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A Novel Edge Detection Algorithm Based on Distance

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Abstract. Under the framework of Canny algorithm, a distance-based edge detection algorithm is proposed to improve the gradient magnitude of Canny. In our algorithm, the gradient magnitude can be acquired by taking the distance from the center of the mask as the weight factor. The operator not only can calculate the image gradient better, but also has good separability in the horizontal and vertical directions, and its gradient amplitude has a certain degree of rotation invariance. Finally, this operator is compared with various gradient operators for the Lena image simulation and the actual waterfront edge detection experiment. It shows that the operator has a better edge detection effect from the experimental results.

1. Introduction

The edge is the curve formed by the point where the brightness changes rapidly in the image [1]. Edge detection is the basis of image analysis and understanding, and its essence is to use algorithms to extract these significant points [2]. Commonly used edge detection methods include first-order differential operators Roberts, Sobel, Prewitt and second-order differential operators Laplacian, LOG and so on. Although these methods are simple and fast, they are sensitive to noise. The Canny edge detection algorithm based on optimization operator is widely used in practice [3].

It not only proposes three criteria to evaluate the performance of edge detection: 1) SNR criterion; 2) positioning accuracy criterion; 3) unilateral response criterion; and it establishes an algorithm framework for edge detection (as shown in Figure 1). First, the Gaussian filter is used to smooth the image, and the finite difference of the first-order partial derivative is used to calculate the amplitude and direction of the gradient, and then the gradient direction and the double threshold are used to find the local maximum point in the image, thus the strong edge (the gradient amplitude is greater than the high threshold) and the weak edge (the gradient threshold is smaller than the high threshold and larger than the low threshold) are obtained. Finally, edge tracking (when the strong edge and the weak edge are connected, the weak edge is determined as the edge) completes the detection of the image edge.

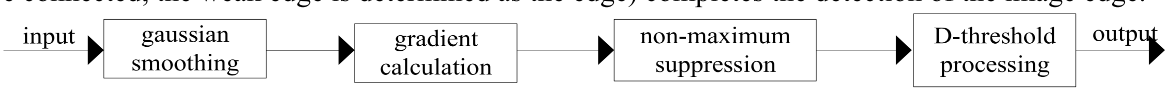

Figure 1. Canny algorithm framework

2. Canny algorithm

2.1. Gauss smoothing

The traditional Canny algorithm uses Gauss filter to smooth the image. The Gaussian function is $G(x,y)=\frac{1}{2\pi\sigma^2}\exp(-\frac{x^2+y^2}{2\sigma^2})$, and σ is the smoothing parameter. The larger the σ, the wider the frequency band and the better the smoothing degree of the Gaussian filter. However, with the increase of the Gaussian smoothing template, not only the edge positioning accuracy is reduced, but also the computation is increased. Usually, in order to speed up the operation, the two-dimensional Gaussian filter is divided into two one-dimensional Gaussian filters. In image smoothing, row and column Gaussian filtering can be performed respectively, that is, the image is convoluted with $G(x)=\frac{1}{2\pi\sigma^2}\exp(-\frac{x^2}{2\sigma^2})$ and $G(y)=\frac{1}{2\pi\sigma^2}\exp(-\frac{y^2}{2\sigma^2})$ respectively.

2.2. Gradient calculation

The traditional Canny algorithm uses the finite difference of 2*2 neighborhood to estimate the gradient magnitude and direction of image $f[x,y]$. such as operator $s_x=\begin{bmatrix}-1 & 1\\ -1 & 1\end{bmatrix}$, $s_y=\begin{bmatrix}-1 & -1\\ 1 & 1\end{bmatrix}$. The partial derivatives of X and Y directions are: $P_x[i,j]=(f[i,j+1]-f[i,j]+f[i+1,j+1]-f[i+1,j])/2$ and $P_y[i,j]=(f[i+1,j]-f[i,j]+f[i+1,j+1]-f[i,j+1])/2$, The gradient magnitude and direction of pixels are: $M[i,j]=\sqrt{P_x[i,j]^2+P_y[i,j]^2}$, $\theta[i,j]=\arctan(P_x[i,j]/P_y[i,j])$.

A large number of scholars have done some researches on the traditional Canny algorithm which uses 2*2 template to calculate the gradient amplitude and is easily affected by noise. Reference [4] without affecting the traditional Canny algorithm, a diagonal template operator is used to synthesize the information of original gradient and diagonal direction gradient, which enhances the edge detection of 45 degree and 135 degree images. In reference [5], the gradient operator is extended from 2*2 to 3*3. The gravitational edge detection method in reference [6] is adopted, and a set of gradient operators for calculating X and Y directions are given. Reference [7] indicates that the first derivative of Gaussian function is the optimal edge detector, that is, in two-dimensional case, the derivative of two-dimensional Gaussian function is used as the image smoothing filter. In this paper, we call it Gauss gradient operator and get the gradient graph. $I[x,y]=(\nabla G(x,y))*f[x,y]=\nabla(G(x,y)*f[x,y])$, $\nabla G(x,y)$ is the derivative of Gauss function.

Generally, in order to improve the speed, the two-dimensional filter is divided into two one-dimensional filters, that is, the derivative of Gaussian function is divided into the derivative of X and Y direction, $\nabla G(x,y)=\begin{bmatrix}\frac{\partial G(x,y)}{\partial x}\\ \frac{\partial G(x,y)}{\partial y}\end{bmatrix}$,where $\frac{\partial G(x,y)}{\partial x}=kx\bullet\exp(-\frac{x^2+y^2}{2\sigma^2})$, $\frac{\partial G(x,y)}{\partial y}=ky\bullet\exp(-\frac{x^2+y^2}{2\sigma^2})$, Then, the derivative and the image are convoluted to get the gradient components in the direction of X and Y, $P_x[i,j]=\frac{\partial G(x,y)}{\partial x}*f[x,y]$, $P_y[i,j]=\frac{\partial G(x,y)}{\partial y}*f[x,y]$.

2.3. Non-maximum suppression

In order to ensure the precise positioning of the edge, the gradient amplitude image $M[i,j]$ needs to be refined, and only the point with the largest local gradient amplitude is retained, which is the non-maximum value suppression process. The specific method is as follows: a neighborhood of 2*2 size is used to draw a straight line along the gradient direction and intersect the neighborhood boundary through the center point. The gradient amplitude of two intersecting points is obtained by interpolation, and then the gradient amplitude of the center point and two intersecting points is compared. If the amplitude of the center point is not greater than the interpolation result, the point is considered as non-

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edge, and set to zero, otherwise, it may be an edge point, which needs to be further processed by double thresholds. Literature [8] has improved the interpolation method by extending the neighborhood, taking four points in the gradient direction, and then using bilinear interpolation.

2.4. Double threshold processing

Assuming low threshold δ_1 and high threshold δ_2, the edge images $T_1[i, j]$ and $T_2[i, j]$ are obtained by using these two thresholds. Image $T_2[i, j]$ contains few false edges, but the edges may not be closed due to the high threshold. To solve this problem, another low threshold is adopted. In the high threshold image, the edge is linked to the contour. When the end point of the contour is reached, the algorithm will find the point satisfying the low threshold in the eight neighborhood points of the breakpoint, and then collect new edges according to this point until the whole image edge closure.

In other words, the double threshold method is that the algorithm keeps collecting edges in $T_1[i, j]$ until $T_2[i, j]$ is connected to get a relatively comprehensive edge. So the selection of threshold is very important. Traditional threshold parameters are obtained by gradient histogram. Specifically, the accumulated number of pixels and the gradient value at 0.7 of the total number of pixels in the gradient histogram are set as high threshold, and the low threshold is 0.4 of the high threshold. However, this method is only a general engineering method. A large number of scholars have carried out relevant research and proposed an adaptive threshold method based on the maximum inter-class variance [9][10], adaptive threshold method based on genetic algorithm [11].

3. Improved edge detection algorithm

Traditional gradient operators do not solve the problem of gradient amplitude rotation. If two edges of the same strength, one is horizontal and the other is 45 degrees inclined to the level, according to the usual 2*2 neighbourhood up and down the four adjacent points difference method to calculate the gradient, the horizontal edge of the X direction of the gradient is 0, the Y direction of the gradient is 1, the 45 degree edge of the X direction of the gradient is 1, the Y direction of the gradient is 1. So, the gradient amplitude is $\sqrt{2}$ instead of 1.

To solve this problem, an improved 3 * 3 template operator is proposed in [12], which sets the weight in the diagonal direction to $1/\sqrt{2}$ in the horizontal and vertical directions, therefore, the gradient amplitude has 45 degree rotation invariance. But if the horizontal edge rotates at other angles, the rotation invariance of the gradient amplitude cannot be satisfied. For example, if the horizontal line rotates the arctan(1/2) angle counterclockwise, the 3*3 template operator is not sufficient. In this paper, a distance-based gradient operator is proposed, whose coefficients are the reciprocal of the distance from the point to the center.

$$S=\begin{bmatrix} 1/R_{(i-n)(j-n)} & \cdots & \cdots & 1/R_{(i-n)(j)} & \cdots & \cdots & 1/R_{(i-n)(j+n)} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & 1/R_{(i-1)(j-1)} & 1/R_{(i-1)(j)} & 1/R_{(i-1)(j+1)} & \cdots & \cdots \\ 1/R_{(i)(j-n)} & \cdots & 1/R_{(i)(j-1)} & 1/R_{(i)(j)} & 1/R_{(i)(j+1)} & \cdots & 1/R_{(i)(j+n)} \\ \cdots & \cdots & 1/R_{(i+1)(j-1)} & 1/R_{(i+1)(j)} & 1/R_{(i+1)(j+1)} & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ 1/R_{(i+n)(j-n)} & \cdots & \cdots & 1/R_{(i+n)(j)} & \cdots & \cdots & 1/R_{(i+n)(j+n)} \end{bmatrix}$$

Where $R_{(i-n)(j-n)}$ represents the distance between the image pixel $I[i-n, j-n]$ and the template center $I[i, j]$, that is, $R_{(i-1)(j-1)}=1/\sqrt{2}$. For example, when the operator length is 3, S is 3*3 operator $S=\begin{bmatrix} 1/\sqrt{2} & 1 & 1/\sqrt{2} \\ 1 & 0 & 1 \\ 1/\sqrt{2} & 1 & 1/\sqrt{2} \end{bmatrix}$ (This is the same as the improved Sobel operator). The gradients of X and Y are respectively $S_x=\begin{bmatrix} -1/\sqrt{2} & 0 & 1/\sqrt{2} \\ -1 & 0 & 1 \\ -1/\sqrt{2} & 0 & 1/\sqrt{2} \end{bmatrix}$ $S_y=\begin{bmatrix} -1/\sqrt{2} & -1 & -1/\sqrt{2} \\ 0 & 0 & 0 \\ 1/\sqrt{2} & 1 & 1/\sqrt{2} \end{bmatrix}$. Similarly, when the operator length is 5, $S=\begin{bmatrix} 1/\sqrt{8} & 1/\sqrt{5} & 1/2 & 1/\sqrt{5} & 1/\sqrt{8} \\ 1/\sqrt{5} & 1/\sqrt{2} & 1 & 1/\sqrt{2} & 1/\sqrt{5} \\ 1/2 & 1 & 0 & 1 & 1/2 \\ 1/\sqrt{5} & 1/\sqrt{2} & 1 & 1/\sqrt{2} & 1/\sqrt{5} \\ 1/\sqrt{8} & 1/\sqrt{5} & 1/2 & 1/\sqrt{5} & 1/\sqrt{8} \end{bmatrix}$. Next, the operator had been detected the edge of Lena image.

4. Simulation experiment and result analysis

Simulation experiment: the test platform is Intel Core i5-3470CPU, 4G memory, Win7 system and Visual C++ editor. Lena image is processed by various edge detection algorithms.

4.1. Experiments on Lena image

The experimental results are shown in Figure. 2. The edge images are obtained by Sobel operator, improved Sobel operator, Prewitt operator, 7*7 Gaussian gradient operator and 7*7 distance gradient operator. 7*7 Gauss smoothing had been used in the left column, while the right column had not.

For Lena images, it can be seen from the result: Gauss gradient operator and the operator proposed in this paper use 7 * 7 template, its size is larger than other gradient operators, and the effect is better. The gradient operator of 3 * 3 template produces a large number of pseudo-boundaries, and the Gaussian gradient operator produces fewer pseudo-boundaries. Whether or not Gauss filtering is used, the operators in this paper are the best and basically do not depend on Gauss filtering.

4.2. Experiments on noisy Lena images

The Gauss noise is added to the Lena image and the simulation experiments are redone. First, the Gauss white noise of variance 0.01 is added to the Lena image, and then various operations are processed.

The experimental results are shown in Figure.3. The edge images are obtained by Sobel operator, improved Sobel operator, Prewitt operator, 7*7 Gaussian gradient operator and 7*7 distance gradient operator. Gauss smoothing had not been adopted in the left column, while the middle column had, and 7*7 mean filtering had been adopted in the right column.

It can be seen from the Figure.3: Mean filtering is effective for Gauss noise. The distance operator with the same template size is better than the Gauss gradient operator. The operators proposed in this paper are not basically depended on mean filtering.

Comparing the above images, we can know whether the filtering function is used or not, the gradient operator based on distance has the best edge detection effect in the framework of Canny algorithm. The experiment is done again for salt and pepper noise.

First, the salt-and-pepper noise of density 0.01 is added to the Lena image, and then various operations are processed.

As can be seen from the Figure.4, the edge image obtained by gradient operator is better than other operators, and the distance gradient operator is better than Gaussian gradient operator.

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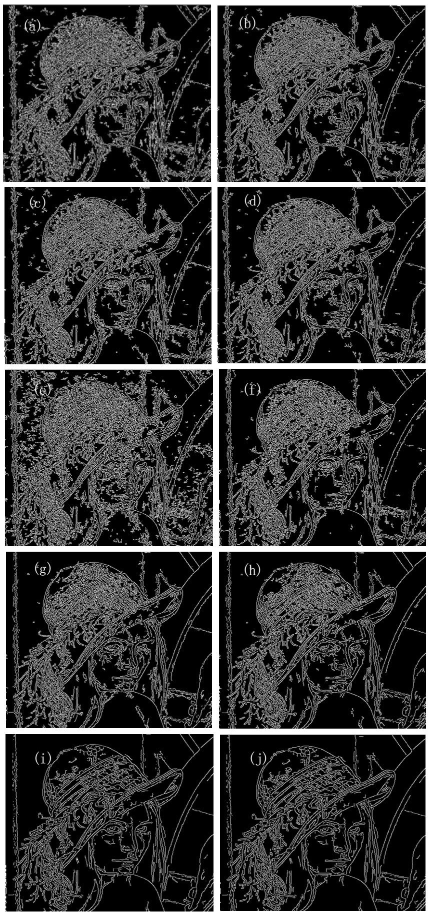


Figure 2. Lena edge images from various operators.

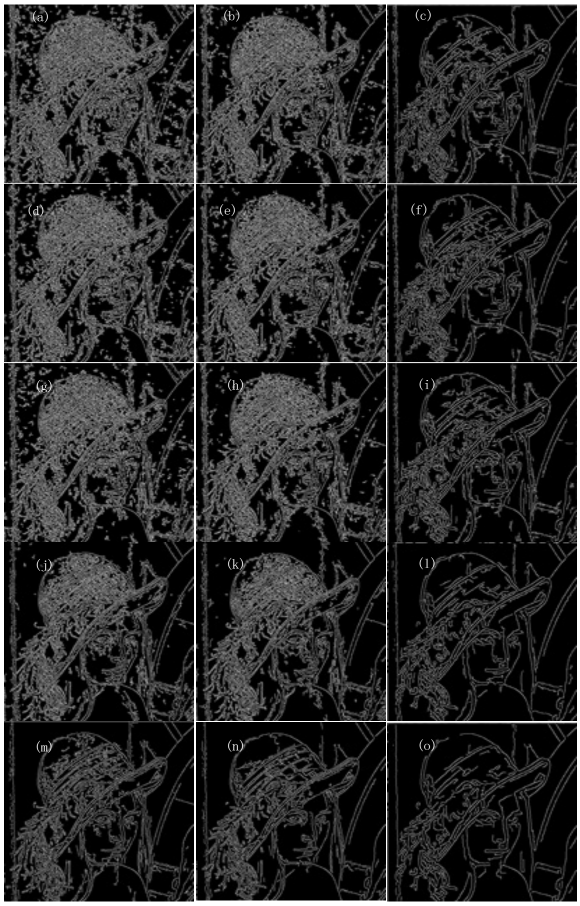
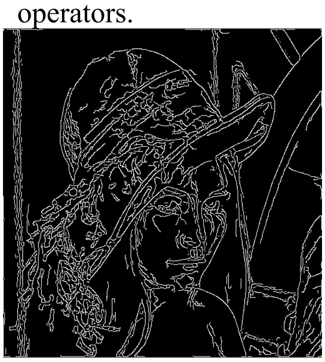
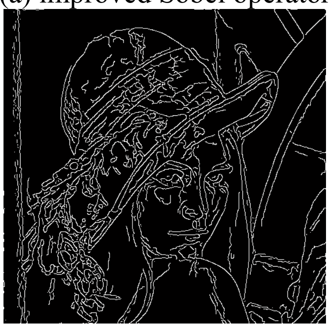


Figure 3. Edge images with various operators under noise.



(a) improved Sobel operator

(b) Prewitt operator



(c) 7*7 Gaussian gradientoperator

(d) 7*7 distance gradient operator

Figure 4. Edge images with various operators under noise.

4.3. Experiments on gradients in X and Y directions

For Lena images, the Gaussian gradient operator and the distance gradient operator are compared in the X and Y directions with or without Gaussian filtering.

The gradients in X and Y directions are obtained by using the Gauss gradient operator and the distance gradient operator proposed in this paper. The7*7 Gauss filter is adopted the right column in Figure 5, but the left column not. The7*7 Gaussian gradient operator is adopted the first two rows, and The7*7 distance gradient operator is adopted the last two rows.

It can be seen from the Figure.5:

Gauss *filter has a certain effect, but in comparison, Gauss filter has a greater impact on the Gauss gradient.*

Whether *Gauss filter is used or not, the gradients in X and Y directions obtained by the proposed operator are better than those by the Gauss gradient operator, and get fewer pseudo-edges.*

In other words, the operator decomposition is more powerful. For those images whose main edges are detected only in horizontal or vertical directions, the proposed method is obviously stronger than the Gaussian filtering method.

5. Field experiment and result analysis

In order to verify the validity of the gradient operator proposed in this paper, the images was collected from the ship "Huang Helou" in the field of the Yangtze River inland.

The experimental results had been shown, the graph (a), (b), (c) is the original image, under the framework of Canny algorithm, using the distance gradient operator to get (d), (e), (f) graph, using the Gaussian gradient operator to get (g), (h), (i) graph, using the [0 -1 0;-1 0 1;0 1 0] gradient operator to get (j), (k), (l) graph, using the [1 -1;1 -1]and[-1-1;1 1] operator to get (o), (p), (q) graphs.

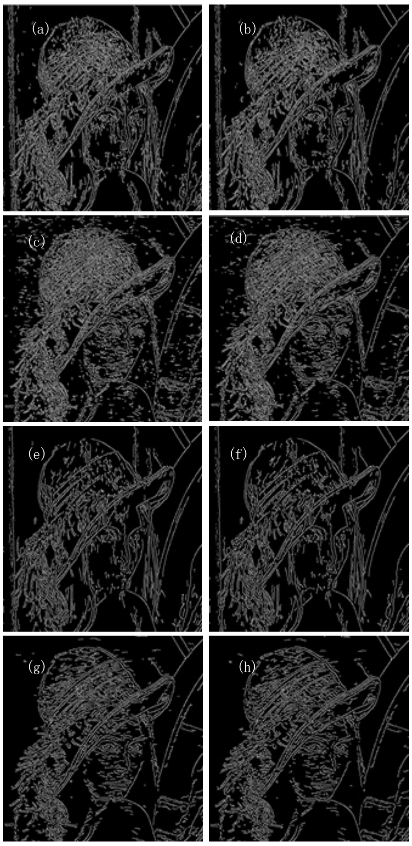


Figure 5. Gradient images with various operators in X and Y directions

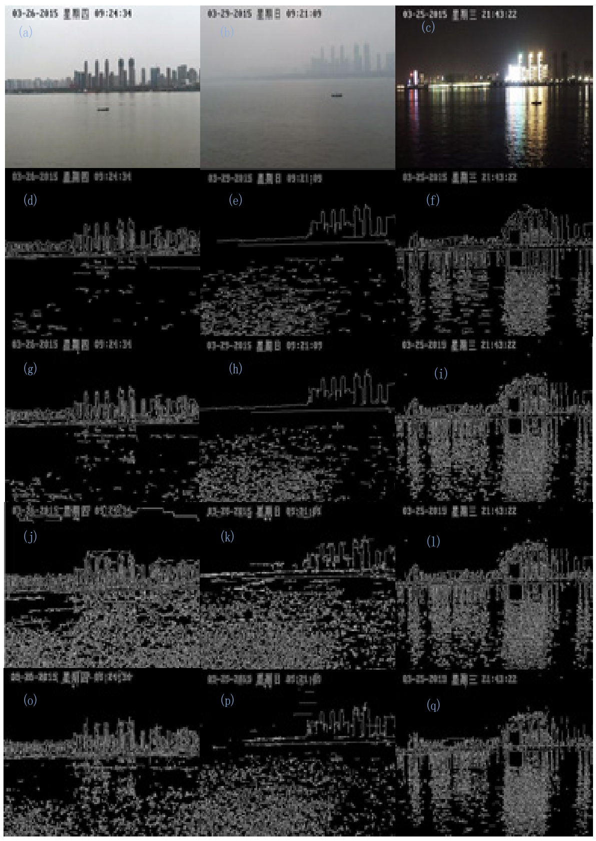


Figure 6. Field experiment result images

As can be seen from Figure.6, the distance gradient operator is superior to Gauss gradient operator and other gradient operators when the number of pseudo-boundary is taken as the evaluation criterion

6. Conclusion

In this paper, the defect of gradient calculation in Canny algorithm is deeply studied, and a gradient operator based on distance is proposed. Then, the performance of the gradient operator is compared with other gradient operators. Simulation results show that the proposed operator outperforms other operators under any noise conditions. Field experiments also show this conclusion. However, the proposed distance-based gradient operator cannot completely satisfy the rotation invariance of the gradient amplitude, which is the direction of further work.

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