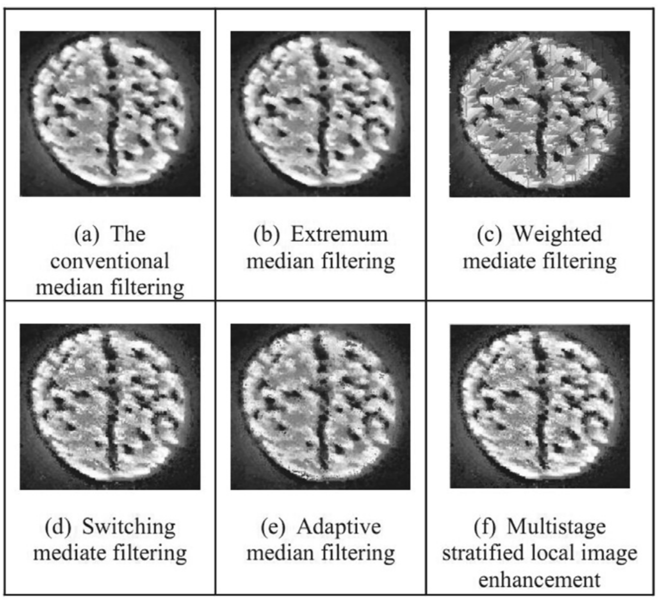

Fig. 22. The comparison of some filters.

6. Conclusion

This paper proposed a method for detecting the crack of the specimen based on the PCNN model. By improve the model, it can select the threshold dynamically to the magnetic optic image. The output image is the pulsed image and it can be well used to detect the crack by using the magnetic domain spots filter. The result has proved that this method could be used to detect the crack, especially the small crack. In the future work, it will be researched that how to quantify the size of the crack.

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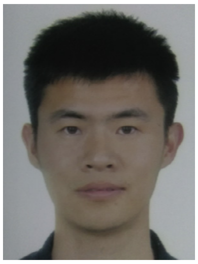

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