Bridge Crack Detection Algorithm Based on Bilateral-frangi Filter

Jiang Yang1,*

1Department of Track and electrical and mechanical engineering, Chongqing, Jianzhu, 400072, China

*Corresponding author e-mail: 921601160012@cqjzc.edu.cn

Abstract. The crack detection algorithm based on Bilateral-Frangi filtering can effectively reduce the influence of noise on the crack detection results at the bottom of the bridge. This algorithm effectively removes noise while enhancing cracks at the bottom of the bridge. Through this algorithm, the data analysis results are more accurate. This effectively provides a new idea for crack detection in high-noise images.

Keywords: Image Processing, Bilateral Filter, Frangi Filter, Crack Detection

1. Introduction

In recent years, the number of bridges in our country has increased sharply, so the detection of bridge damage has great significance. In actual engineering, we must not only detect cracks, but also analyze the characteristic information, such as the length and width of the cracks. The accuracy of crack detection determines the accuracy of crack feature analysis and crack classification. Therefore, crack detection is an important basis for follow-up work. Compared with the detected small cracks, the engineering pays more attention to the measurement of the maximum width and length of the main crack. Therefore, it is very important to detect cracks without destroying the edges of the main cracks [1].

2. History of crack detection algorithms at home and abroad

In recent years, research teams at home and abroad have proposed a variety of crack detection algorithms. There are many methods used:

1) Using wavelet transform to decompose the image. Although this method can remove high-frequency noise, it will also remove the high-frequency information of the cracks, resulting in large errors between the detected cracks and the actual cracks, which is not conducive to the subsequent analysis of the crack characteristics.
2) Gabor filter is used to enhance the cracks, but the method is not ideal for the processing of noisy images, and the false detection rate is high [2].

3) Use Top-hat morphological filtering to preprocess the image, and then use the snake model under GVF (Gradient Vector Flow) to track the crack boundary. The detection result of this method is also not ideal when the noise is large, and the background is judged as a crack target for tracking.

4) In 2017, Cubero-Fernandez et al. used Bilateral filtering to preprocess the image. On this basis, the Canny operator was used to extract the cracks. However, the Canny operator not only detects the edges of the cracks, but also detects more noise, which is not conducive to Follow-up analysis of crack characteristics.

5) In 2018, David Jenkins et al. proposed a pixel-scale crack semantic segmentation algorithm based on convolutional neural network (CNN), which can classify each pixel of the input image to obtain a picture containing only cracks and background. The detection accuracy of binary images can reach 92.46%, which has a good guiding significance for the application of CNN in crack detection. Since the algorithm proposed in this paper does not involve CNN, the follow-up experiments only compare with conventional algorithms.

The actual image of the bottom of the bridge is noisy, and it is necessary to reduce the impact of noise before detecting the cracks, but the conventional algorithm will smooth the noise while destroying the edge of the crack, resulting in insufficient measurement of the length and width of the main crack, and the existing algorithm cannot Solve this problem well. The Frangi filtering algorithm is an algorithm for blood vessel enhancement proposed by Frangi et al. in 1998. It uses the eigenvalues of the image Hessian matrix to construct a transfer function, so that the pixels at the blood vessel have a higher response value to the transfer function, thereby realizing the effect of the blood vessel. Enhanced [3]. In response to the above problems, this paper proposes a crack detection algorithm based on Bilateral-Frangi filtering based on the characteristics of the Frangi filtering algorithm's physical model that is highly responsive to the gray value distribution of the tubular structure and has been maturely used in the field of three-dimensional blood vessel enhancement. This algorithm improves the physical model of the conventional Frangi filtering algorithm. In the spatial Gaussian kernel function, the gray value domain Gaussian kernel function affected by the gray value of adjacent pixels is added to form a Bilateral Gaussian kernel function with edge preserving and denoising function to solve The crack detection algorithm smoothes the noise problem while keeping the crack edges.

3. Principles of Bilateral-Frangi filtering algorithm

3.1. Conventional Frangi filtering algorithm

For a two-dimensional image, the Hessian matrix can be expressed as formula (1):

$$H = \begin{bmatrix} I_{xx} & I_{xy} \\ I_{yx} & I_{yy} \end{bmatrix}$$

(1)
Where: $I_{xx}$ represents the second-order partial derivative of the image in the x direction; $I_{yy}$ represents the second-order partial derivative of the image in the y direction; $I_{xy} = I_{yx}$ represents the mixed partial derivative of the image in the x and y directions [4]. Since the second-order partial derivative is more sensitive to noise, Gaussian smoothing is usually performed before calculating the Hessian matrix of the image, which can be expressed as formula (2):

$$I_{xx} = I \otimes G_\sigma(x, y) \otimes \nabla^2_x$$  \hspace{1cm} (2)

Where: $I$ represents the input image; $G_\sigma(x, y)$ represents the two-dimensional Gaussian function with standard deviation $\sigma$; $\nabla^2_x$ represents the second-order differentiation of the input image $I$ in the x direction. Since convolution is commutative, we can first $G_\sigma(x, y)$ obtain the second-order differential in the x direction, which can be expressed as formula (3):

$$I_{xx} = I \otimes [G_\sigma(x, y) \otimes \nabla^2_x]$$  \hspace{1cm} (3)

For a two-dimensional image, the Hessian matrix has two eigenvalues: $\lambda_1, \lambda_2$ (where $\lambda_1 < \lambda_2$), which represents the gradient of the point along the direction of the corresponding eigenvector. The larger the eigenvalue, the greater the gradient, and vice versa. According to the different responses of the eigenvalues of the Hessian matrix to different regions in the image, construct the variables $Rb, S$, and set $Rb = \lambda_1/\lambda_2$, $s = \sqrt{\lambda_1^2 + \lambda_2^2}$ The transfer function of the Frangi filter constructed according to these two variables can be expressed as formula (4):

$$v_0 = \begin{cases} 
  \exp\left(-\frac{Rb^s}{2c^s}\right)\left[1 - \exp\left(-\frac{S^2}{2c}\right)\right], & \lambda^2 > 0 \\
  0, & \text{else}
\end{cases}$$  \hspace{1cm} (4)

In the formula: $\beta$ is the sensitive coefficient to distinguish the strip area; $c$ is the overall smoothing coefficient; $\lambda$ is the eigenvalue of the Hessian matrix.

Let $A = \exp\left(-\frac{Rb^s}{2c^s}\right)$, $B = 1 - \exp\left(-\frac{S^2}{2c}\right)$, use $|A|$ and $|B|$ to represent the absolute values of $A$ and $B$, respectively, and the response to the three types of areas in the image is as follows: the response value of the background point to $|A|$ is less than 1, for $|B|$ The response value of the isolated point is small, the response value of the isolated point to $|A|$ is small, and the response value of the $|B|$ is less than 1, which causes the background point and the isolated point to have a small response value to the transfer function V0; the crack point is to $|A|$; $|B|$ all have a larger response value, which makes the response value of the transfer function V0 larger. Therefore, the traditional Frangi filtering algorithm can effectively enhance the fracture area and suppress the non-fracture area [5,6].

3.2. Bilateral-Frangi filtering algorithm

In engineering applications, it is necessary to obtain information such as the length and width of the main crack after the crack is detected. Therefore, it is necessary to smooth the noise while maintaining the edge of the crack. The conventional Frangi filtering algorithm needs to perform Gaussian smoothing on the image before calculating the Hessian matrix. Although the second-order differential of the Gaussian function has a very high degree of matching to the gray value distribution of the crack, the use
of Gaussian filtering in the spatial domain for preprocessing will smooth the noise and cause the same degree of smoothing on the edge of the crack, resulting in the detection of the edge of the crack becoming blurred [7].

In response to the above problems, this paper proposes a method to increase the kernel function affected by the gray value domain in the preprocessing step of the conventional Frangi filter algorithm, that is, add the gray value of the neighboring pixels to the physical model that originally only has the spatial Gaussian kernel function. The affected Gaussian kernel function constitutes the Bilateral Gaussian kernel function. This not only considers the impact of the distance between pixels in the spatial domain, but also considers the impact of the gray value difference between each pixel in the convolution kernel and the center pixel. From the physical model level, it solves the problem of conventional Frangi filtering losing crack edge information when smoothing noise problem. The Bilateral Gaussian kernel function can be described as formula (5):

\[
w(i, j, k, l) = \exp \left[ -\frac{(i-k)^2 + (j-l)^2}{2\sigma_d^2} \right] \cdot \exp \left[ -\frac{\|I(i,j) - I(k,l)\|^2}{2\sigma_r^2} \right]
\]  

(5)

Where: \(\sigma_d\) and \(\sigma_r\) are the standard deviations of the kernel function in the spatial domain and the gray value domain, respectively; \((i, j)\) are the target pixels; \((k, l)\) are the other pixels of the convolution kernel; \(I(i, j)\) and \(I(k, l)\) are the gray values of pixels \((i, j)\) and \((k, l)\) respectively. In equation (5), \(\exp \left[ -\frac{(i-k)^2 + (j-l)^2}{2\sigma_d^2} \right] \) represents the spatial Gaussian kernel function, and its size is related to the Euclidean distance between \((k, l)\) and the central pixel \((i, j)\), that is, the closer the distance to the central pixel, the greater the weight \(\exp \left[ -\frac{\|I(i,j) - I(k,l)\|^2}{2\sigma_r^2} \right] \) represents the Gaussian kernel function of the pixel value domain. Its size is affected by the difference in gray value of two pixels. The smaller the difference in gray value, the higher the weight [8].

Therefore, the Bilateral Gaussian kernel function in the background area where the gray value changes smoothly is equivalent to Gaussian smoothing of noise in the spatial domain, and the gray value domain has almost no effect; and where the gray value changes drastically, it is equivalent to the first Calculate the weight of each pixel in the gray value domain, increase the weight of the pixel close to the gray value of the center pixel, and then smooth it in the spatial domain. The improved algorithm can smooth the noise while preserving the crack edges. Using Bilateral preprocessing instead of spatial Gaussian filtering in Frangi filtering, its physical model will also change accordingly [9]. The Gaussian kernel function of the traditional Frangi filtering algorithm: should be replaced with the Bilateral Gaussian kernel function \(w(i,j,k,l)\) to obtain the second-order partial derivative of the image in the x direction, which is formula (6).

\[I_{xx} = I \otimes [w(i, j, k, l) \otimes \nabla_i^2] \]  

(6)

The second-order partial derivative of the Bilateral kernel function can be expressed as formula (7).
In the formula: \( \sigma_d \) is the standard deviation of the kernel function in the spatial domain; \((x, y)\) is the target pixel; \((k, l)\) is the other pixels of the convolution kernel.

The physical model constructed using Eq. (7) not only retains the feature of the Frangi filter’s high matching of the crack gray value distribution, but also solves the problem of smooth noise and loss of crack edge information by increasing the gray value domain Gaussian kernel function. Therefore, the Bilateral-Frangi filtering algorithm can significantly improve the efficiency of crack detection [10].

4. Conclusion

In summary, this algorithm can effectively realize the functions of edge preservation, noise reduction and crack enhancement. I believe that with the continuous improvement of computer algorithms, there will have better algorithms and computer technology in the future. In this way, it can effectively solve the problem that the crack detection results at the bottom of the bridge are affected by noise.

Acknowledgments

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