Article

Research on Image Denoising in edge detection Based on Wavelet Transform

You Ning [1,*], Han Libo [2] , Zhu Daming[1,*] and Song Weiwei[1]

[1] Faculty of Land Resources Engineering,Kunming University of Science Technology and, Kunming,650093,China
[2] PLA Army Academy of Artillery and Air Defense,Zhengzhou,450000, China
* Correspondence: youning0801@163.com (Y.N.); 11301066@kust.edu.cn(Z.D.)

Abstract: In the process of image feature extraction, noise in the image will greatly affect the accuracy of edge detection. In this paper, the image is filtered to remove noise before edge detection by using the algorithm of wavelet transformation. Different wavelet functions are used to decompose image. Based on the experimental results, the best denoising wavelet function is selected. Canny algorithm is used to detect the edge of the denoised image, and the result of edge detection is evaluated according to the Pratt quality factor. It is proved that wavelet transform can improve the edge detection results.

Keywords: edge detection; wavelet transform; wavelet basis function; canny; Pratt quality factor

1. Introduction

Edges are the dividing line between different areas of an image and contain a wealth of image information, making them the most fundamental image feature. Edge detection is a fundamental tool in the fields of graphic image processing and machine vision. Edge detection is generally the process of finding) the region of the graphic where the gradient changes significantly, and then selecting the pixel with the highest amplitude, or confirming the boundary by searching the traversal of the second order derivative to zero. Thus, the information of the region boundary contour can be obtained. Generally, the edge detection operator includes Sobel operator, Laplace operator and Canny operator. [1,2] At present, the Canny operator is theoretically sound, but it is sensitive to noise in the image. So in the application it is necessary to do appropriate filtering on the image first to eliminate the effect of noise on the original image, so that the edge detection effect of the Canny operator can be improved[3-7] .

Traditional filters, such as mean filtering, median filtering and Gaussian filtering can produce blurred boundaries, lost edges and even pseudo-edges while achieving a smoothing effect on the image. The wavelet transform inherits and carries forward the idea of localization of the short-time Fourier transform, and solves the defect that the scale of the information window does not change with frequency, through the transformation can fully highlight the characteristics of certain aspects of the information, and then use the telescopic translation algorithm to gradually divide the information into more scales, and finally can achieve time subdivision at high frequencies and frequency subdivision at low frequencies, so as to focus on more details of the information. The wavelet transform is widely used in signal analysis and image processing due to its multi-resolution, low entropy and decoupling properties.

Yang X et al [8,9] proposed a wavelet transform-based Gaussian progressive decomposition method for analyzing the data results of large spot full-waveform LiDAR waveforms, solving the problem of superimposed and weak waves in them; LIU R L et al [10,11] gave a wavelet transform-based seam hole face aperture extraction method for wavelet transform mode maximum value image segmentation of electric imaging logging data, so as to obtain the corresponding parameters that meet the experimental need. CHEN S et al

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[12,13] presented a blind image deblurring method based on the depth wavelet transform, which can learn the mapping relationship between the blurred image and the clear image sub-bands in the wavelet domain, and achieve the deblurring of dynamic scenes in an end-to-end way; LIU F et al [14,15] used a batch image classification method based on wavelet transform and depth network to improve the classification accuracy.

In this paper, we want to test the edge detection of a bridge image superimposed with Gaussian noise. In order to achieve a better edge detection effect, we choose to remove its noise by means of wavelet transform. In the denoising process, after several experiments and comparisons, the sym5 wavelet function is chosen to decompose the image in 3 layers, and the hard threshold function is used to filter the decomposed coefficients to achieve the overall optimisation of the denoising effect. After the denoised image was edge-detected, the Pratt quality factor of the image was calculated to have been improved.

2. Study Area and Data

2.1. Study Area

In this paper, a bridge in Wenzhou, Zhejiang Province, China, is selected as the experimental area. Wenzhou, in the western part of Zhejiang Province, China, lies between 27. 3′ and 28. 36′ N latitude and 119. 37′ and 121. 18′ E longitude, and has a well-developed water system and rich hydraulic resources. The bridge is an arch-shaped structure that has been in use for many years and has provided great convenience for local residents to transport.

2.2. Data

During the maintenance of the bridge, an unmanned aerial vehicle was used to take relevant photographs of the bridge, and a picture reflecting the full view of the bridge was selected as the source of data for this paper. The camera on the drone was a DJI ZH20 with a focal length of 7mm and the picture has an exposure time of 1/725th of a second, with a horizontal and vertical resolution of 72dpi.

3. Materials and Methods

3.1. Wavelet Transform

The wavelet transform, as opposed to the Fourier transform, is equivalent to a basis substitution, where the infinitely long trigonometric basis is replaced by a finite, decaying wavelet transform basis. The wavelet basis has a finite energy, usually concentrated around a certain point, and has an integral value of zero. In the Fourier transform, the variable is only ω, while the wavelet transform contains two variables, namely the scale a and the translation b. The scale a corresponds to frequency and the translation b corresponds to time, so the wavelet transform can be used for time-frequency analysis to obtain the time-frequency spectrum of the signal. The wavelet sequence can be derived using the scaling and translation of the mother wavelet function, and the general form of the wavelet sequence is given below.

$$\psi_{a,b}(t)=\frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \qquad a,b\in R \tag{1}$$

In the process of performing the wavelet transform, the scale factor a and the time shift b are theoretically continuously varying, but this is a calculation that a computer cannot complete in a finite amount of time, so in the wavelet transform, the scale factor a and the time shift b are taken to be discrete according to certain rules, also known as the discrete wavelet transform (DWT). The scale factor a and the time shift b are chosen according to a power of 2, and the analysis of the signal becomes more accurate and efficient [16,17]. The wavelet function can be further written as.

$$\psi_{m,n}(k) = 2^{-\frac{m}{2}}\psi(2^{-m}k - n) \qquad m, n \in Z \tag{2}$$

The wavelet transform can decompose the original image information into approximate and detailed components, and the noise in the image is mainly reflected in the detailed components. After the process of adding threshold value, the wavelet reconstruction is then performed to obtain smoother image information.

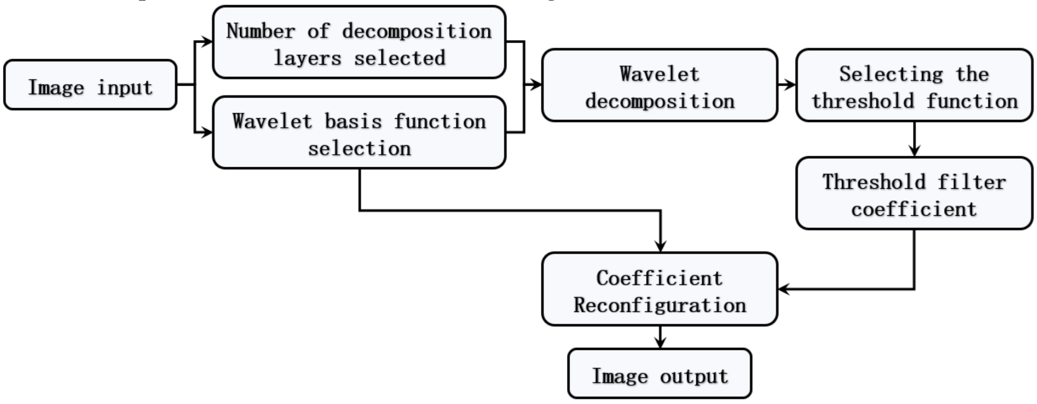

Figure 1. Transform denoising general process

The wavelet transform is based on the theory of function spaces, which enables multi-scale analysis. Under different scale and space conditions, a set of scaling function vectors and a set of wavelet function vectors are created, that is, the scaling function vector space V and the wavelet function vector space W. At a particular level, the convolution of a signal in the scale space gives an approximation of the signal, which is a low-frequency signal. The details of the signal obtained by convolving the signal in the wavelet space W are the high frequency signal. During the decomposition process, the signal data is passed through a low-pass filter and a high-pass filter. The low-pass filter produces the low-frequency component of the signal, which is the approximation coefficient, while the high-pass filter produces the high-frequency component, which is the detail coefficient.

In the wavelet transform, the use of wavelet basis functions is very critical and needed to comprehensive considerate the support length, symmetry, regularity and similarity and so on. The most popular ones are db, sym and coif[18-22]. The choice of the number of decomposition layers is also crucial. The higher the number of layers, the clearer the distinction between information and noise, and the better the distinction between the two, but the increased number of layers also leads to increased distortion of the reconstructed signal, which may affect the reconstruction of the signal.

3.2. Data Processing

PSNR (Peak Signal-to-Noise Ratio) is the ratio of the maximum possible power of the information to the noise that affects its fidelity. In image processing, PSNR is mainly used to measure the reconstruction effect of pictures and images disturbed by lossy compression. PSNR can be expressed as:

$$PSNR = 20\lg(MAX_1) - 10\lg(MSE) \tag{3}$$

Where MSE is the mean square error between images and MAX1 is the maximum possible pixel value in the image. In this paper, the peak signal-to-noise ratio and the inter-image mean square error are used as the main basis for selecting the optimal wavelet function and the number of decomposition layers.

3.2.1. Selecting Wavelet Function and Number of Layers

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The wavelet functions sym5, db5, coif5 and fk6 were chosen to decompose the target image with three decomposition layers. A hard thresholding function was used for denoising, and the PSNR and MSE of the reconstructed results were calculated.

Table 1. The PSNR and MSE of different image denoised by different wavelet functions

wavelet functions	PSNR(dB)	MSE
sym5	23.48	299.49
db5	23.37	300.53
coif5	23.22	309.89
fk6	23.28	305.4

Comparing the results of this image processing, the performance of the four wavelet functions do not differ much from each other. However, overall, sym5 corresponds to a PSNR and MSE of 23.48dB and 299.49, which are the maximum and minimum values in the results respectively. Therefore, sym5 as a whole performs is slightly better than the other wavelet functions. The sym5 wavelet function is now used, and the image is decomposed into different layers for denoising, and the PSNR and MSE of the processing results are again calculated.

Table 2. The PSNR and MSE of different layers denoised

layers	PSNR(dB)	MSE
2 layers	17.14	1251
3 layers	23.48	299.49
4 layers	23.31	303.25
5 layers	22.72	347.75

Comparing the PSNR and MSE of the results, we can see that when the number of decomposition layers is 3, the PSNR is the largest and the MSE is the smallest, which is 23.48dB and 299.49 respectively. That is to say, the denoising effect on the image is more obvious. Therefore, in the next step of edge detection in this paper, the sym5 wavelet function will be used to decompose the original image in 3 layers.

3.2.2. Image denoising

For two-dimensional image information, multi-resolution decomposition can be achieved by filtering in the horizontal and vertical directions respectively. The decomposition gives the approximate coefficients, horizontal detail coefficients, vertical detail coefficients and diagonal detail coefficients of each layer. The wavelet transform of the image is carried out using sym5 as the wavelet function, and the number of decomposition layers is chosen to be 3. The decomposition results are shown in Figures 2 and 3.

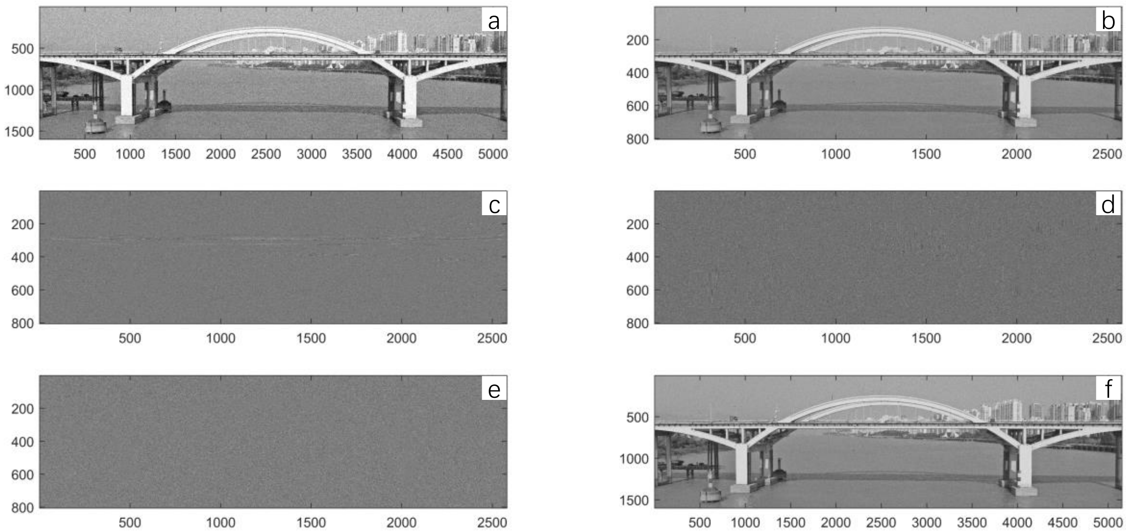

Figure 2. The first layer of decomposition (**a**) noisy image (**b**) approximation coefficient (**c**) detail coefficient (**d**) detail coefficient (**e**) detail coefficient (**f**) reconstruction result

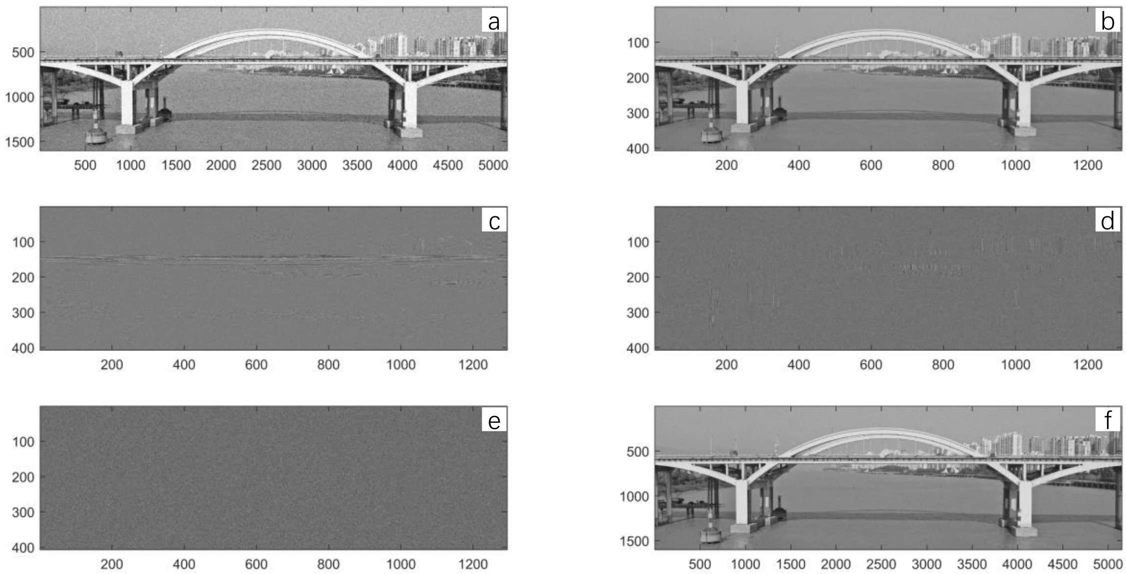

Figure 3. The second layer of decomposition (**a**) noisy image (**b**) approximation coefficient (**c**)detail coefficient (**d**) detail coefficient (**e**)detail coefficient (**f**)reconstruction result

After the decomposition is completed, the effective part of the signal corresponds to larger coefficients and the noise corresponds to relatively small coefficients. Setting a suitable threshold and threshold function can filter the coefficients in a certain interval, and at the same time suppress the noise. In general, the threshold function can be selected as a hard or soft threshold function, both of which have advantages and disadvantages. Hard thresholding has advantages in the sense of mean squared deviation. Soft thresholding functions, however, may produce jump points, while soft thresholding functions have better continuity but produce biases that affect the reconstructed signal [5,23-26] .

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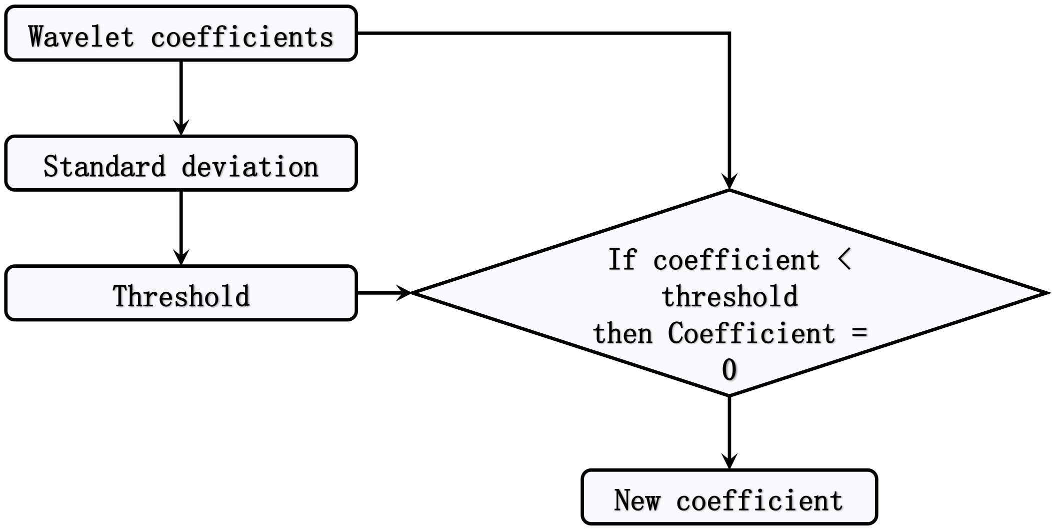

Figure 4. Hard threshold function working process

In this paper a hard thresholding function is chosen to process the coefficients, followed by wavelet reconstruction. The wavelet function used in the reconstruction process is to be consistent with the decomposition process. After thresholding of the bridge image containing noise, the coefficients are reconstructed as in Figure 5.

Figure 5. Image denoising (**a**) Noise-laden images (**b**) Denoised images

4. Results and Verification

The Canny edge detection algorithm has been proposed for more than thirty years and is still one of the classic image edge detection algorithms. Compared to other edge detection algorithms, Canny has significant improvements in non-extreme value suppression based on the direction of the edge gradient and lag thresholding with double thresholding. The operation process generally consists of four stages: noise removal, calculation of gradient amplitude and direction, non-maximum suppression and hysteresis thresholding[27-29] .

In this paper, edge detection is performed on the bridge image after noise removal by wavelet transform, and the results obtained are shown in Figure 6.

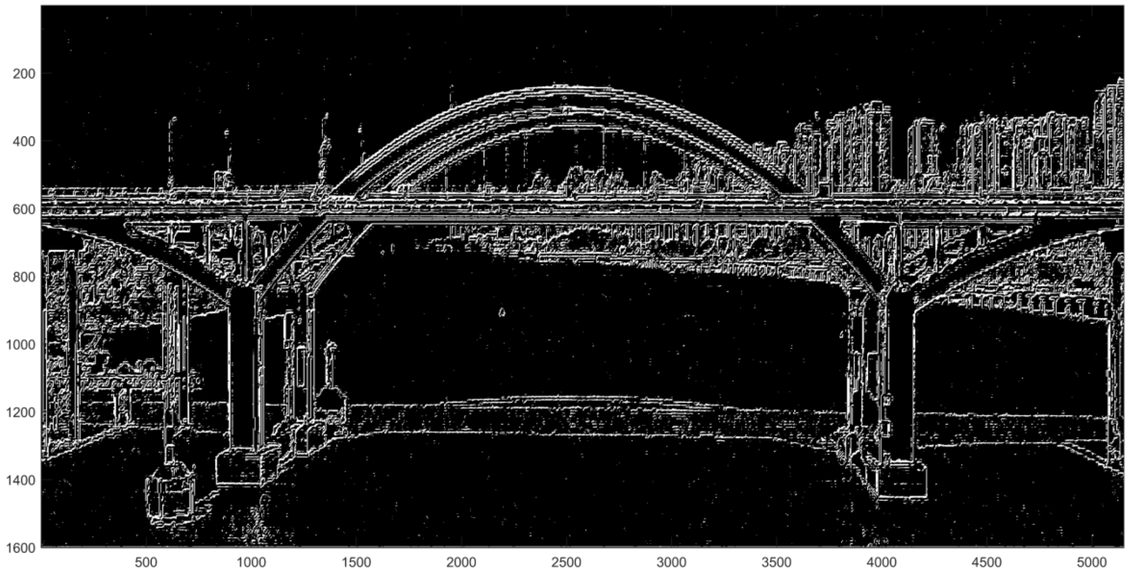

Figure 6. Canny operator edge detection results

5. Analysis and Discussion

The quality of edge detection can be expressed in terms of the Pratt quality factor, which focuses on the three errors of missing valid edges, edge localization errors and misjudging noise as edges[30-31], and takes values from 0 to 1. It is calculated as follows:

$$FM = \frac{1}{\max(I_A, I_I)} \sum_{i=1}^{I_A} \frac{1}{1 + ad_i^2} \tag{4}$$

where IA, II, di and a are the detected edge point, the edge point for reference, the distance between the detected edge point and the reference edge point and the design constant used to penalise misaligned edges, respectively. Generally, a = 1/9 is taken.

Table 3. Figure of Merit for edge detection

Denoising Method	Pratt Quality Factor
Gaussian filter	0.47
wavelet transform	0.53

The quality factor of edge detection was 0.47 and 0.53 for the Gaussian filtered and wavelet transform denoised images respectively, which showed that the quality factor of edge detection increased after wavelet transform noise removal, i.e., the edge detection effect was improved.

6. Conclusions

In this paper, different wavelet functions and decomposition layers are used to decompose the noisy bridge images, and the optimal combination of wavelet functions and decomposition layers is selected based on the comparison of PSNR and MSE. Afterwards, the Canny operator is used to perform edge detection on the denoised images, and the comparison of the calculated Pratt quality factors shows that the wavelet transform is used to remove the superimposed noise from the UAV images of the bridge, which has a certain improvement on the subsequent edge detection effect.

In this paper, in order to verify the effectiveness of the wavelet transform, the color bridge image taken by the UAV was changed to black and white before superimposing noise, but in many scenarios, the user would prefer to correlate within the color image, so

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how to apply wavelet transform based image denoising to edge detection of color images will be the next research direction for the authors of this paper.

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