International Journal of Hybrid Information Technology
Vol.8, No.10 (2015), pp.359-370
http://dx.doi.org/10.14257/ijhit.2015.8.10.33

An Improved Canny Edge Detection Algorithm

Yu Chen, Caixia Deng* and Xiaxia Chen

School of Applied Science, Harbin University of Science and Technology, Harbin150080, China
Email:dengcx2001@hotmail.com

Abstract

Aimed at the defects of the traditional Canny operator, this paper puts forward an improved algorithm in edge detection. First, this paper gives a new method on self-adaptive image block based on threshold value. Next, by proposing a new hybrid filter-bank of self-adaptive median and morphology, we adopt this hybrid filter-bank to smooth the noise image. Then, we add the information of gradient in two bevel directions, so that the information of gradient is more complete. Last, by using the threshold value to process the image of gradient which is after non-maxima suppression, we obtain the image edge. For the noise image, this improved algorithm not only can filter out noise well, but also the image edge is continuous, smooth, clear. The experimental results show that the improved algorithm has a good effect in edge detection, strong capability of noise immunity. The objective evaluation and visual effect are good, too.

Keywords: *edge detection, Canny operator, threshold, image block*

1. Introduction

Image edge is one of the most basic characteristics of image, which not only contains a large amount of information, but also is an important basis on image analysis and image segmentation. Therefore, image edge has a very broad application prospect [1-3].

Edge detection is widely used in image segmentation, image matching, feature extraction, and other fields. It is an important research of computer vision. In the classical methods of the edge detection, there are many first-order differential operators: Roberts operator, Prewitt operator, Sobel operator, etc. The second-order differential operators have: Log operator, Wallis operator, *etc*. These operators are simple, easy to implement and have a good real-time performance. But anti-noise performance of them is generally poor. It is difficult to detect the edge of the complex image [4]. Compared to traditional differential operators, the Canny operator based on the optimization algorithm is widely used because of good signal to noise ratio and the detection accuracy. Canny operator has become the evaluation criteria of other edge detection algorithms [5]. However, the choices of its filter parameter and hysteresis threshold value exist passive resistance, Canny operator also has some shortcomings in terms of real-time [6, 7]. On the basis of in-depth study of this algorithm, scholars mainly improved the algorithm in the following two aspects. First, improve the noise processing. For example, the literatures [8, 9] proposed the improved morphological filtering and bilateral filtering, but the results showed that they blurred the image, would not detect edge detail well, or would not filter out the noise well. Next, improve the choice of high and low threshold value. For example, the literatures [10-12] proposed the improved methods on choice of threshold value, but their results appeared the pseudo edge and losing the real edge. So they cannot achieve the good effect.

Two aspects of studies above have different defects. In order to improve the anti-noise ability of Canny operator and make the edge continuous, complete and without jagged, on the basis of choosing high and low threshold value adaptively and simultaneously in the literature [12], this paper proposes a new algorithm based on self-adaptive image block and hybrid filter-bank. Experimental results show that this algorithm is superior to the literatures [8-12].

2. Traditional Canny Edge Detection Algorithm

One of edge detection algorithms was proposed by John Canny in 1986, which is the Canny operator. John Canny converted the edge detection problem into receiving the maxima of unit function. He considered that a good operator of edge detection should have the following three features, good performance, fine positioning performance, and low frequency response for the same edge. Thus three criteria for the decision of the edge detection operator were proposed [13]: signal-noise ratio criteria, localization precision and unilateral response criteria. The achievement of Canny operator consists of four parts, smooth image, calculate the gradient magnitude and direction, non-maxima suppression, dual-threshold method for detecting and connecting edge.

1) Smooth image

Typically, Canny operator smoothes image by Gaussian filtering. Gaussian function is

$$G(x,y)=\frac{1}{2\pi\sigma^2}\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) \tag{1}$$

The smoothed image is

$$f_1(x,y)=G(x,y)*f(x,y) \tag{2}$$

Where σ is the parameter of Gaussian filtering. It controls the degree of de-noising. $f(x,y)$ is the original image.

2) Calculate the gradient magnitude and direction

Calculate the partial derivative of the smoothed image $f_1(x,y)$ in the directions of x and y by using the finite difference of the first order partial derivatives in the 2×2 neighborhood.

$$\begin{cases} p_x(x,y)=\left(f_1(x+1,y)-f_1(x,y)+f_1(x+1,y+1)-f_1(x,y+1)\right)/2 \\ p_y(x,y)=\left(f_1(x,y+1)-f_1(x,y)+f_1(x+1,y+1)-f_1(x+1,y)\right)/2 \end{cases} \tag{3}$$

After calculating the partial derivative in the directions of x and y, we use the two-norm to calculate gradient magnitude G and direction of gradient θ

$$G(x,y)=\sqrt{[p_x(x,y)]^2+[p_y(x,y)]^2} \tag{4}$$

$$\theta(x,y)=\arctan\left(p_x(x,y)/p_y(x,y)\right) \tag{5}$$

3) Non-maxima suppression

In order to obtain the single pixel edge of the image, the roof ridge of gradient magnitude image shall be refined. Detailed process: first iterate through the image, if the gradient magnitude $G(x,y)$ of the point (x,y) is not greater than the two adjacent interpolation in the direction of $\theta(x,y)$, the point (x,y) will be marked as non-edge point, otherwise marked as the edge point.

4) Dual-threshold algorithm detection and edge connection

In the histogram distribution of the gradient magnitude image after non-maxima suppression, the number of pixels is accumulated by the direction of increasing gradient magnitude. When the accumulated value reaches a certain percentage of the total number (like 80%), the corresponding gradient magnitude is a high threshold value. The half of the high threshold value is a low threshold value. In the gradient magnitude image which is after non-maxima suppression, if the gradient magnitude of one point is greater than the high threshold value, the point will be regarded as the edge. If the gradient magnitude of one point is less than the low threshold value, the point will be regarded as the background point, it will be deleted. If the gradient magnitude of one point is between the two threshold values and connects to the edge point, the point will be regarded as the edge, otherwise, it will be deleted. Then, judge the retention points whether they have edge pixels greater than the high threshold value in eight directions, if it is, it is edge point, otherwise, it considered as background point.

While traditional Canny operator is better than Sobel operator and Prewitt operator, etc. But it still has some deficiencies.

1) The traditional Canny operator smoothes the image by Gaussian filtering. σ is the parameter of Gaussian filtering. σ controls the degree of smooth de-noising. When σ is larger, Gaussian filtering is conducive to removal of noise, but it can cause the edge excessive fuzzy at the same time. When σ smaller, Gaussian filtering is cannot achieve the effect of de-noising. Because the σ value is fixed artificially in this algorithm, the detection results will appear overmuch pseudo edge and the true edge undetected for complex image with noise.

2) The traditional Canny operator needs to set the high and low threshold value artificially. It requires much prior experience. In order to find an appropriate threshold value, we need to test several times repeatedly. Threshold value set too high that may lead to the edge fractured and discontinuous, thereby lead to loss the information of the edge. Threshold value set too low that may lead to overmuch pseudo edge in the image of edge, even the noise may be extracted as the edge. The actual image is susceptible to light, scenes and other uncertainties, so the ratio of high and low threshold value can not be a fixed value in different images. Therefore, the traditional Canny operator is not adaptive on determining the threshold value.

3. Improved the Edge Detection Algorithm

3.1. Use Threshold for Image Block

A segmentation algorithm was put forward based on the maximum between-class variance by Otsu in 1979, which has been considered the best method for selecting the segmentation threshold value automatically [14]. The basic idea is to make the image pixels into two types. One is the background and the other is objective. By searching and computing the maximum between-class variance, then we obtain the optimal threshold value.

Suppose that N is the total pixels in the image. $[0, L-1]$ is gray-level range. N_i is the number of pixels corresponding to the gray-level i. Its probability is $p_i = N_i / N$ $(i = 0,1,2,\cdots, L-1)$. The gray mean of the whole image is $\mu = \sum_{i=1}^{L-1} i * p_i$.

The background is comprised of the pixels whose grays are between the $[0, T]$. The objective is comprised of the pixels whose grays are between the $[T+1, L-1]$. The gray means of the background and objective are shown as

$$\mu_b(T) = \frac{\sum_{i=0}^{T} i * p_i}{\omega_b(T)}, \qquad \mu_o(T) = \frac{\sum_{i=T+1}^{L-1} i * p_i}{\omega_o(T)}.$$

Where $\omega_b(T) = \sum_{i=0}^{T} p_i$, $\omega_o(T) = \sum_{i=T+1}^{L-1} p_i$, $\omega_b(T) + \omega_0(T) = 1$.

Between-class variance of the background and objective is defined as

$$\sigma^2(T) = \omega_b(T) * [\mu_b(T) - \mu]^2 + \omega_o(T) * [\mu_o(T) - \mu]^2 \tag{6}$$

Let T take values successively in the range of $[0, L-1]$. The best threshold value of Otsu algorithm is the T value, which makes $\sigma^2(T)$ maximum, then the optimal threshold value.

Since the gray scale distributes unevenly in different parts of the entire image, some portions may have many details, and some portions appear slightly simple. However, the traditional Canny edge detection algorithm uses the same pair of high and low threshold value to detect the entire image, which results in the edge information too rich in the relatively flat areas and unable to detect the edge detail in the areas where have too rich information of the edge.

According to the problems above, this paper will split image adaptively based on the threshold value. It is that to split an image into a number of appropriate sub-regions, next we process each of sub-region separately, then combine with the results of processing to obtain the global information of the entire image. Image block not only can compress the amount of data, to reduce the storage space, but also can improve the speed, to reduce the workload of the subsequent analysis and processing. When using the improved Canny operator for edge detection on each sub-image, the detection results better reflect edge characteristics certainly in the sub-region, and the geometric feature information of each sub-region is intact. The contrast is basically in line on each sub-region, and the ability of de-noising is strong. Image block can guarantee to achieve higher detection accuracy, *etc*. Therefore, the detection results will not lose the detail of the real edge, will not also produce pseudo edge.

In order to make the edge continuous, there are some overlaps between the sub-blocks in this paper. The specific segmentation algorithm is as follows.

Step 1. Divide the object of processing (m, n) into four parts with a certain overlapping. The size of minimum block is $\overline{m} \times \overline{n}$ of the four parts, if $\min(\overline{m}, \overline{n}) < size_{\min}$, then the end, otherwise continue.

Step 2. Use Otsu method to calculate the threshold value T_i $(i = 1,2,3,4)$ of each block, then determine the maximum threshold value $T_{\max}$ and minimum threshold value $T_{\min}$ of the four thresholds.

Step 3. Calculate $\Delta T = T_{\max} - T_{\min}$, if $\Delta T > bt$, it is one effective segmentation. So we divide the object of processing into four parts. Then each block sees as a new object of processing, and to do step 1.

Where $size_{\min}$ is the lowest limit value of each block size. bt is block threshold, which describes the degree of splitting.

3.2. A New Hybrid Filter-bank About Adaptive Median and Morphology

When adopting the Gaussian smoothing filtering or the smoothing filtering which was put forward in the literatures [8, 9] for edge detection, the results of detection show that they would not filter out noise extremely, or the edge appeared fuzzy, discontinuous and jagged. In order to overcome these shortcomings, it is necessary to improve the existing smoothing filtering. So this paper proposes a new hybrid filter-bank about self-adaptive median and morphology.

Mathematical morphology filtering is an important nonlinear filtering emerging in recent years. By using its geometric features and algebraic properties, morphological filtering has been widely used in shape recognition, edge detection, texture analysis, image restoration and enhancement, and other fields. Morphological filtering uses the open and close operations for filtering mainly.

Assume that $f(x,y)$ is the input gray image. $s(x,y)$ is a structural element. D_f and D_s are the domains of function $f(x,y)$ and $s(x,y)$ respectively. For the morphology, the definition of dilation, erosion, open and close are shown as follows.

Definition 1 The dilation operation is

$$(f \oplus s)(x,y) = \max\left\{f(x-x_1, y-y_1) + s(x_1,y_1) \middle| x-x_1, y-y_1 \in D_f, x_1, y_1 \in D_s\right\}$$

Definition 2 The erosion operation is

$$(f \Theta s)(x,y) = \min\left\{f(x+x_1, y+y_1) - s(x_1,y_1) \middle| x+x_1, y+y_1 \in D_f, x_1, y_1 \in D_s\right\}$$

Definition 3 The open operation is

$$f \circ s = (f \Theta s) \oplus s$$

The open operation is erosion followed by dilation. It can smooth the contour of image and remove small extrudes.

Definition 4 The close operation is

$$f \bullet s = (f \oplus s) \Theta s$$

The close operation is dilation followed by erosion. It can smooth the image outline and pad the holes and cracks.

The close operation of morphology can fill the small space, connect to nearby objects and smooth the boundary. The image's overall position and shape do not change. The close operation filters image by filling the re-entrant angle of image. The open operation of morphology removes the small bulges. It separates objects in the tiny place and smoothes outline of image. The image's overall position and shape do not change, too. The open operation of morphology is a filtering based on geometric calculation. As the effect of the morphology for image processing is not only related to morphological transformation way, but also related to the selection of structural elements. We can combine morphological transformation mode with structure elements to constitute a multi-structure element composite filtering. It is

$$\hat{f}_1 = \left((f \circ s_1 \bullet s_2) + (f \bullet s_1 \circ s_2)\right)/2 \tag{7}$$

Where f is the input gray image. s_1 and s_2 are structural elements.

However, the de-noising ability of small-scale structural elements is weak, but it can maintain image detail well. The de-noising ability of large-scale structural elements is strong, but it will blur image detail. So this paper needs to use other ways to improve. The adaptive median filtering can choose different operations to perform depending on the circumstances of local neighborhood. It can also process the noise and image signal by using different methods. Self-adaptive median filtering uses median filtering for noise point, and keeps the same gray-values for the signal points. This method filters out serious noise effectively, and maintains image detail well.

Assume that $f(x,y)$ is the gray of the pixel at the point (x,y). $B(x,y)$ is the gray window. $f_{\max}$, f_{med}, $f_{\min}$ are the maximum, median, minimum of gray. $B_{\max}$ is the allowable largest window.

Implementation of self-adaptive median filtering is as follows.

Step 1. If $f_{\min} < f_{med} < f_{\max}$, then go to step 2. Else increase the size of the window $B(x,y)$. If the size of $B(x,y)$ less than $B_{\max}$, step 1 again. Else output $f(x,y)$.

Step 2. If $f_{\min} < f(x,y) < f_{\max}$, then output $f(x,y)$. Else output f_{med}.

Therefore, this paper adopts hybrid filter-bank which is composed of self-adaptive median filtering and morphology composite filtering with small structural elements to smooth the image.

The hybrid filter-bank is

$$\tilde{f}_1 = \left((M \circ s_1 \bullet s_2) + (M \bullet s_1 \circ s_2)\right)/2 \tag{8}$$

Where M is the image after the self-adaptive median filtering. s_1 and s_2 are 3×3 structural elements with different shapes.

Thus, the improved hybrid filter-bank not only retains the image detail, but also eliminates the image noise effectively.

3.3. Calculate the Gradient Magnitude

The traditional Canny operator only extracts the information of gradient about x direction and y direction in the 2×2 neighborhood. So it is more sensitive to noise and loses some important information of edge, especially some information on the bevel edge. We can calculate the gradient in the 3×3 neighborhood, and extract the information of gradient in the directions of two bevels to enrich the information. Therefore, we integrate the information of gradient in the directions of two bevels and the information of gradient in the directions of x and y finally [15].

The information of gradient in the four directions is obtained by using four convolution templates (Figure 1) to weighted average.

x Direction

1	0	−1
2	0	−2
1	0	−1

y Direction

1	2	1
0	0	0
−1	−2	−1

45° Direction

0	1	2
−1	0	1
−2	−1	0

135° Direction

−2	−1	0
−1	0	1
0	1	2

Figure 1. The Convolution Template

The corresponding partial derivatives respectively are

$$\tilde{p}_x(x,y)=\tilde{f}_1(x-1,y+1)+2\tilde{f}_1(x,y+1)+\tilde{f}_1(x+1,y+1)-\tilde{f}_1(x-1,y-1) \\ -2_1\tilde{f}_1(x,y-1)-\tilde{f}_1(x+1,y-1) \tag{9}$$

$$\tilde{p}_y(x,y)=\tilde{f}_1(x+1,y-1)+2\tilde{f}_1(x+1,y)+\tilde{f}_1(x+1,y+1)-\tilde{f}_1(x-1,y-1) \\ -2_1\tilde{f}_1(x-1,y)-\tilde{f}_1(x-1,y+1) \tag{10}$$

$$\tilde{p}_{45^\circ}(x,y)=\tilde{f}_1(x,y-1)+2\tilde{f}_1(x+1,y-1)-\tilde{f}_1(x-1,y)+\tilde{f}_1(x+1,y) \\ -2\tilde{f}_1(x-1,y+1)-\tilde{f}_1(x,y+1) \tag{11}$$

$$\tilde{p}_{135^\circ}(x,y)=2\tilde{f}_1(x-1,y-1)+\tilde{f}_1(x,y-1)+\tilde{f}_1(x-1,y)-\tilde{f}_1(x,y+1) \\ -2\tilde{f}_1(x+1,y+1)-\tilde{f}_1(x+1,y) \tag{12}$$

Where $\tilde{f}_1$ is the filtered image that is given by formula (8).

The gradient magnitudes of bevel directions and x and y direction are

$$\tilde{G}(x,y)=\left(\tilde{p}_x^2+\tilde{p}_y^2\right)^{\frac{1}{2}} \tag{13}$$

$$G_2(x,y)=\left(\tilde{p}_{45^\circ}^2+\tilde{p}_{135^\circ}^2\right)^{\frac{1}{2}} \tag{14}$$

Suppose that G_1 is the gradient magnitude image after processing the $\tilde{G}$ by non-maxima suppression. G_2 is the gradient magnitude image that is extracted from the bevel directions. $G_3 = \max\{G_1, G_2\}$ is the gradient magnitude image after the comprehensive.

3.4. Improved Algorithm Process

This paper splits image adaptively based on the Otsu threshold value, then adopts the new hybrid filter-bank about self-adaptive median and morphology to remove the noise for getting more edge details. We use the improved Canny operator for edge detection. The implementation steps are as follows.

Step 1. Split the noise image adaptively based on the Otsu threshold value.

Step 2. Adopt the new hybrid filter-bank to remove the noise of each sub-image. Then the filtered sub-image is obtained.

Step 3. Calculate the gradient magnitude image $\tilde{G}_i$ of the filtered sub-images in the directions of x and y. Then $\tilde{G}_i$ is made non-maxima suppression to get images G_{1i}. At the same time, we extract gradient magnitude image G_{2i} of bevel directions.

Step 4. Get $G_{3i} = \max\{G_{1i}, G_{2i}\}$.

Step 5. Process G_{3i} based on dual-threshold that was proposed in literature [12] to obtain the final edge E_i of sub-image.

Step 6. Connect E_i into a complete image E.

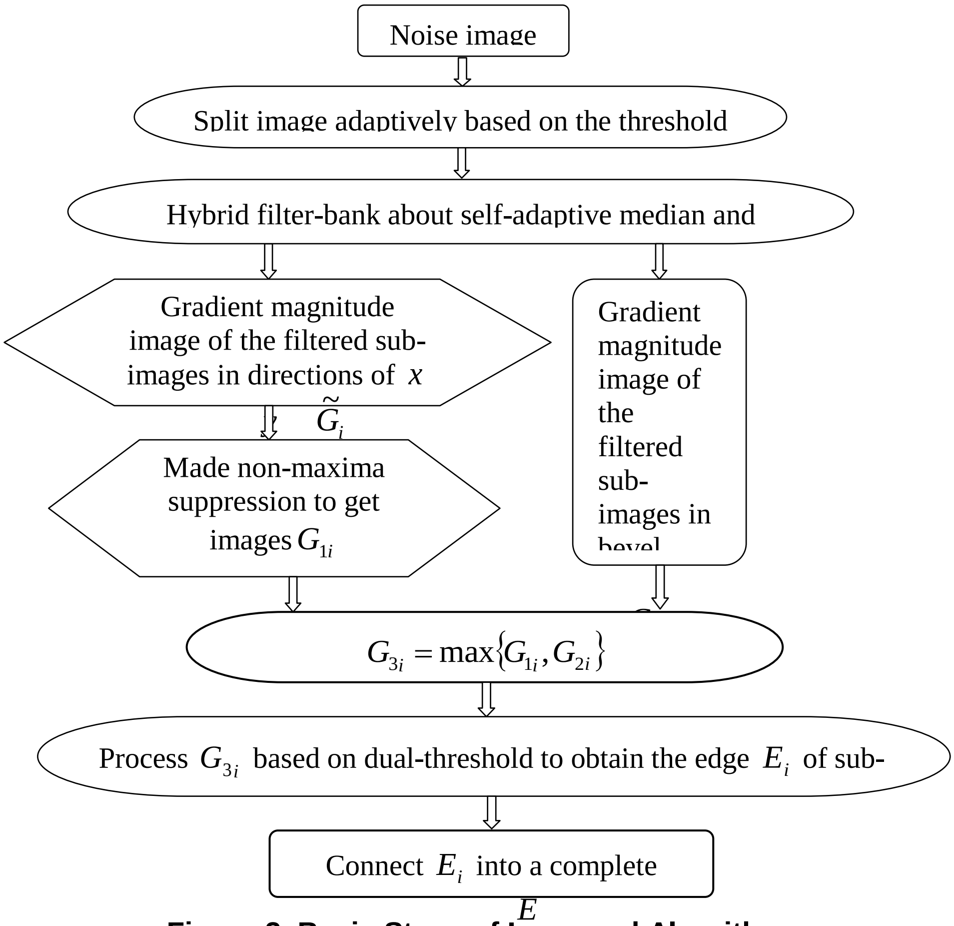
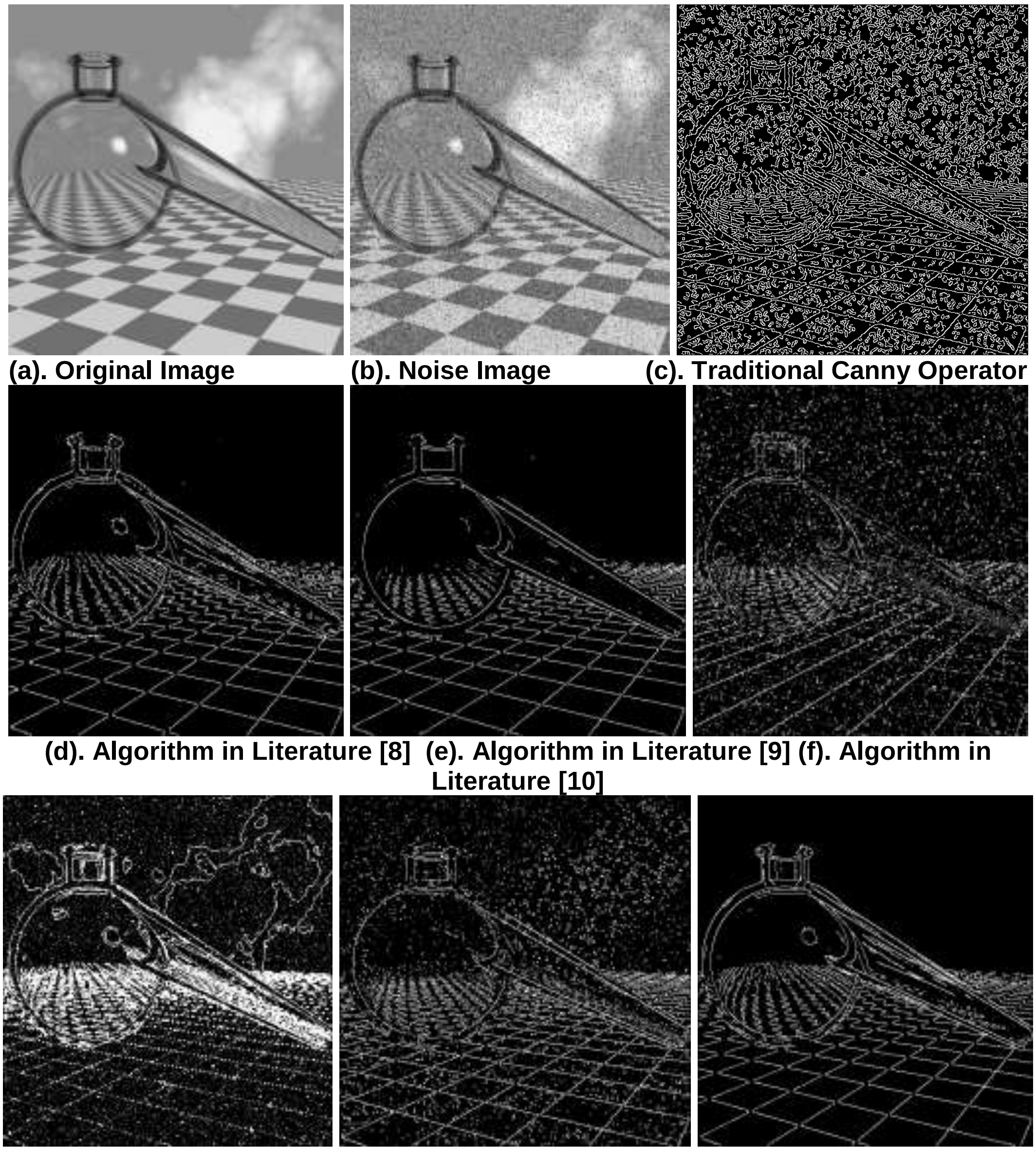


Figure 2. Basic Steps of Improved Algorithm

4. The Results and Analysis of Simulation

In order to verify the feasibility of the algorithm in this paper, we add 'salt and pepper' noise with density of 0.1 into the images of bottle, man, watch and flower. Then we use the traditional Canny operator, the algorithms in literatures [8-12] and the improved algorithm in this paper to detect the edge of the noise images. The results of detection are shown in Figures 3-6. From the analysis of simulation results, we can see that traditional Canny operator is susceptible to noise. The algorithms can filter out the noise well in literatures [8, 9], but the detection results appear jagged edge and losing the information of the edge. For example, the edge of the bottle's neck is discontinuous, the edges of the man's hand and coat buttons and distant buildings are missing, and the edge of watch's line at the upper lift is missing, *etc*. The algorithms can make the edge continuous in literatures [10-12], but can not filter out the noise completely. The improved algorithm not only filters out the noise well, but also retains the edge continuous, complete and no jagged in this paper.



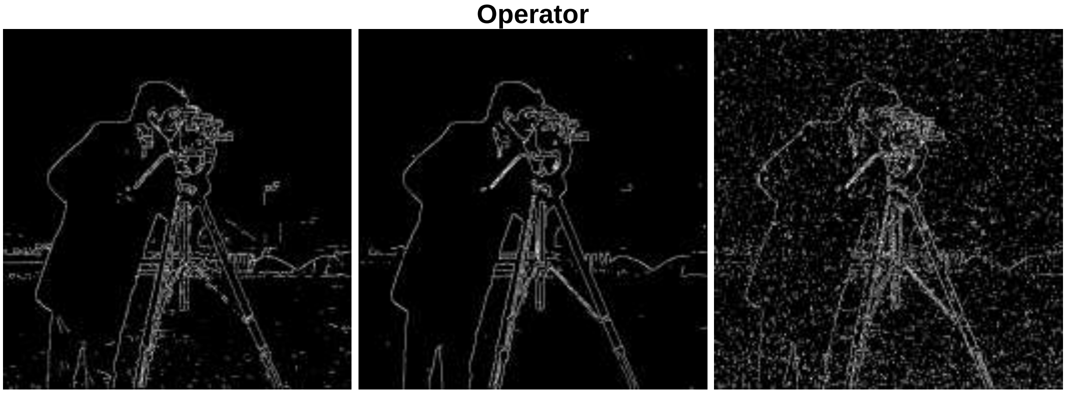
(a). Original Image (b). Noise Image (c). Traditional Canny Operator

(d). Algorithm in Literature [8] (e). Algorithm in Literature [9] (f). Algorithm in Literature [10]

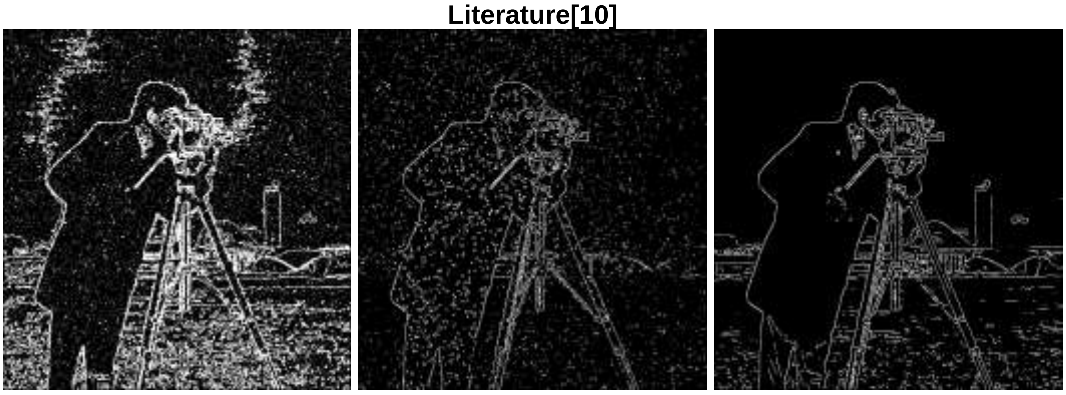
(g). Algorithm in Literature[11] (h). Algorithm in Literature[12] (i). Algorithm in This Paper

Figure 3. Edge Detection Results of Bottle Image

(a). Original Image **(b). Noise Image** **(c). Traditional Canny Operator**

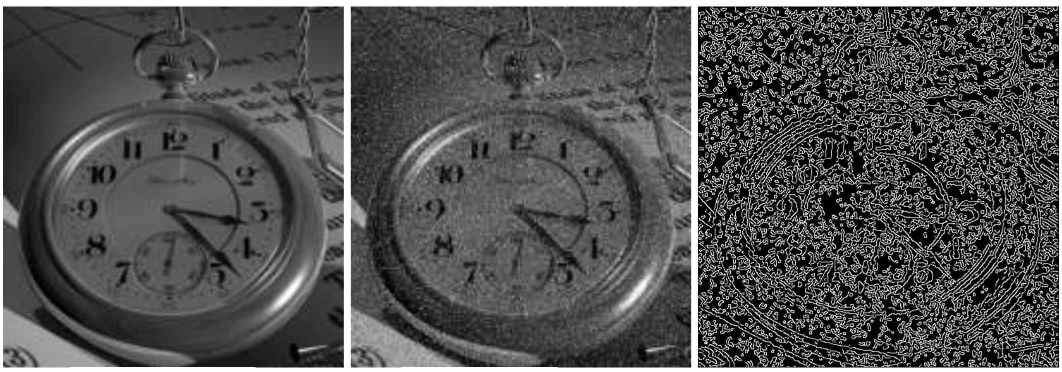


(d). Algorithm in Literature[8] **(e). Algorithm in Literature[9]** **(f). Algorithm in Literature[10]**

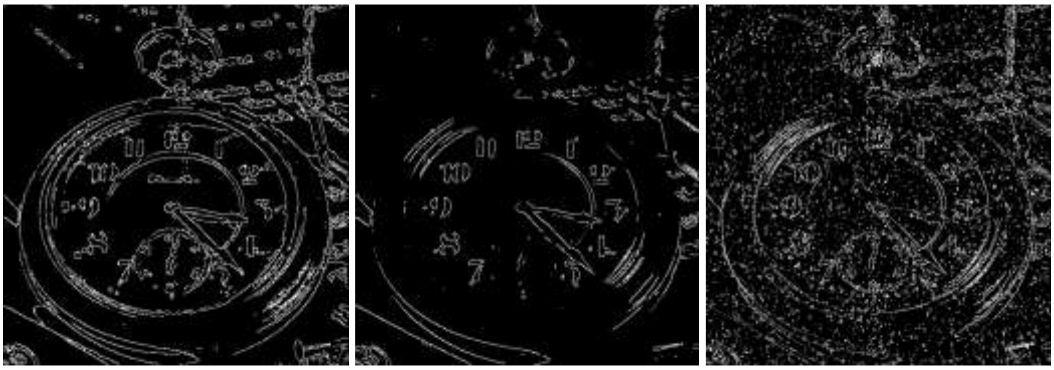


(g). Algorithm in Literature[11] **(h). Algorithm in Literature[12]** **(i). Algorithm in This Paper**

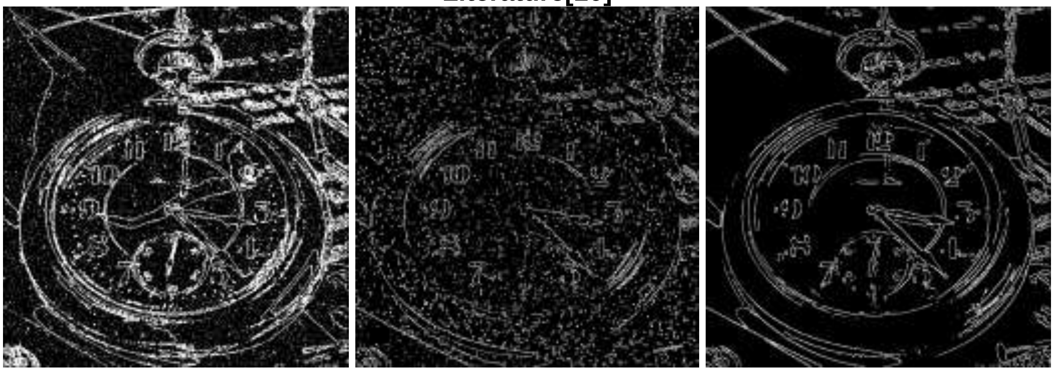
Figure 4. Edge Detection Results of Man Image



(a). Original Image **(b). Noise Image** **(c). Traditional Canny Operator**

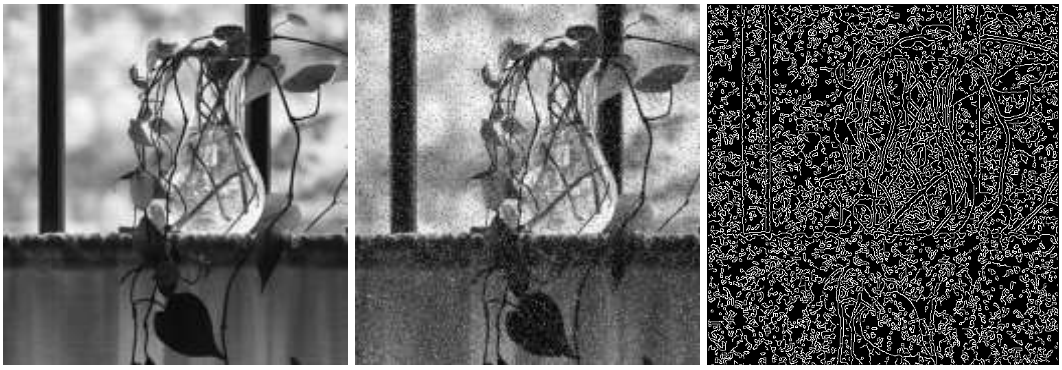


(d). Algorithm in Literature[8]   (e). Algorithm in Literature[9]   (f). Algorithm in Literature[10]

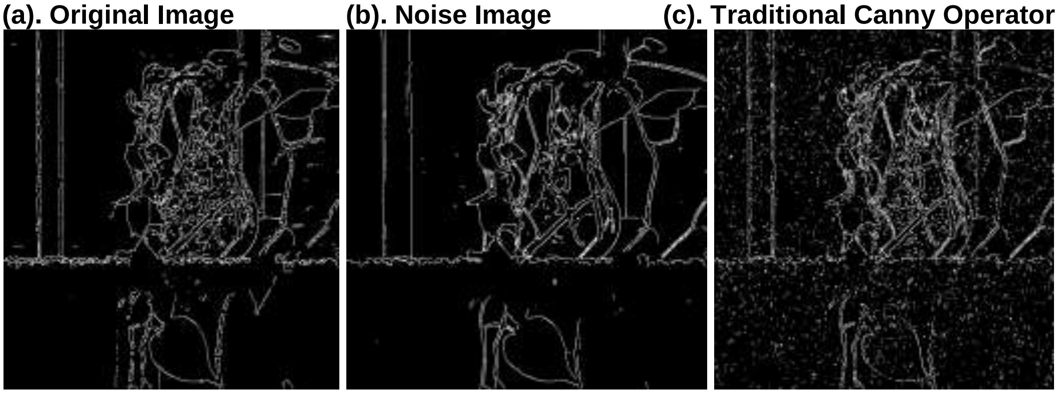


(g). Algorithm in Literature[11]   (h). Algorithm in Literature[12]   (i). Algorithm in This Paper

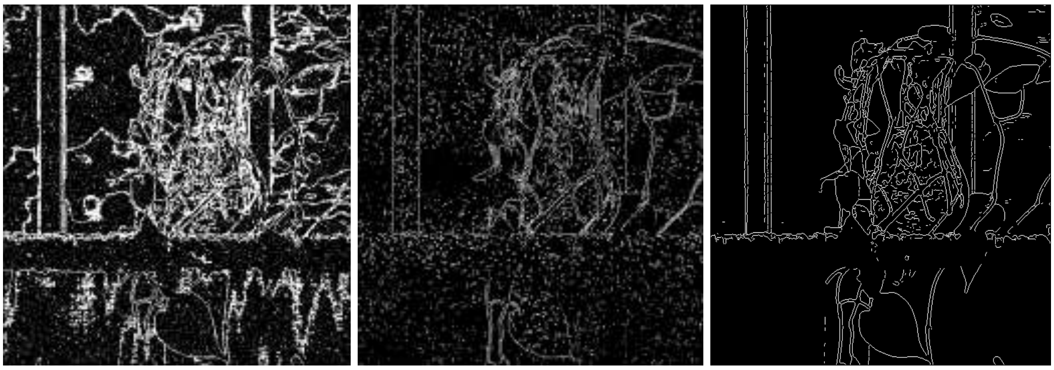
Figure 5. Edge Detection Results of Watch Image



(a). Original Image   (b). Noise Image   (c). Traditional Canny Operator



(d). Algorithm in Literature[8]   (e). Algorithm in Literature[9]   (f). Algorithm in Literature[10]



(g). Algorithm in Literature[11] (h). Algorithm in Literature[12] (i). Algorithm in This Paper

Figure 6. Edge Detection Results of Flower Image

In order to evaluate the effect of improved algorithm more objectively and effectively in this paper, we use the MSE (Mean Square Error) and PSNR (Peak Signal to Noise Ratio) as evaluation standards. The results are shown in Table 1 and Table 2.

Table 1. The Comparison of MSE in Six Algorithms

MSE	bottle	man	watch	flower
Algorithm of Literature [8]	24884	18327	8956.1	19396
Algorithm of Literature [9]	24930	18159	7661.4	19050
Algorithm of Literature [10]	25233	18480	9424.1	19600
Algorithm of Literature [11]	23734	18001	7090.9	18993
Algorithm of Literature [12]	24368	18806	9460.4	19550
Algorithm of This Paper	21944	17833	6904.1	18832

Table 2. The Comparison of PSNR in Six Algorithms

PSNR	bottle	man	watch	flower
Algorithm of Literature [8]	4.1716	5.5236	8.6142	5.3214
Algorithm of Literature [9]	4.1636	5.5400	9.2877	5.4217
Algorithm of Literature [10]	4.1111	5.4637	8.3884	5.2752
Algorithm of Literature [11]	4.2771	5.5784	9.6304	5.4311
Algorithm of Literature [12]	4.2327	5.3998	8.2741	5.3093
Algorithm of This Paper	4.4611	5.6186	9.7397	5.4838

From the Table 1 and Table 2, they show that the data of this paper are superior to literatures [8-12] in these two indicators of MSE and PSNR.

Consequently, the improved algorithm has a very good effect in visual and objective evaluation aspects in this paper.

5. Conclusions

Edge detection is an important research subject in image processing and computer vision, Canny operator is a kind of more effective method of image processing. Aiming at the shortcomings of the traditional Canny operator, this paper puts forward a new algorithm for image block and a new hybrid filter-bank. Experimental results show that this algorithm can suppress the influence of a variety of noises on edge detection effectively, it can also detect the detailed information of image edges preferably, and the detected edges are continuous and complete. The algorithm in this paper is superior to the literatures [8-12], which is more conducive to the image analysis and processing.

ACKNOWLEDGEMENTS

The paper is supported by Science and Technology Research Project of Heilongjiang Province Education Department (No.12531100).

References

[1] P. Gaur and S. Tiwari, "Recognition of 2D Barcode Images Using Edge Detection and Morphological Operation", International Journal of Computer Science and Mobile Computing, vol. 3, no. 4, **(2014)**, pp. 1277-1282.
[2] D. L. Naidu, C. H. S. Rao and S. Sureshchandra, "A Hybrid Approach for Image Edge Detection Using Neural Network and Particle Swarm Optimization", Advances in Intelligent Systems and Computing, vol. 337, **(2015)**, pp. 1-9.
[3] Y. Ling, Z. Zhi-Ming, L. Guo-hong and L. De-yang, "Mist Image Processing Method of Basing on Multi-scale Edge Extraction", Journal of Harbin University of Science and Technology, vol. 19, no. 5, **(2014)**, pp. 94-98.
[4] D. Cai-Xia, Y. Yin, M. Wei-Feng and J. Wei, "Edge Detection Based on Improved LOG Operator and Wavelet Transform", Journal of Harbin University of Science and Technology, vol. 17, no. 5, **(2012)**, pp. 87-90.
[5] R. Medina-Carnicer, R. Muñoz-Salinas and E Yeguas-Bolivar, "A Novel Method to Look for the Hysteresis Thresh-olds for the Canny Edge Detector", Pattern Recognition, vol. 44, no. 6, **(2011)**, pp. 1201-1211.
[6] X. Li-Xia, L. Tao and W. Zuo-Cheng, "Adaptive Canny Edge Detection Algorithm", Application Research of Computers, vol. 27, no. 9, **(2010)**, pp. 3588-3590.
[7] W. Wei-Xing, W. Li-Ping and Y. Zhi-chao, "Edge Detection Algorithm of Canny Based on Maximum between-class Posterior Probability", Journal of Computer Applications, vol. 29, no. 4, **(2009)**, pp. 962-965.
[8] W. Zuo-Cheng, L. Xiao-Dong and X. Li-Xia, "Improved Method of Canny Operator Edge Detection", Computer Engineering and Applications, vol. 46, no. 34, **(2010)**, pp. 202-204.
[9] Q. Xiao-Wei and C. Xiu-Hong, "Bilateral Filtering Approach to Edge Detection Based on Modified Otsu", Computer Engineering and Applications, vol. 48, no. 31, **(2012)**, pp. 150-155.
[10] Z. Ping, Y. Wen-Jun, X. Yao-Jie and W. Qi, "An Improved Canny Algorithm for Edge Detection", Journal of Computational Information Systems, vol. 7, no. 5, **(2011)**, pp. 1516-1523.
[11] A. Mohamed, "A New Algorithm Based Entropic Threshold for Edge Detection in Images",, International Journal of Computer Science Issues, vol. 8, no. 1, **(2011)**, pp. 71-78.
[12] T. Lu-Lu, Z. Qi-Can and H. Song, "An Improved Algorithm for Canny Edge Detection with Adaptive Threshold", Opto-Electronic Engineering, vol. 38, no. 5, **(2011)**, pp. 127-132.
[13] W. Xiao-Hua and Q. Yue-Jing, "An Improved Canny Edge Detection Algorithm", Mechanical & Electrical Engineering Magazine, vol. 25, no. 12, **(2008)**, pp. 60-63.
[14] N. Otsu, "A Threshold Selection Method from Gray-level Histogram", IEEE Transactions on system Man Cybernetics(S1083-4419), vol. 9, no. 1, **(1979)**, pp. 62-66.
[15] D. Cai-Xia, W. Gui-Bin and Y. Xin-Rui, "Image Edge Detection Algorithm Based on Improved Canny Operator", Proceedings of the 2013 International Conference on Wavelet Analysis and Pattern Recognition, **(2013)** July 14-17, Tianjin, China.

