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# Canny Optimization Algorithm Based on Improved Anisotropic Diffusion Function Filtering

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### *Abstract*

*Image edge detection is an important part of image processing, and the effect of edge detection is also directly affected by image analysis, recognition and understanding. Canny operator is the most commonly used image edge detection operator. However, this operator has some limitations. The traditional Canny operator uses Gaussian filtering which may bring problems such as missing edge information and false edge. Besides, the selection of high and low thresholds of the traditional Canny operator are not accurate, and cannot be carried out by self-adaption. In order to solve these problems, this paper presents an optimized algorithm for Canny operator. In this paper, an improved anisotropic diffusion function is used to filter the image, and the improved filtering not only reduces the noise, but also maintains the edge information of the image. Additionally, this paper has improved the maximum between-class variance method (OTSU) to select the high and low thresholds of Canny operator by self-adaption. The improved algorithm is applied to edge detection of various images, and the results indicated that the improved Canny operator is effective in reducing noise and extracting edge.*

***Keywords**: Image edge detection, Canny, P-M model*

## 1. Introduction

Image edge is important featured information of the texture, which is also the basis of shape feature analysis. Therefore, edge detection is the important part of digital image processing, and it is also the key and difficult point in the image analysis and computer vision field. In order to extract edge, many scholars propose many kinds of edge detection operator such as Roberts operator, Sobel operator, Prewitt operator, Krisch operator, Laplacian operator and LoG-Laplacian operator. Canny operator is one of the most classical operators, and is widely used. However, the traditional Canny operator has a lot of limitations. Many domestic and foreign scholars have carried out a lot of improved methods on the Canny operators. Wojciech Mokrzycki [1], *et al*. have a paper about the Canny operator. In this paper the novel modification of the well-known Canny edge detection algorithm is presented. But, it does not effectively filter the noise and increase edge information. Xiaoju Ma [2], *et al*. improved the parameter Sigma and the method to obtain high threshold. The improved algorithm has the advantage of low computational complexity, less calculation time. But, this method does not have strong noise-restrain ability. In order to solve the above mentioned problems, this paper proposes an optimized algorithm for Canny image edge detection based on an improved anisotropic spread filtering function. By using the improved anisotropic

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spread filtering function to replace the Gaussian filtering for smoothing the image, the edges are kept during the filtering, and with the improved maximum between-class variance method, the selection of the high and low thresholds of the Canny operator could be conducted through self-adaption. The results of the experiment indicated that the optimized algorithm can improve the filtering effect of the Canny operator, thus improving the precision and accuracy of edge detection.

## 2. The Traditional Edge Detection Algorithm of Canny Operator

A new edge detection algorithm, called Canny operator, is proposed in 1986 by John Canny. Canny turned the problem of edge detection into a problem of detecting the maximum value of the unit function. Frankly speaking, Canny operator is an excellent detection operator for edges. The steps of traditional edge detection algorithm with Canny operator is as following [3]:

Step 1: Using the Gaussian filtering to smooth the image. The algorithm of edge detection is mainly based on the first derivative and second derivative of the image intensity. However, the derivatives are generally sensitive to the noise, thus the performance of the edge detector with the noise related to the filter must be improved. The commonly used filtering method is Gaussian filtering, firstly using the discrete filter function to generate a set of normalized Gaussian kernels, then calculating the weighed sum of each point in the gray matrix image based on Gaussian kernel function. The Gaussian filtering of the image can be implemented by double weighing two 1D Gaussian kernels, or a convolution of a 2D Gaussian kernel. Formula 1 is the 2D discrete Gaussian function, and the vector of the 2D kernel can be obtained by substituting with specific parameters.

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

Here, $\sigma$ is a parameter of the Gaussian filter which controls the smoothness level. Assume $g(x, y)$ is the smoothed image, then the smoothness of $f(x, y)$ by $G(x, y)$ could be formulated as:

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

Step 2: Using the finite difference of the first partial derivative to calculate the amplitude and direction of the gradient. The gradient of smoothed the image $g(x, y)$ is calculated by the approximate expression of the finite difference of the first partial derivative in the $2 \times 2$ domain. The arrays $f_x^{'}(x, y)$ and $f_y^{'}(x, y)$ of partial derivative *x* and *y* are expressed respectively as:

$$f_x^{'}(x, y) \approx G_x = [f(x+1, y) - f(x, y) + f(x+1, y+1) - f(x, y+1)]/2 \tag{3}$$

$$f_y^{'}(x, y) \approx G_y = [f(x, y+1) - f(x, y) + f(x+1, y+1) - f(x+1, y)]/2 \tag{4}$$

$$G(x, y) = \sqrt{G_X^2(x, y) + G_y^2(x, y)} \tag{5}$$

$$\theta(x, y) = \arctan\left(\frac{G_x(x, y)}{G_y(x, y)}\right) \tag{6}$$

Step 3: Conducting non-maximum suppression on the amplitude of the gradient. It's not a sufficient condition to identify the edges by the overall gradient itself. Therefore, to identify the edges, it's a must to keep the maximum point in the partial gradient and suppress the non-maximums. At each point, comparing the center pixel M of the neighboring regions with two pixels along with the gradient line, if the gradient value of M is smaller than the gradient value of the two pixels along with the gradient line, then M=0, otherwise, M=1.

Step 4: Using dual thresholds algorithm to detect and connect the edges. In the dual thresholds algorithm, set the two thresholds as $T_h$ and $T_l$ for the image with suppression on non-maximums, and $T_l \approx 0.4 T_h$. An edge image will be obtained based on the high threshold, which rarely has false edge. Using the high threshold to obtain the profile of the edge, then at each breaking point, the algorithm will search for a point which meets the low threshold among the neighboring eight points, then start from that point to search for the new edge. Above process will be repeated again and again till the whole image edge is closed.

The traditional Canny operator utilizes the Gaussian function to smoothing filter the image, which may cause the image excessive smoothness to cause the edge loss [4]. Furthermore, when using the dual thresholds algorithm to detect and connect the edge, it's a common problem that the thresholds are unreasonable, when the thresholds are not able to be selected by self-adaption. A higher threshold value may cause important edge information to be missed, while a lower threshold value is not capable of suppressing the noise. A satisfactory effect is hard to implement using this method. Therefore, this paper deeply studies the problems which limit the performance of Canny operator, and proposes an improved method.

## 3. Improved Canny Edge Detection Optimization Algorithm

### 3.1. Improved Anisotropic Diffusion Function Filtering

In the traditional Canny algorithm, Gaussian filtering is used for filtering. The main purpose of the image smoothing filter is to enlarge the Signal to Noise Ratio (SNR) [5] and eliminate noise. However, excess smoothness may occur during the Gaussian smoothing for the image. The edge will be smoothed as a high frequency element, which will turn some edges into slow-changing edges. The slow-changing edges will then disappear during the non-maximum suppression. In 1990, Perona and Malik presented the Anisotropic Diffusion Model [6], which can excellently smooth the image and eliminate noise while keeping the edge features of the image.

Assume $u_0(x, y)$ is the original gray image, *i.e.* the initial condition. After time variable t been introduced, the change of the image could be expressed as a partial differential function [6]:

$$\begin{cases} \dfrac{\partial u(x, y, t)}{\partial t} = div\left[c(x, y, t)\right]\nabla u \\ u\,|_{t=0} = u_0 \end{cases} \tag{7}$$

Here, $\nabla$ is the gradient operator, $div$ is the divergence operator, and $c(x, y, t)$ refers to the diffusion coefficient. Assuming $c(x, y, t) = g(|\nabla u|)$, $|\nabla u|$ would be the gradient amplitude. Then, the Formula 7 can be rewritten as:

$$\begin{cases} \dfrac{\partial u(x, y, t)}{\partial t} = div\left[g(|\nabla u|)\right]\nabla u \\ u\,|_{t=0} = u_0 \end{cases} \tag{8}$$

This partial differential equation can be regarded as a kind of medium in the definition domain of the original image $u_0$, which diffuses across the image with variable speed, and forms a series of smoothed images $u_t$ with its diffusing traces. The diffusion function $g(x)$ determines the diffusion level, which is a non-negative decreasing monotone function and meets the condition that if $g(0) = 1$, when $x \to \infty, g(x) \to 0$. Thus, the diffusion of the image will stop at the edges to safeguard the edge information.

Here are the functions of the two diffusion coefficients $g(x)$ in the P-M model:

$$g(x) = e^{-\left(x/k\right)^2} \tag{9}$$

$$g(x) = \frac{1}{1 + \left(x/k\right)^2} \tag{10}$$

Where, constant k can be preset. When k=1, the functions of the two $g(x)$ are shown as Figure 1:

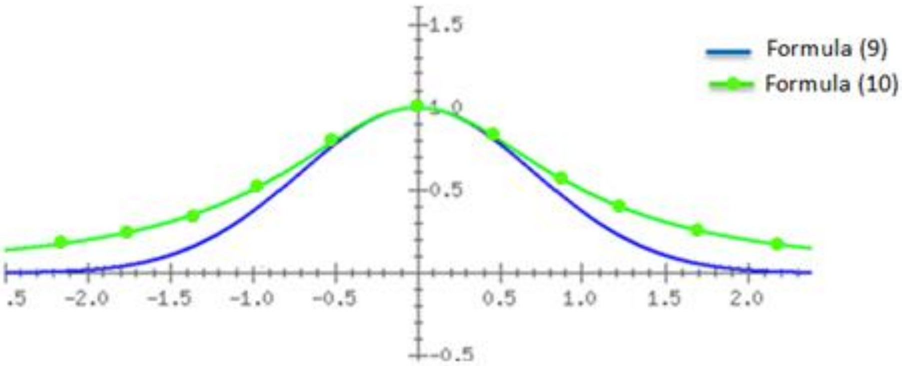



**Figure 1. Two Diffusion Coefficients $g(x)$ in the p-m Model**

For an image, at the edge, the $|\nabla u|$ is generally very large, and $g(|\nabla u|)$ is very small, indicating the weakening of diffusion. While at the flat region, $|\nabla u|$ is very small, and $g(|\nabla u|)$ is very large, indicating the strengthening of diffusion. By this method, the different parts of the image can be smoothed accordingly [7]. In Figure 1, it is easy to observe that $|\nabla u|$ is enlarging, and at the edge, Formula 9 closes to 0 with faster speed than Formula 10. If the speed of closing to 0 is too fast, the diffusion at the edge area will slow down quickly, which will cause insufficient smoothness and weaken the noise reduction effect. Because of this, usually Formula 10 is preferred. However, compared with Formula 9, a small part of the smoothness of $|\nabla u|$ at the flat area is overly large, which may cause excess smoothness. Additionally, the slow speed of closing to 0 cause the image edge to be influenced by the diffusion of neighboring pixels even when the gradient is very large, which will cause edge fog, or even failure.

With the above analysis on the advantages and disadvantages of the P-M model diffusion function [8], this paper has analyzed the smoothing principle of the diffusion function and proposed a new diffusion function which can be applied in P-M model to dramatically speed up the smoothness of image while keeping the advantages of the original model. The diffusion function proposed by this paper is as Figure 2:

$$g(x) = \frac{1}{\ln\left(e + \left(\frac{x}{k}\right)^2\right) + x^2} \tag{11}$$

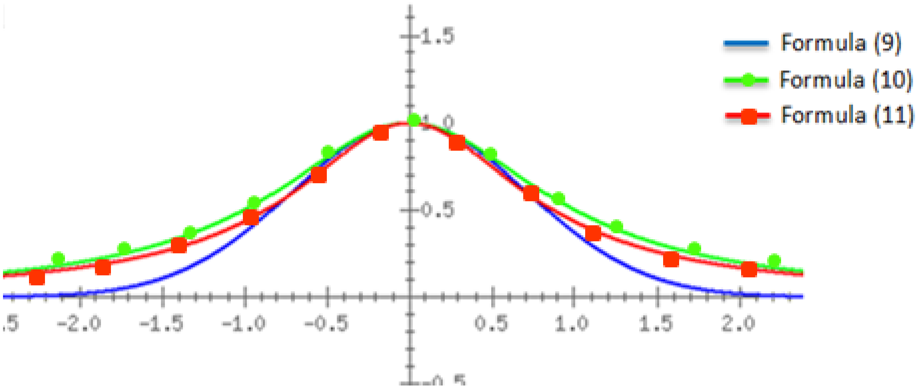



**Figure 2. The New Diffusion Function**

The new diffusion function is shown as Figure 2. Compared with the previous two functions, the speed of closing to 0 of the new function is in the middle. Therefore, this new function presents an improvement for smoothness, noise reduction and keeping edge.

### 3.2. The Self-Adaptive Selection of the Threshold

When using the traditional Canny operator to detect the edge, it's a must to set the high and low thresholds manually [7]. As the threshold has great influence on the results of the edge detection, for achieving the best edge detection results, the threshold should be selected accordingly based on the images, which troubles the edge detection as well. Besides, if applying the same thresholds for every image, there will be problems with false edge or partial edge missing. Therefore, this paper used the maximum between-class variance method to determine the threshold, and by doing so, the high and low thresholds could be selected by self-adaption, thus achieving better edge detection of the image.

The maximum between-class variance method is proposed by a Japanese scholar Otsu in 1997 for determination of the threshold by self-adaption [9]. It's also called the Otsu method. The basic idea of the maximum between-class variance method is using one threshold to classify all data into two classes. If the maximum of the variance between the two classes is the best, the threshold is the best.

Assuming the gray level range of the image $f(x, y)$ is $G = \{0,1, \ldots, L-1\}$, the probability of the gray level value $i$ is $p(i)$. The selected initial threshold k divides the image into two classes: target area $C_1 = \{0,1, \ldots, k\}$ and background area $C_2 = \{k+1, k+2, \ldots, L-1\}$. Formula 12 below is for selecting the initial threshold k [10].

$$k = \frac{(g_{\min} + g_{\max})}{2} \tag{12}$$

Where, $g_{\min}$ is the minimum gray level value, $g_{\max}$ is the maximum gray level value.

Formula 13 is for calculating the sum of probabilities of each gray level of $C_1$ [11]:

$$w_k = \sum_{i=0}^{k} p_i \tag{13}$$

The mathematical expectation of the target area $C_1$ is expressed as Formula 14, and the mathematical expectation of background area $C_2$ is expressed as Formula 15. The average value of area $C_1$ is expressed as Formula 16, and the average value of area $C_2$ is expressed as Formula 17. The within-cluster variance of $C_1$ is expressed as Formula 18, while the within-cluster variance of $C_2$ is expressed as Formula 19:

$$\mu_1(k) = \sum_{i=0}^{k} ip_i \tag{14}$$

$$\mu_2(k) = \sum_{i=k+1}^{L-1} ip_i \tag{15}$$

$$\mu_A = \frac{\sum_{i=0}^{k} ip_i}{w_k} = \frac{\mu_1(k)}{w_k} \tag{16}$$

$$\mu_B = \frac{\sum_{i=k+1}^{L-1} ip_i}{1 - w_k} = \frac{\mu_2(k)}{1 - w_k} \tag{17}$$

$$\sigma_A^2 = \frac{\sum_{i=0}^{k} (i - \mu_A) p_i}{w_k} \tag{18}$$

$$\sigma_B^2 = \frac{\sum_{i=k+1}^{L-1} (i - \mu_B) p_i}{1 - w_k} \tag{19}$$

Next, the optimal threshold $k^*$ is the maximum value obtained by using Formula 20 in the maximum between-class variance method [10]:

$$k^* = \arg\max_{k \in G} \left[ w_k (1 - w_k)(\mu_B - \mu_A)^2 \right] \tag{20}$$

The maximum between-class variance method is very sensitive to noise and the size of the target area, so it only has good division effect to image whose maximum between-class variance is a single peak. When the size of the target area is much larger or smaller than the background area, the criterion function of the maximum between-class variance may appear dual peaks or multiple peaks. The effect is not good at this time, but the maximum between-class variance method has the least time consumption at the methods. For obtaining a more accurate threshold, this paper takes $k^*$ as an initial value and conducts the iteration on it. A detailed procedure is as follows: use the obtained $k^*$ to divide the image into two areas $G_1$ and $G_2$, then calculate the average gray levels $\mu_{G1}$ and $\mu_{G2}$ for these two areas, and then calculate the new threshold as shown as Formula 21 till the difference between T values obtained by successive iterations is less than $k^*$.

$$T = \frac{1}{2}(\mu_{G1} + \mu_{G2}) \tag{21}$$

This then, makes T the highest threshold $T_h$ of Canny operator, $T_l$=0.4$T_h$.

## 4. Experimental Results

### 4.1. Analysis of the Filtering Effect

Due to impact from various factors in the environment, there are noises existing in the image. Therefore, before the edge detection it's a must to filter the noises in the image to get more accurate edges. The original image with noise is shown as Figure 3. The Figure 3 has been treated with Gaussian filtering, anisotropic diffusion filtering, and improved anisotropic diffusion filtering. The result is shown as Figure 4. It is easy to observe that the Gaussian filtering will slightly fog the image edge.

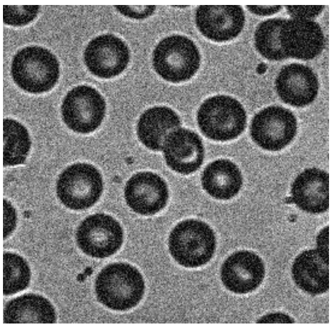
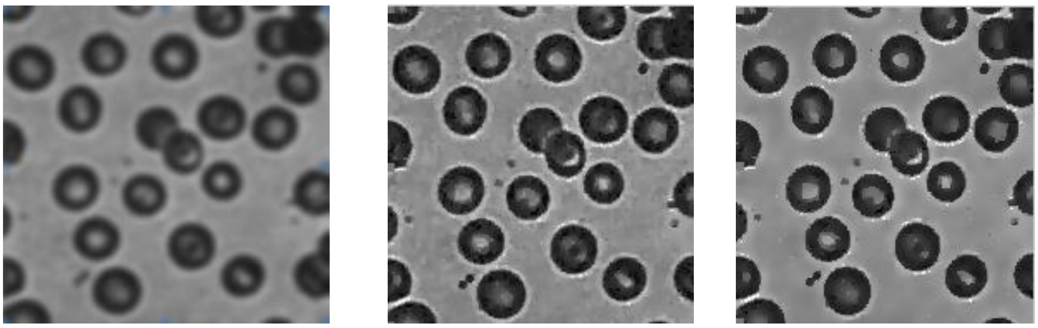


**Figure 3. Original Image with Noise**



(a) The Gaussian Filtering (b) Anisotropic Diffusion Filtering (c) Improved Filtering

**Figure 4. Contrast Analysis of the Effects of Filtering**

Compared with the original image, the filtered image has dim edges. The Gaussian filtering cannot reflect the edge features of the original image, while the edge features of the image treated with anisotropic diffusion are basically the same as the original image. This is because the anisotropic diffusion can maintain the image edge, but with poor effects on noise reduction. Finally, the image filtered with improved anisotropic diffusion safeguard the edges, and with ideal effect on noise reduction.

It's subjective to compare the noise reduction effect from the appearance of the images. Therefore, this paper used the peak signal to noise ratio (PSNR) [12] to evaluate the experimental results objectively. The PSNR is the ratio of the maximum possible power to the destructive noise power which influences the former's representing precision, and the bigger the value, the less the distortion. The expression is shown as Formula 22 [13]:

$$PSNR = 10 \times \lg\left( \frac{255^2}{\frac{1}{I \times J} \sum_{i=1}^{I} \sum_{j=1}^{J} \left[ x(i,j) - x'(i,j) \right]^2} \right) \tag{22}$$

Where $I \times J$ refers to the size of the image; $i$ and $j$ are the coordinates of the pixel; $x$ and $x'$ are the image before and after treatment respectively. The results are shown as Table 1.

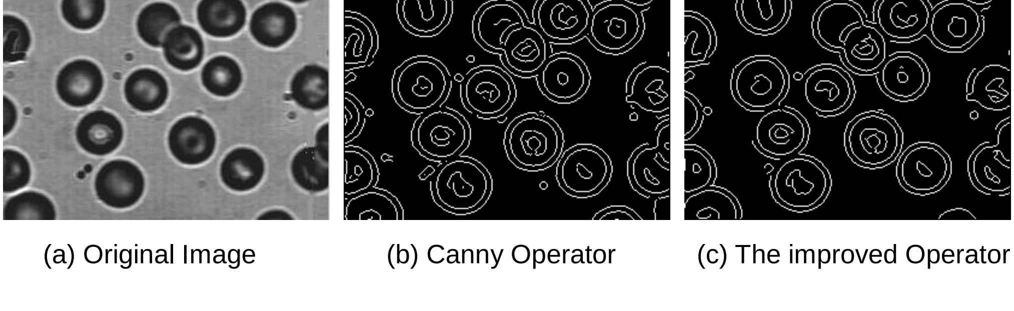
**Table 1. PSNR**

| Gaussian filtering | Anisotropic diffusion filtering | Improved filtering |
|---|---|---|
| 29.3172 | 45.3563 | 45.9861 |

Learning from the data of Table 1, the PSNR of the image filtered with the anisotropic diffusion function is larger than the one filtered with the Gaussian function, while the PSNR of the image filtered with improved anisotropic diffusion function is slightly larger than the one filtered with anisotropic diffusion function. Therefore, the improved anisotropic diffusion function has better performance in smoothness and filtering of the images.

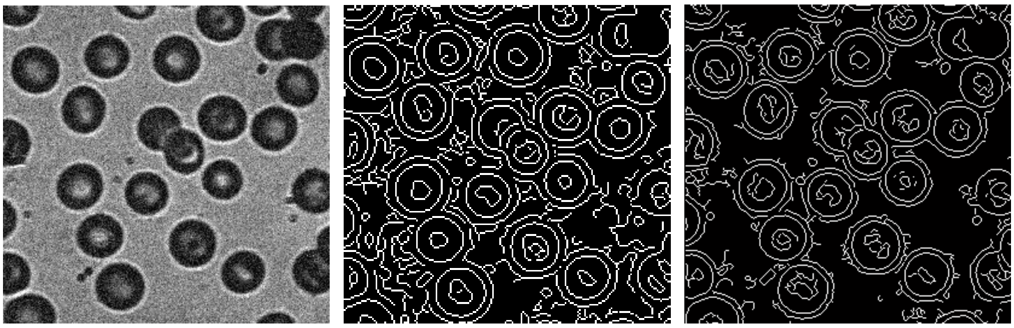
### 4.2. Contrast Analysis of the Effects of Edge Detection

For verifying the performance of the improved algorithm, this paper conducted contrast experiments between the traditional Canny algorithm and the improved Canny algorithm under Matlab7.0. The images selected for the experiment are an image of blood cells, an image of the section texture of nature wood, and an image of people. The results of the experiment are shown as Figure 5, Figure 6 and Figure 7.



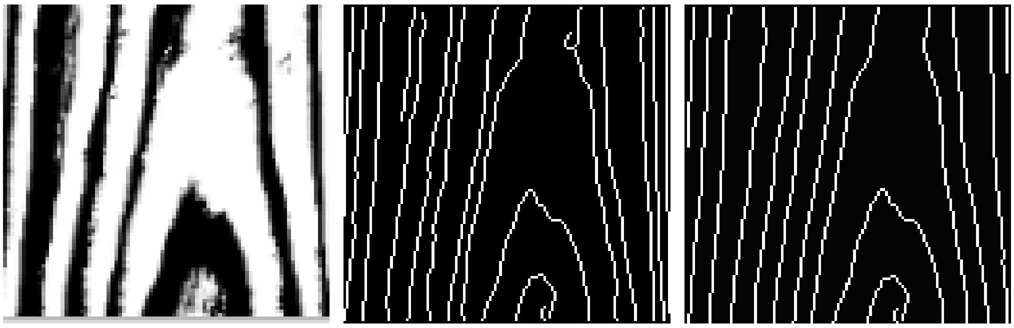
(a) Original Image (b) Canny Operator (c) The improved Operator

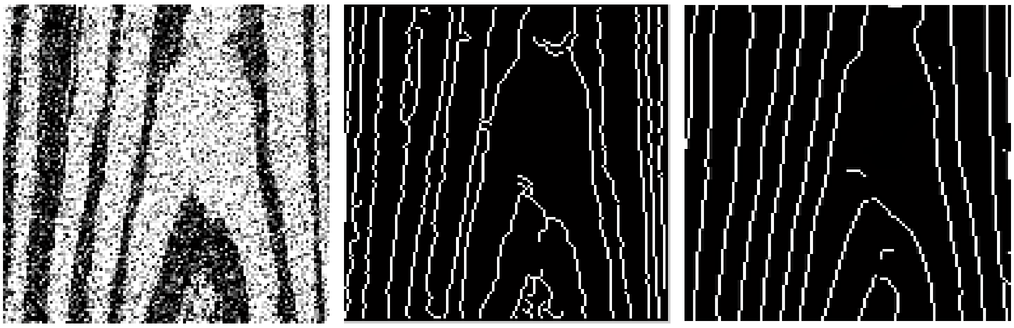


(d) Original Image with Noise (e) Canny Operator (f) The improved Operator

**Figure 5. A Comparison of Edge Detection Effect of the Blood Cells**



(a) Original Image (b) Canny Operator (c) The improved Operator



(d) Original Image with Noise (e) Canny Operator (f) The improved Operator

**Figure 6. A Comparison of Edge Detection Effect of the Wood Texture**

(a) Original Image (b) Canny Operator (c) The improved Operator

(d) Original Image with Noise (e) Canny Operator (f) The improved Operator

**Figure 7. A Comparison of Edge Detection Effect of the Person**

From the results of the experiment, it can be found that with the traditional Canny algorithm, there often appear fracture phenomenon, the edge details are not kept well, and the detection effect is great influenced by the noise. With the improved Canny algorithm, the image edge connectivity and details of the edges are preferred, without burs and block effects, and is rarely influenced by the noise. Experiments show that the algorithm proposed by this paper can effectively reduce the impact of noise, detect more real edges, and accurately locate the image edge with better treatment on the details.

## 5. Conclusion

This paper mainly studied the optimization of the traditional Canny operator by use of the modified anisotropic diffusion function and the maximum between-class variance method. The modified anisotropic diffusion function replaces the Gaussian filtering process of the traditional Canny operator. It overcomes the limitations of the Gaussian filtering, and enhances the effect of noise reduction and edge protection. The improved maximum between-class variance method implemented the self-adaptive selection of the high and low thresholds in the Canny operator. In this paper, the improved algorithm is applied to edge detection of various kinds of images. The experimental results showed that the modified algorithm improved the edge extraction effect of Canny operator under the noise interference, and effectively enhanced the precision and accuracy of the edge detection.

## References

[1] W. Mokrzycki and M. Samko, "Canny Edge Detection Algorithm Modification, in Computer Vision and Graphics", Springer Berlin Heidelberg, **(2012)**.
[2] X. Ma, "The Canny Edge Detection and Its Improvement", in Artificial Intelligence and Computational Intelligence, Springer Berlin Heidelberg, **(2012)**.
[3] L Yitao, "The Application Study on the Improved Canny Algorithm for Edge Detection in Fundus Image", in Software Engineering and Knowledge Engineering: Theory and Practice, **(2012)**.
[4] J. Li and S. Ding, "A Research on Improved Canny Edge Detection Algorithm", in Applied Informatics and Communication, **(2011)**.
[5] J. Wong, "Signal-to-Noise Ratio (SNR)", in Encyclopedia of Radiation Oncology, **(2013)**.
[6] P. Perona and J. Malik, "Scale-Space and Edge Detection Using Anisotropic Diffusion", IEEE Trans. Pattern Anal. Mach. Intell, vol. 12, **(1990)**.
[7] E. A. S. Galvanin, G. M. Vale and A. P. D. Poz, "The canny detector with edge region focusing using an anisotropic diffusion process", Pattern Recognition and Image Analysis, vol. 16, no. 4, **(2006)**.
[8] C. C. Leng, "Improvement of P-M Model Diffusion Function", Computer and Modernization, **(2008)**.
[9] L. Han and A. Han, "An Edge Detection Algorithm Based on Morphological Gradient and the Otsu Method", in Bio-Inspired Computing - Theories and Applications, **(2014)**.
[10] C. Rafael and R. E. W. Gonzalez, Steven L. Eddins, **(2009)**.
[11] D. Y. Huang and C.-H. Wang, "Optimal Multi-level Thresholding Using A Two-stage Otsu Optimization Approach", Pattern Recognition Letters, vol. 3, no. 30, **(2008)**.

[12] S. H. Choi, "A study on evaluating the image quality in DR a system with and without a grid", Journal of the Korean Physical Society, vol. 11, no. 60, **(2012)**.
[13] Z. Y. Zhen, X. F. Luo and X. Yang, "Edge Extraction Algorithm Based on Anisotropic Diffusion Filtering", Journal of Shenyang University of Technology, **(2014)**.

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