Edge Detection Combining Wavelet Transform and Canny Operator Based on Fusion Rules

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Abstract

Aiming for the problem of discarding some important details of high-frequency sub-image when detecting the edge based on wavelet transform, and the edge detection result is poor because of the noise influence. This paper proposed a new edge detection algorithm based on wavelet transform and canny operator. In the wavelet domain, the low-frequency edges are detected by canny operator, while the high-frequency edges are detected by solving the maximum points of local wavelet coefficient model to restore edges after reducing the noise by wavelet. Then, both sub-images edges are fused according to fusion rules. Experiment results show the proposed method can detect image edges not only remove the noise effectively but also enhance the edges and locate edges accurately.

Keywords:
Edge detection; Wavelet transform; Canny operator; Image denoise; Fusion rules;

1. Introduction

Edge detection plays an important role in computer vision and image analysis, and is an important processing in the image analysis and pattern recognition. Edges are the abrupt change points in the image which are the basic features of the image. These abrupt change points give the locations of the image contour that shows the important feature [1]. The edge representation of an image reduces the amount of data to be processed, and it retains important information about the shapes of objects in the scene. The description of an image is easy to integrate into a large number of recognition algorithms used in computer vision and other image processing applications [10].

Wavelet analysis developed rapidly as a useful research method, this method based on multi-scale wavelet is one of the new edge detection methods [10]. The traditional edge detection method based on wavelet transform is to perform the wavelet multi-resolution for image firstly, and then extract the low-frequency sub-image to further process, which will discard some important details and the effect of edges extracting will be affected by lots of noise in the high-frequency sub-images [2]. In this paper, we proposed a new fusion algorithm based on wavelet transform and canny operator to detect image edges, which can reduce the noise and obtain the continuous and distinct edges.

2. Image decomposition based on Wavelet transform

Based on image decomposition model of wavelet transform, the original image can be divided into low-frequency information and high-frequency information. After two-dimensional frequency decomposition of wavelet transform, low-frequency information can be decomposed low-frequency area LL and high-frequency area LH, high-frequency information can be decomposed low-frequency area HL and high-frequency area HH. LL shows the smoothing image of the original image which contains the most information of the original image. LH preserves the vertical edge details. HL preserves the horizontal edge details. HH preserves the diagonal details which are influenced by noise greatly. The result can be decomposed as needed. The process is shown in Figure.1

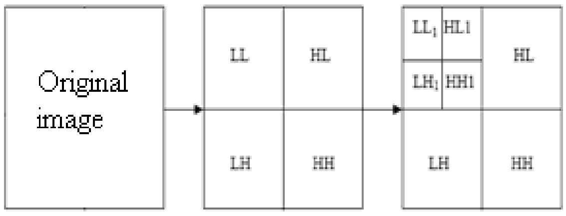


Figure.1 Image decomposition based on wavelet transform

3. Fusion algorithm of edge detection combining wavelet transform and canny operator

Though the edge extracted by wavelet transform can reduce the most noise of the image, the real edges of the image are also mixed with much noise, especially HH areas are affected by the noise greatly. Thus many methods of edge detection will discard these HH areas [5]. The four areas obtained from two-dimensional decomposition of wavelet transform contain the useful information of the original image, so these areas should be used completely when detecting the image edges. This paper presents a new fusion algorithm based on wavelet transform and canny operator to detect image edges, which can reduce the noise and obtain the continuous and distinct edges.

3.1. Low-frequency sub-image edge detecting based on canny operator

The LL area shows the smoothing image of the original image which contains the most information of the original image. Canny operator is a edge detecting operator based on an optimal algorithm, which has the most stringent criterions of edge detecting. The good effect will be obtained adopted canny operator when processing the image contaminated by additive white Gaussian noise. So canny operator [3,9] are adopted to detect the edges of the low-frequency sub-image. The realization process is as follows.

(1) Smoothing image. Gaussian function is used to smooth the image; the method use 5×5 Gaussian template and the original image to weight neighborhood [4]. Denote any point (x, y) of the image as the center when processing and extracting 5×5 neighborhood, the weighting neighborhood can be indicated as follows:

$$I^*(x,y) = \frac{1}{5\times 5}\sum_{i=-2}^{2}\sum_{j=-2}^{2} I(x+i, y+j)\times M(2+i, 2+j)$$

x=1,2,…,m; y=1,2,…,n (1)

Where the pixel value of the low-frequency sub-image is *I*(x, y), M is Gaussian template, the pixel value of the smoothed image is *I*(x, y)*.

(2) Computing gradient direction and amplitude. Computing gradient direction and amplitude of smoothed image *I*(x,y)* adopting first order partial finite difference of 2×2 neighborhood.

$$M(x,y) = \sqrt{g_x^2(x,y) + g_y^2(x,y)} \qquad (2)$$

$$Q(x,y) = \arctan[g_x(x,y), g_y(x,y)] \qquad (3)$$

$$f_x = \begin{bmatrix} -1/2 & 1/2 \\ -1/2 & 1/2 \end{bmatrix} \qquad f_y = \begin{bmatrix} 1/2 & 1/2 \end{bmatrix} \qquad (4)$$

Where g_x and g_y are the results of the original image filtered along rows and lines.

(3) Gradient image with non-maximum suppression. If the gradient amplitude of the pixel is no less than the gradient amplitude between two adjacent pixels in the gradient direction, the point can be judged as the edge point possibly.

(4) Dual threshold method of detecting and connecting the edges. Select two thresholds, Hth and Lth. Hth denotes the high threshold and Lth denotes the low threshold to process the gradient image. Where Hth=Lth*h, h=1.5 ~ 2. There will be two detecting results, one resulted from high threshold detecting, and the other resulted from low threshold detecting. Connecting the edge contour from the former and finding weak edge points from the latter to recoup the former edge gaps when connecting to the endpoint.

Through adopting canny operator to detect the low-frequency sub-image can obtain clear edge image which will miss some real edges and exist some sham edges. Thus the edges of the high-frequency sub-images should be fused.

3.2. High-frequency sub-image edges detecting based on wavelet transform

After two-dimensional frequency decomposition of wavelet transform, there will be three high-frequency sub-images LH、HL and HH where contain the noise and the details of the image. When extracting the edges from the high-frequency sub-images, the result will be affected because of much noise. Thus, this paper presents that the noise should be reduced before extracting the edges from the high-frequency sub-images. The algorithm can not only keep the important details of the high-frequency sub-images but also restrain the noise.

3.3. Denoising algorithm of the high-frequency sub-images based on wavelet transform

Among the wavelet coefficients of the high-frequency sub-image, the wavelet coefficients which have smaller amplitude present the most noise part, and the wavelet coefficients which have larger amplitude present the details of the image [2]. Based on the characteristic of the high-frequency sub-images, we proposed a method based on wavelet transform to reduce the noise in the high-frequency sub-images. The wavelet coefficients are multiplied by a denoising factor which is relative to their own coefficients' value. This denoising factor is less than 1 and will decrease if the absolute value of the wavelet coefficients increases. This algorithm considers energy distribution property of the wavelet decomposition of the image globally, and obtains a better denoising result, which support the foundation for extracting the edge of the high-frequency sub-images. The process function is as follows.

$$F(x,y) = \begin{cases} w(x,y) & |w(x,y) \geq 3\sigma| \\ 0 & |w(x,y) \leq |aver|| \\ w(x,y)\times k & else \end{cases} \qquad (5)$$

Where $w(x,y)$ denotes the high-frequency coefficient, $F(x,y)$ denotes the high-frequency coefficient gained after denoising; σ 、 $aver$ indicate the variance and the mean value of the high-frequency coefficient in different wavelet decomposition levels. On the basis of the statistic property of the wavelet coefficients, k is a function which is relative to the coefficient:

$$k = e^{-aw(x,y)+b} - 1 \qquad (6)$$

When $w(x,y)$ is greater than 3σ, $w(x,y)$ can be considered as consisting of the signal completely. So k=1, it will be:

$$e^{(-3\sigma a+b)} - 1 = 1 \qquad (7)$$

When $w(x,y)$ is smaller than $aver$, $w(x,y)$ will approaches 0, it will be:

$$e^{-a\times aver+b} - 1 = 0 \qquad (8)$$

It can be obtained from the two upper equations:

$$a = \frac{-\ln 2}{3\sigma - aver} \qquad b = a \times aver \qquad (9)$$

Denoising factor k will be obtained when a and b substituted into the equation (6).

$$k = e^{-\frac{\ln 2}{3\sigma - aver}\times w(x,y) + \frac{-\ln 2}{3\sigma - aver}\times aver} - 1 \qquad (10)$$

Denoising algorithm will be computed when k substituted into equation (5). This algorithm is aiming for the wavelet coefficients multiplied by different denoising factors from different wavelet decomposition levels and different high-frequency sub-image, which can reduce the image noise and keep useful details.

3.4. Edge detecting of denoising high-frequency sub-image based on wavelet transform

After eliminating noise of the high-frequency sub-image, the edges of the high-frequency sub-image can be detected using wavelet modulus maxima algorithm [7]. The wavelet modulus maxima algorithm is obtained from an irregular sampling based on multiscale wavelet transform which can describe mechanism singularity of the signal. The wavelet modulus maxima algorithm can describe multiscale edges of the target in the image which has translation, scale and rotation-invariant performance. Thus the wavelet modulus maxima algorithm is an effective algorithm to detect the edges. The realization process is as follows:

$\theta(x,y)$ denotes Gaussian smoothing function, supposing:

$$\theta_s(x,y) = \frac{1}{s^2}\theta\left[\frac{x}{s},\frac{y}{s}\right] \qquad (11)$$

Calculating the partial derivative of the smoothing function $\theta(x,y)$, the wavelet function will be:

$$\phi_s^1(x,y) = \frac{\partial\theta(x,y)}{\partial x} = \frac{1}{s^2}\phi^1\left[\frac{x}{s},\frac{y}{s}\right] \qquad (12)$$

$$\phi_s^2(x,y) = \frac{\partial\theta(x,y)}{\partial y} = \frac{1}{s^2}\phi^2\left[\frac{x}{s},\frac{y}{s}\right] \qquad (13)$$

Convolution of $f(x,y)$ will obtain two components of two dimensional wavelet transform in scale s:

$$W_s^1 f(x,y) = f * \phi_s^1(x,y) \qquad (14)$$

$$W_s^2 f(x,y) = f * \phi_s^2(x,y) \qquad (15)$$

The gradient module in scale s is:

$$M_s f(x,y) = \sqrt{\left|W_s^1 f(x,y)\right|^2 + \left|W_s^2 f(x,y)\right|^2} \qquad (16)$$

The angel in scale s is:

$$A_s f(x,y) = \arctan\left[\frac{W_s^2 f(x,y)}{W_s^1 f(x,y)}\right] \qquad (17)$$

Detecting the edges of the high-frequency sub-images LH、HL and HH using wavelet modulus maxima algorithm. Computing the local modulus maxima of three sub-images after wavelet transform using equation (16) and (17), then their edge images G_{LH} , G_{HL} and G_{HH} will be obtained. Those high-frequency sub-images contain the details of the original image, so we proposed that the wavelet coefficients of three edge images should be computed with weighting fusion rules. Computing formula [13] is described as follows:

$$D_H(i,j) = r_{LH} * D_{LH}(i,j) + r_{HL} * D_{HL}(i,j) + r_{HH} * D_{HH}(i,j) \qquad (18)$$

Where $D_{LH}(i,j)$、$D_{HL}(i,j)$、$D_{HH}(i,j)$ indicate the wavelet coefficients corresponding to the edge images G_{LH} 、 G_{HL} and G_{HH} . $D_H(i,j)$ denotes the wavelet coefficient after fusion. r_{LH} 、 r_{HL} and r_{HH} indicate the corresponding weights, the sum of the three weights is 1.

After these processes, we can get the edges of the low-frequency sub-image and the weighting edges of the high-frequency sub-images. The final edge images are obtained through wavelet composition from the fusion edge sub-images [13].

4. Experimental results

In order to verify the efficiency and accuracy of the proposed algorithm, some images with 256 gray-level are used as experimental subjects. Figure 2 shows the edge detect result of image 'Lena'. Figure.3 shows the edge detect result of the tire image. Figure.4 shows the edge detect result of the noisy image Lena (SNR=15.8dB). The experimental results show that our proposed algorithm, which combined wavelet transform and canny operator to detect the edges, can reduce the noise and obtain the continuous and distinct edges.

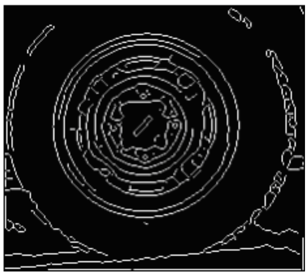
(a) The original image

(b) Detecting result by wavelet Algorithm

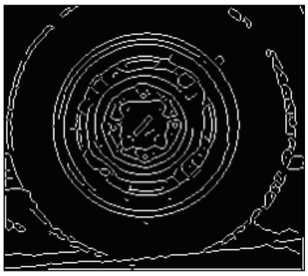
(c)Detecting result by proposed algorithm

Figure.2 Edge detecting result of the 'Lena' image

(a) The original image



(b) Detecting result by wavelet Algorithm



(c)Detecting result by proposed algorithm

Figure.3 Edge detecting result of the tire image

(a) The original noisy image (SNR=15.8dB)

(b) Detecting result by wavelet Algorithm

(c)Detecting result by proposed algorithm

Figure.4 Edge detecting result of the noisy image Lena

5. Conclusion

Aiming for the problem of discarding some important details of high-frequency sub-images when detecting the edge based on wavelet transform, and the effect of edge extracting is poor because of the noise. This paper proposed a new edge fusion detection algorithm based on wavelet transform and canny operator, its advantages are to reduce the noise simply and keep the fine image edges. Experiment results show that using this method to detect the image edges can not only get rid of the noise effectively but also enhance the image edge's details and locate the edge accurately.

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