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A Multi-Scale Line Filter for Automatic Crack Inspection Based on X-Ray Images

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Abstract

Crack inspection is a critical processing step in an AXI (automatic X-ray inspection) system. There are challenges for crack inspection since images are usually with serious noise, non-uniform brightness, etc. This paper proposes a novel line filter that can segment various widths of crack regions in those inhomogeneity brightness and noisy X-ray images. First, the input image is smoothed by the Gaussian functions with different scales, resulting in an image pyramid. Second, the adjacent images in the pyramid are subtracted to generate a Difference of Gaussian (DoG) pyramid and the extreme points from the subtracting result are selected as the output of the method. An edge suppression function is then defined to remove the edge response of the filter. Finally, the output of the proposed filter is defined as the combination of the DoG extreme result and the suppression function. The proposed method was applied to an AXI system and it performed better than the other two exited approaches. Experimental results showed that the proposed filter is robust to the image noise, crack sizes and brightness.

Keywords*: Line filter, X-ray image, AXI, Difference of Gaussian, Crack inspection*

1. Introduction

Due to the increasing safety and quality requirements of products, detection of cracks in metal is an essential step of the product quality control. In most of the cases, metal cracks happen inside the metal and thus they cannot be seen with the naked eyes. With the ability to penetrate materials and be attenuated according to the material's thickness and density, X-ray inspection rapidly became the accepted technology for non-destructive identification and evaluation of internal defects. In some cases, an inspection system can generate thousands of X-ray images if we want to inspect a large object completely, such as the metallic piping with large diameter and great length.

In a conventional X-ray inspection system, the captured X-ray images are examined manually by an operator in order to determine if there is any defect in the product. However, there are many disadvantages with the manual inspection. It can be summarized as follows:

The operator can experience fatigue quickly due to the large number of X-ray images.

The inspection quality depends on the operator's experiences, and it's time-consuming.

The low image quality (such as low contrast or noise) can present many problems to the operator and make the interpretation of the image content very difficult.

Therefore, to improve the inspection results and reduce the workload of the operator, automatic inspection systems [1-5] based on image processing technique were developed in the past decades. For the automatic inspection system, segmentation of the cracks in the

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X-ray image is an essential processing step. However, as our previous work [6] summarized, there are several challenges for automatic crack detection in metal X-ray images, such as the image noise, the inhomogeneity brightness, and low contrast.

In order to automatically detect cracks in the X-ray image, Shao *et. al.*, [3] proposed a segmentation method based on double-thresholding and fuzzy set theory. The system obtains cracks from the X-ray image by preprocessing, thresholding segmentation and post-processing. This method can detect small cracks whereas it has limitations in detecting cracks with non-uniform backgrounds and it is not robust to the crack sizes. H. Y. Chai, *et. al.*, [7] proposed a method using GLCM (Gray-Level Co-occurrence Matrix) [8] computerized techniques to automatically detect femur bone fracture in X-ray images. Since this method uses GLCM, it is sensitive to image noise. Y. Hu, *et. al.*, [9] proposed a novel LBP (Local Binary Pattern) [10] based operator for pavement crack detection. In the proposed method, local patterns extracted by $LBP_{ri}^{P,R}$ [11] were redefined into 5 subclasses. Pixels with patterns that belong to the edge or corner subclasses were considered as crack candidates. Finally, statistics characteristics like length, area, numbers of pixels, orientation were calculated to reject the fake cracks. Recently, we proposed a crack filter based on a Gaussian model and multi-scale analysis to inspect cracks in metal blades [6]. The algorithm showed good performance in detecting cracks of various sizes in X-ray images with noise and inhomogeneity brightness problems. However, it was time-consuming.

The motivation of this paper is to develop a real time line filter that can quickly segment various widths of cracks from the X-ray image with the challenges of image noise, inhomogeneity brightness and low contrast. To do so, the input image is first sent to the low pass filter for noise reduction. An image pyramid is then constructed by smoothing the image with various scales of Gaussian filters. A DoG pyramid is then generated by subtracting the adjacent smoothed images of the Gaussian pyramid. Finally, the output of the proposed method is defined as the combination of the maximum output of the DoG pyramid and the edge suppression function.

The remainder of this paper is organized as follows: Section II introduces the related works. The proposed method is described in Section III, and the experimental result and conclusion are presented in Section IV and Section V, respectively.

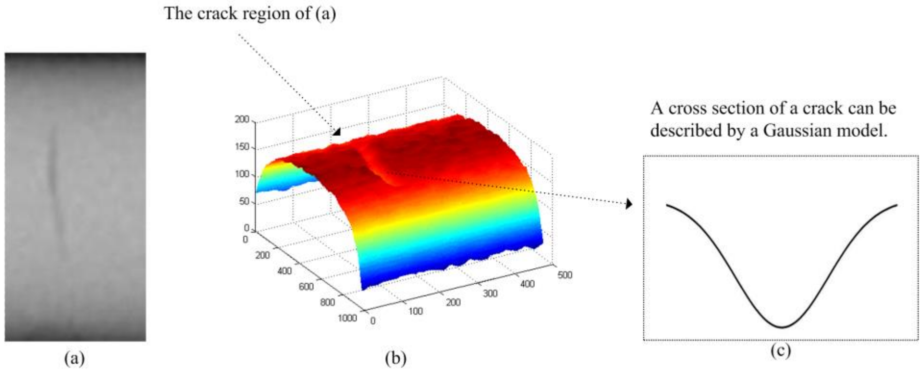


Figure 1. The Gaussian Model for the Crack

2. Related Works

In the previous work [6], a crack filter based on the local intensity variation and multi-scale analysis was proposed to inspect the metal blade cracks. A Gaussian model was applied to represent the cross section of the crack. Figure 1 (b), is a crack model of Figure 1 (a), demonstrated in 3D and Figure 1 (c), is a cross section of the crack.

To enhance the crack regions in the X-ray image, a function based on the Gaussian model was defined as:

$$F(x,\sigma)=\begin{cases} f_g(x,\sigma)=\frac{1}{\sqrt{2\pi\sigma}}e^{-\frac{(x-c)^2}{\sigma^2}} & |x-c|\le\frac{\sigma}{2} \\ f_a(x,\sigma)=\frac{F_g(x,\sigma)}{\sigma} & \frac{\sigma}{2}\le c-x<\sigma \\ f_b(x,\sigma)=\frac{F_g(x,\sigma)}{\sigma} & \frac{\sigma}{2}\le x-c<\sigma \end{cases} \tag{1}$$

where σ is the scale of the Gaussian function, c is the center of the Gaussian model (as shown in Figure 2), and $F_g(x, \sigma)$ is defined as:

$$F_g(x,\sigma)=\sum_{x=c-\frac{\sigma}{2}}^{c+\frac{\sigma}{2}} f_g(x,\sigma) \tag{2}$$

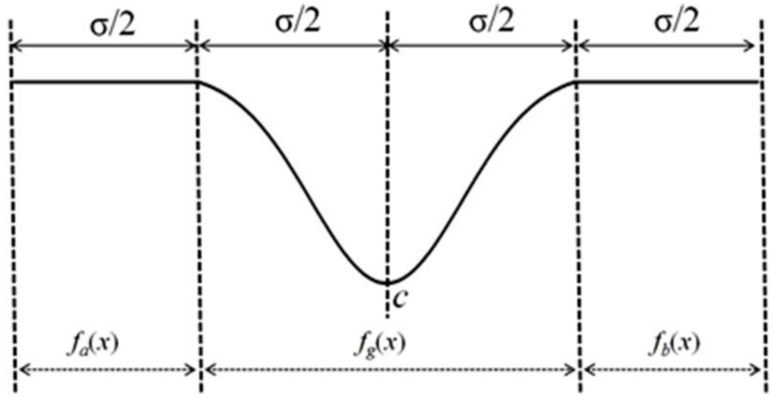


Figure 2. The Defined Function Based on the Gaussian Model

Let the digital image be $I(x, y)$, the output of the proposed crack filter in x-direction was defined as:

$$F_{out}(x,\sigma) = D(x,\sigma) - \alpha * |F_a - F_b| \tag{3}$$

where α is a user defined constant which is used to emphasize the uniformity of the cross section's neighbors, $D(x, \sigma)$, F_a and F_b are defined as:

$$D(x,\sigma) = F_a + F_b - I(x,y) * f_g(x,\sigma) \tag{4}$$

$$F_a = I(x,y) * f_a(x,\sigma) \tag{5}$$

$$F_b = I(x,y) * f_b(x,\sigma) \tag{6}$$

In equation (3)-(6), '*' denotes the convolution operation. Performing this filter with different of Gaussian scale σ, the filter can enhance different sizes of crack in x-direction. Applying the filter in x- and y-direction using different scales can enhance all directions of cracks with different sizes. This filter has shown its good detection ability in detecting different sizes of cracks in serious noise image.

3. The Proposed Method

3.1. Line Region Segmentation By the DoG Detector

For a crack region in the X-ray image, it is line-shape and its pixel values are greater (for a bright crack region) or smaller (for a dark crack region) than its background. As defined by X. Li *et. al.*, [12], cracks can be characterized in the X-ray images by local changes in the image intensity, resulting in the corresponding local discontinuities in the gray values of the acquired image. To estimate the local changes of the image intensity, the multiscale Laplacian of Gaussian (LoG) detector is a 2D isotropic measure of the second spatial derivative of an image with different scales. It can highlight regions of fast intensity change [13]. This method takes an input image to perform series of convolutions with the Gaussian kernel by different scales and calculates the second spatial derivative of the smoothed image:

$$L(x, y, z, \sigma^2) = I(x, y, z) * \sigma^2 \Delta^2 G(x, y, z, \sigma^2) \tag{7}$$

Where $I(x, y, z)$ is the input images in a 3D space, $G(x, y, z, \sigma^2)$ is a 3D Gaussian function with variance σ^2, and Δ indicates the calculation of derivative. The second derivatives (I_{xx}, I_{yy}, I_{xy}) of an image $I(i, j)$ are defined as:

$$L_{xx}(i, j) = I(i+1, j) + I(i-1, j) - 2 * I(i, j) \tag{8}$$

$$L_{yy}(i, j) = I(i, j+1) + I(i, j-1) - 2 * I(i, j) \tag{9}$$

$$L_{xy}(i, j) = \frac{I(i+1, j+1) - I(i+1, j-1)}{4} + \frac{I(i-1, j-1) - I(i-1, j+1)}{4} \tag{10}$$

Where $I(i, j)$ is the image, L_{xx} and L_{yy} denote the second partial derivatives in the x and y directions. L_{xy} (L_{yx} is equal to L_{xy}) is the mixed partial second derivative in the x and y directions. As shown in (8) ~ (10), L_{xx} and L_{yy} are the intensity changes between a pixel $P(i, j)$ and its four neighbors. L_{xy} denotes the intensity changes of the neighboring pixels. Therefore, equation (7) can be used to estimate the intensity changes of the image. It has been proved that the LoG detector can well estimate the intensity changes of the image in the recent researches [13-15].

However, the calculation of the second derivative in both horizontal and vertical directions is time consuming. To speed up the processing, this paper makes use of the DoG detector, which has been proved to be an approximation of the LoG detector [16], to calculate the local intensity changes of the image. First, the input image is smoothed by the Gaussian function with several scales. As shown in Figure 3, the smoothing processing generates a Gaussian pyramid. A DoG pyramid is then built by subtracting the adjacent smoothed images and it can be summarized as:

$$D(x, y, \sigma) = (G(x, y, \sigma_i) - G(x, y, \sigma_{i+1}) * I(x, y) \tag{11}$$

As we can see from equation (11), this simple subtraction can greatly reduce the calculation complexity. For segmenting the bright cracks, the maximum response of the DoG pyramid is selected to produce the final output image. Note that the minimum response of the DoG pyramid can be used to segment the dark cracks.

Figure 4 (a), is an input X-ray image with a crack region (marked by red rectangle) and Figure 4 (b), is the performing result by using the DoG model. As we can see, the DoG model can enhance the crack regions in the X-ray image. However, since it estimates the local intensity changes of the image, the image edges are enhanced too. The edge response is a disadvantage since it can introduce false positive results.

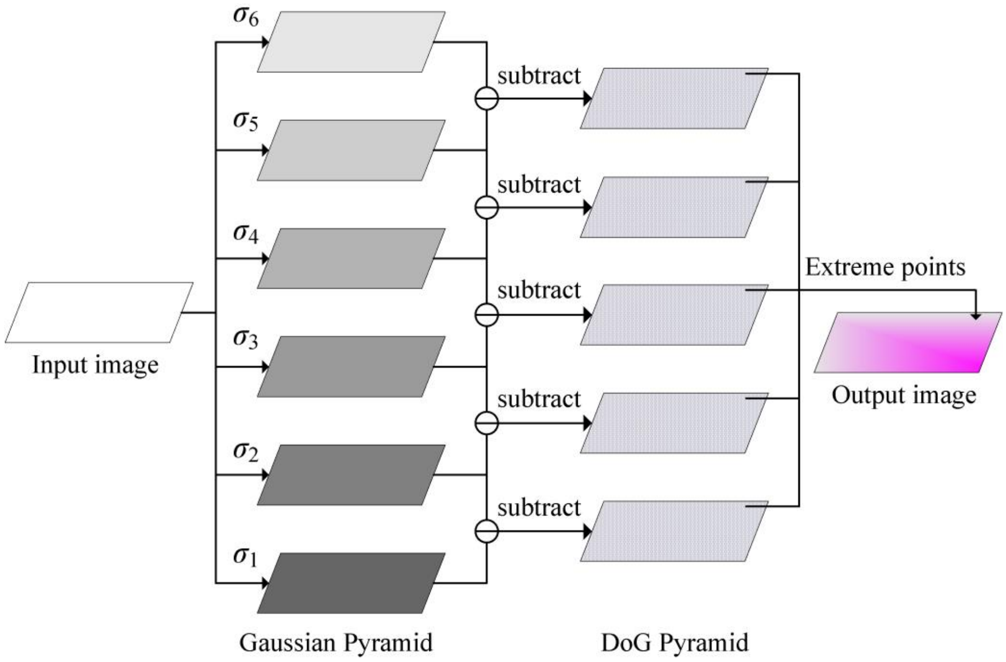


Figure 3. The DoG Model for Crack Segmentation

3.2. Edge Suppression

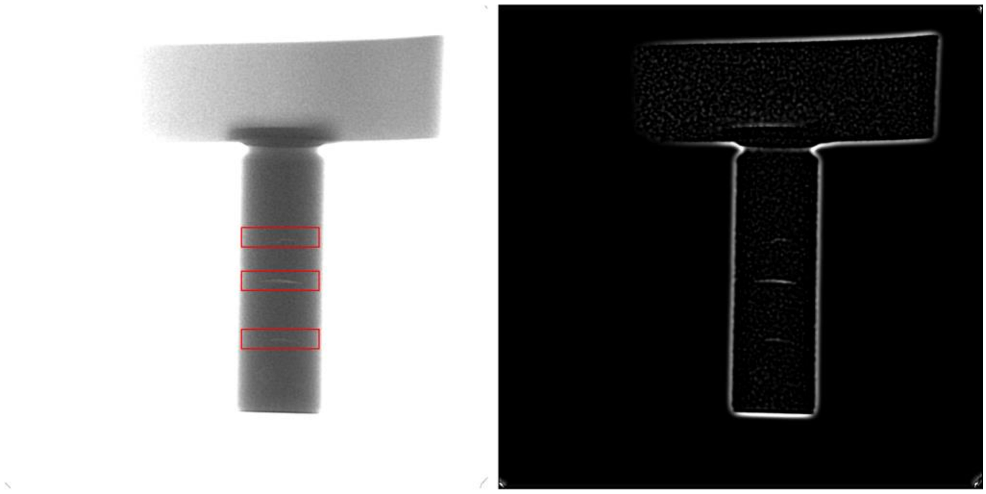
In order to suppress the response of the image edges, this paper proposes a local intensity variation function based on the shape feature of the crack regions. As shown in Figure 4 (a), the crack regions have line-like shape features and the directions of the crack regions are unpredictable. As shown in Figure 5, p_1, p_0, and p_5 are three points in a crack region (suppose that the width of the crack region is one pixel). In order to suppress the response of the image edges, a function for evaluating the variation of p_0's neighbors is defined as:

$$V_{p_0} = \sum_{i=1}^{4} \left| I(p_i) - I(p_{i+4}) \right| \tag{12}$$

As shown in equation (12), it is obvious that V_{p0} obtains a small value when p_0 is a point of a crack region and its value can be drastically increased of an edge region. Therefore, V_{p0} is applied to suppress the edge response of the DoG detector. Finally, suppose that the maximum response from the DoG pyramid of a pixel $p(i,j)$ is $D_m(i,j)$, the final output of the proposed algorithm is defined as:

$$O_{p(i,j)} = D_{p(i,j)} - \beta V_{p(i,j)} \tag{13}$$

where β is a user defined factor using to control the edge suppressing level. Figure 6, is the output of Figure 4 (a), by adding the edge suppression (β=0.2). As we can see from Figure 6, due to usage of equation (13), the edge of the image is well suppressed.



(a) An input X-ray image (b) The output by the DoG model

Figure 4. Crack Segmentation By the DoG Detector

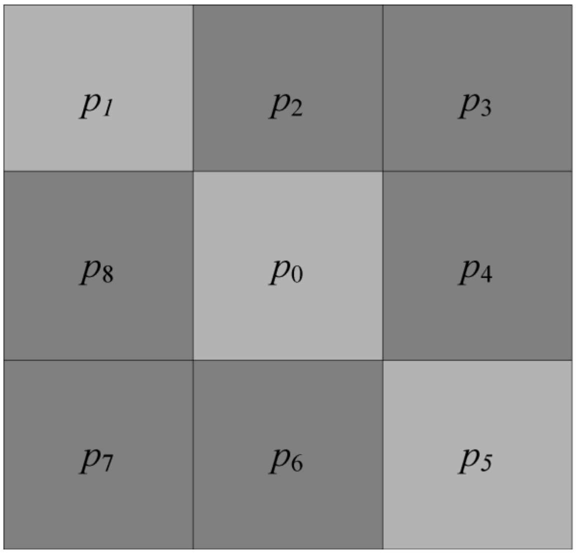


Figure 5. A Fragment of a Crack Region

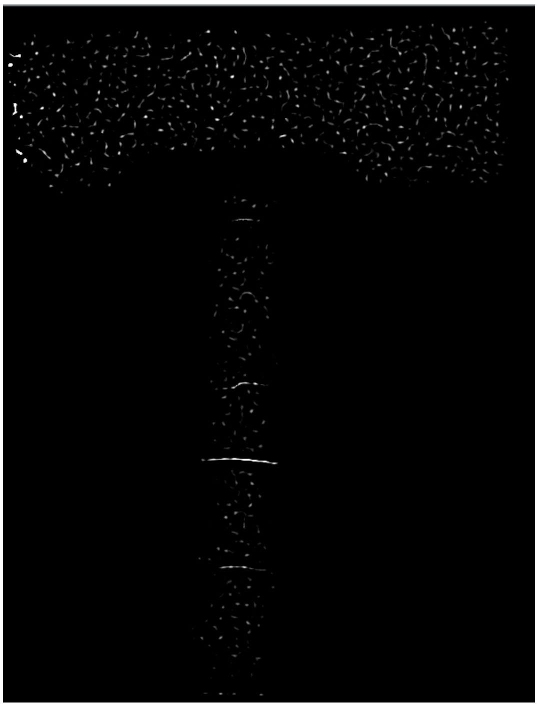


Figure 6. Segmentation Result of the Proposed Method

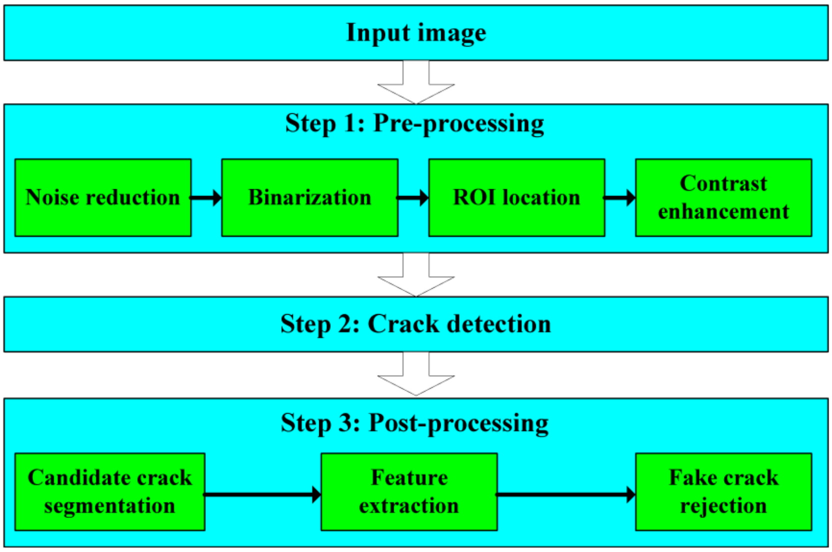


Figure 7. The System for Automatic Crack Inspection

4. Experimental Results

The performance of the proposed line filter was tested by applying the filter to an automatic crack inspection system, which was the same as the system presented in [6]. The system includes three main steps (Figure 7): 1) pre-processing; 2) crack detection; and 3) post-processing. In the pre-processing step, a median value filter with a window size of 3-by-3 was applied to partially reduce the image noise. The OTSU method [17] was used to get a binary image after the low pass filter processing. The region of interest (ROI) was then obtained by region growing. Finally, the contrast of the ROI was enhanced by the histogram stretch method [6]. In the second step, the proposed line filter was applied to the pre-processed image to get a crack enhanced image (Figure 6). In the post-processing step, a threshold (100 for the three filters) was first used to segment the candidate crack regions from the crack enhanced image. And the morphology method (close) was applied to the binary image so as to link those broken crack regions. The features of the candidate crack regions (as described in [6]) were then extracted and used to reject the fake crack regions. In the system, the candidate cracks whose sizes were greater than 2000 pixels or less than 70 pixels were regarded as fake cracks.

The performance of the proposed method was tested by comparing with the method in [6] and Hu's method [2] with respect to the detection accuracy and the false detection ratio, which are defined as follows:

$$Detection\ Accuracy = \frac{TP}{CN} \times 100\% \tag{13}$$

$$False\ Detection\ Ratio = \frac{FP}{CN} \times 100\% \tag{14}$$

Where *TP* (true positive) denotes the number of cracks that are correctly detected, *FP* (false positive) is the number of normal regions that are incorrectly detected as crack regions, and *CN* is number of true cracks. Note that *TP*, *FP* and *CN* were inspected by two radiologists from the X-ray machine company and are regarded as an accurate representation. As described in Equation (13) and (14), a good algorithm can achieve a high detection accuracy and low false detection ratio.

For the performance testing, 484 blade X-ray images including 353 cracks were used as [6] did. Two image sets were formed with respect to the voltage of the X-ray machine. The detailed information of the images is shown in Table 1, (Set 1 and Set 2 were collected by setting the voltage of the machine as 125 KV and 110 KV, respectively). Note that the gray level of the images used in [6] was reversed before sending to the system, but in this paper, the original images were used. Figure 8 shows some image samples for the testing. The experimental environment is shown in Table 2.

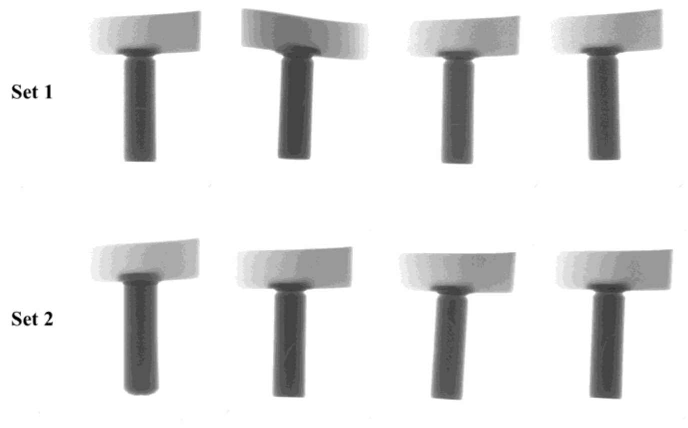


Figure 8. Some Image Samples for the Testing

Table 1. The Detailed Information of the Image Datasets

	Set 1	Set 2
Image Number	102	382
Crack Number	84	269
X-ray Machine	TVX-IMT160	
Image Format	*.JPG	
Image Size	1000*1000 pixels	
Number of Bits	8 bits	

Table 2. The Experimental Environment

Items	Value/Description
CPU:	Intel Core i5-2520M
CPU frequency:	2500 MHz
Number of cores:	2
Number of threads:	4
Operating system:	Windows 7
Memory:	4 GB
Hard disk:	500 GB
Programming tool:	VS 2010 and OpenCV

The inspection results of the three methods are shown in Table 1, Table 2, and Table 3. For the performance of *Set1*, the proposed method and the method in [6] achieved similar detection accuracy. Since the imges in *Set1* were captured by setting the machine with high voltage, the images in *Set1* were with high contrast, leading to good inspection accuracy for both methods. However, the high voltage parameter also brought serious noise to *Set1*. Because Hu's method detected those crack regions by using the LBP based patterns, it was sensitive to the image noise. As a result, the inspection accuracy of Hu's method was lower than the other two methods, and the false ratio was much higher than the other two methods. Since the proposed method suppressed the image edge response by using eight neighbors, it was more robust to the image noise comparing to the method in [6]. Consequently, the proposed method obtained better false detection ratio than the method in [6]. It outperformed the method in [6] and Hu's method by 14.29% and 29.77% with respect to the false detection ratio.

For the performance of *Set2*, because this dataset was captured by low voltage parameter, the contrast of the images were lower than that of *Set1*, which also led to less image noise. As shown in Table 3, Table 4, and Table 5, the proposed method achieved best performance with respect to the detection accuracy and false detection ratio comparing to the other two methods. The application of DoG pyramid enabled the proposed method to enhance the image details, and as a result it was able to detect those low contrast crack regions. As we can see from Table 3, Table 4, and Table 5, the proposed method outperformed the method in [6] and Hu's method by 2.23% and 29.37% with respect to the detection accuracy. Because of the less image noise, all the methods obtained lower false detection ratio by comparing to *Set1*. For the proposed method, it achieved the best false detection ratio compared to the other two methods.

5. Conclusion

In order to inspect crack regions in the X-ray images, this paper proposes a new line filter for line-like region enhancement. The proposed filter employs the DoG method to evaluate the local brightness variation of the X-ray image making it able to enhance those regions that are with local brightness changes and suppress those flat regions in the image. The image edge response of the filter is suppressed by estimating the variation of the eight neighbors for each pixel in the output of the maximum selection of the DoG pyramid. Hence, the combination of the DoG and edge suppression makes the proposed filter robust to the image noise and contrast. This line filter can be widely used for many other applications which need to detect line-like regions in the image, such as detection of crack reigons from the concrete pavement, anc crack detection of float glass.

Table 3. The Inspection Result of the Proposed Method

	Set 1	Set 2
Image Number	102	382
Crack Number	84	269
True Positive	83	261
False Positive	10	4
Accuracy	98.81%	97.03%
False Ratio	11.9%	1.49%
Average Accuracy	97.45%	
Average False Ratio	3.97%	

Table 4. The Inspection Result of the Method in [6]

	Set 1	Set 2
Image Number	102	382
Crack Number	84	269
True Positive	84	255
False Positive	22	11
Accuracy	100%	94.8%
False Ratio	26.19%	4.09%
Average Accuracy	96.03%	
Average False Ratio	9.35%	

Table 5. The Inspection Result of the Hu's Method

	Set 1	Set 2
Image Number	102	382
Crack Number	84	269
True Positive	63	182
False Positive	35	20
Accuracy	75%	67.66%
False Ratio	41.67%	7.43%
Average Accuracy	69.41%	
Average False Ratio	15.58%	

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