Proceedings of 2014 IEEE
International Conference on Mechatronics and Automation
August 3 - 6, Tianjin, China

An Improved Canny Edge Detection Algorithm

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***Abstract* - The traditional Canny edge detection algorithm is sensitive to noise, therefore, it's easy to lose weak edge information when filtering out the noise, and its fixed parameters show poor adaptability. In response to these problems, this paper proposed an improved algorithm based on Canny algorithm. This algorithm introduced the concept of gravitational field intensity to replace image gradient, and obtained the gravitational field intensity operator. Two adaptive threshold selection methods based on the mean of image gradient magnitude and standard deviation were put forward for two kinds of typical images (one has less edge information, and the other has rich edge information) respectively. The improved Canny algorithm is simple and easy to realize. Experimental results show that the algorithm can preserve more useful edge information and more robust to noise.**

Index Terms - Edge detection, Canny algorithm, Gravitational field intensity operator, Adaptive threshold.

I. INTRODUCTION

Image edge information is one of the most important information in an image, which can describe the target outline, the relative position within the target area, and other important information. Edge detection is one of the most important process in image processing, and the detection results will directly affect the image analysis. The traditional edge detection algorithms are done through detecting the maximum value of the first derivative or zero crossing of the second derivative[1]. Although the representative first order differential operators (Roberts operator, Prewitt operator, Sobel operator, etc.) and second order differential operators (Laplace operator, LOG operator, etc.) have many advantages such as simple computation, rapid speed and easy to implement, they are more sensitive to noise and their detection effect are not perfect in engineering application.

In 1986, Canny proposed three criteria to judge edge detection operator' performance: SNR criterion, localization precision criterion and single edge response criterion, and deduced the best Canny edge detection operator[2-3]. Compared with common edge detection algorithm, in most cases, the Canny algorithm has the best performance[4-5]. In recent years, some researchers offered many improved algorithms based on Canny algorithm and applied them to practical engineering. Er-Sen Li improved the image gradient magnitude calculation operator and automaticity of edge detection by Otsu's threshold selection method, and it showed good edge detection results to some extent[6]. Agaian S. introduced an improved Canny operator for Asphalt Concrete(AC) applications[7]. Xiangdan Hou proposed an improved Canny algorithm based on the Histogram-based fuzzy C-means clustering algorithm. It was applied in detecting road surface distress image and it appered good effect[8].

Since the image quality will be influenced by some factors such as noise and illumination in the process of the image acquisition, what's more, to the large view scope of images, its local contrast is different from each other, the parameters of the traditional Canny edge detection algorithm are fixed and cannot adapt to the edge detection process in different conditions. Therefore, this paper improved the image gradient calculation operator, which is helpful to preserve more useful detail edges and more robust to noise. Two adaptive threshold selection methods were presented for two kinds of typical images respectively, and it can contribute to fit diffident conditions automatically.

II. THE TRADITIONAL CANNY ALGORITHM

A. Image Filtering

The first step of the traditional Canny algorithm is to smooth image. Canny deduced the first derivative of Gaussian function, which is the best approximation of the optimal edge detection operator. Choose appropriate 1-d Gaussian function to smooth the image according to the row and column respectively, that is, execute convolution operation to image matrix. Since the convolution operation satisfies commutative law and associative law, Canny algorithm generally uses two-dimensional Gaussian function (as shown in (1)) to smooth image and get rid of the noise.

$$G(x, y)=\exp[-(x^2+y^2)/2\sigma^2]/2\pi\sigma^2 \tag{1}$$

where σ stands for the parameter of Gauss filter, and it controls the extend of smoothing image.

B. Image Gradient Calculation

The second step is to calculate the magnitude and direction of image gradient. The traditional Canny algorithm adopts limited difference of 2×2 neighbouring area to calculate the value and direction of image gradient[9]. The first order partial derivative's approximation on the *X* and *Y* directions can be got from these following formulas：

$$E_x[i,j]=(I[i+1,j]-I[i,j]+I[i+1,j+1]-I[i,j+1])/2 \tag{2}$$

$$E_y[i,j]=(I[i,j+1]-I[i,j]+I[i+1,j+1]-I[i+1,j])/2 \tag{3}$$

Therefore, the templates of the image gradient calculation operator are:

$$G_x = \begin{pmatrix} -1 & 1 \\ -1 & 1 \end{pmatrix} \tag{4}$$

$$G_y = \begin{pmatrix} 1 & 1 \\ -1 & -1 \end{pmatrix} \tag{5}$$

The magnitude and direction of gradient can be calculated. The image gradient magnitude is:

$$\| M(i,j) \| = \sqrt{E_x[i,j]^2 + E_y[i,j]^2} \tag{6}$$

The azimuth of the image gradient is:

$$\theta(i,j) = \arctan\left(E_y[i,j] / E_x[i,j] \right) \tag{7}$$

C. Non-maximum Suppression(NMS)

After acquired the gradient magnitude image M[i,j], it's needed to perform non-maximum suppression on the image to accurately position edges. The process of NMS can help guarantee that each edge is one-pixel width. Canny algorithm uses 3×3 neighboring area which consists of eight directions to execute interpolation to the gradient magnitude along gradient's direction. If the magnitude M[i,j] is bigger than the two interpolation results on the gradient direction, it will be marked as candidate-edge point, otherwise it will be marked as non-edge point. Therefore, the candidate edge image is acquired through the process.

D. Checking and Connecting Edges

The Canny algorithm adopts double-threshold method to select edge points after carrying on non-maximum suppression. The pixels whose gradient magnitude is above the high-threshold will be marked as edge points, and those whose gradient magnitude is under the low-threshold will be marked as non-edge points, and the rest will be marked as candidate edge points. Those candidate edge points who are connect with edge points will be marked as edge points. This method reduces the influence of noise on the edge of the final edge image.

E. Problems of The Traditional Canny Algorithm

Although the traditional Canny edge detection algorithm is more widely used in practical engineering, there are still two aspects to improve. The first one is that the traditional algorithm adopts first order limited difference of 2×2 neighboring area to calculate image's gradient. It's simple for calculation, but it's more sensitive to noise. Because of not join the deviation on the direction of 45° and 135°, it's easy to lose real edge information. The second one is that the double-threshold of the traditional Canny algorithm is set a fixed value. For images with rich edge information, the adaptability of traditional Canny algorithm isn't ideal, and it's easy to lose local characteristic edge information. This paper introduced the concept of gravitational field intensity to replace the image gradient, and proposed two adaptive threshold selection methods for two kinds of typical images.

III. The Improved Canny Algorithm

A. Image Gradient Calculation

Wang extended the 2×2 neighbouring area to 3×3 neighbouring area to calculate image gradient, using the Sobel operator to execute convolution[10]. Li used the Prewitt operator to accomplish convolution[6].Due to the introduction of the diagonal direction partial derivative, more edge information was preserved and the precision of edge location was improved. Experimental results demonstrate that an edge operator with a larger mask may provide a better edge detection result. Sun proposed a novel edge detection method based on the theory of universal gravity, which is called gravitational edge detection algorithm in this paper. It not only performs better than Sobel and Prewitt operators on the edge of the single criterion, but also can retain more useful edge information, and it has good inhibition effect on noise[11-12].As stated by Newton in the law of universal gravity, anything attracts every other body by a force proportional to the product of their masses. The force between two bodies is given by:

$$\vec{F}_{1,2} = \frac{Gm_1 m_2}{\| \vec{r}_{1,2} \|^2} \cdot \frac{\vec{r}_{1,2}}{\| \vec{r}_{1,2} \|} \tag{8}$$

Where m_1 and m_2 are the masses of the bodies, *G* is the gravitational constant, $\vec{r}$ is the vector from body 1 points to body 2.

The law of universal gravity was used in image processing in the gravitational edge detection algorithm, where every pixel was assumed to be a body with a mass equal to its gray value. Therefore, the force $\vec{F}_{total}$ that is the combination of other forces acting on a body can be calculated. Sun et al. utilized the $\vec{F}_{total}$ to do edge detection.

From (8) it's easy to find that the performance of the gravitational edge detection algorithm in bright area or dark area is great different. When a pixel is in dark zone (small gray value, low mass), the resulting total gravitational force on the pixel is smaller than those in the bright zone when they have the same gradient. As a consequence, the gravitational approach tends to give less relevance to the gradient changes in dark zones, which leads to lose edge points easily. Therefore, this paper introduced the gravitational field intensity to overcome the difference between bright zones and dark zones. The gravitational field intensity can be calculated by following formula:

$$\vec{E} = \frac{Gm}{\| \vec{r} \|^2} \cdot \frac{\vec{r}}{\| \vec{r} \|} \tag{9}$$

Where *G* stands for constant, *m* is the "mass" (gray value) of the pixel.

The resulting total gravitational field intensity on one point in the image is the combination of the gravitational field intensity produced by surrounding pixels. In this paper, the resulting gravitational field intensity is understood as image gradient, and when the intensity on a pixel is higher than the threshold, the pixel is considered to be an edge point. The total resulting field intensity assigned to a point can be calculated by the following formula:

$$\vec{E}_{total} = \sum_{i=1}^{n} \frac{Gm_i}{\|\vec{r}_i\|^2} \cdot \frac{\vec{r}_i}{\|\vec{r}_i\|} \tag{10}$$

Pixels' position in 2×2 neighbouring area is shown in Fig.1 Assume that the distance between two horizontal or vertical pixels is 1, the distance between two diagonal pixel is $\sqrt{2}$, so the gravitational intensity on the point O in the 2×2 neighbouring area (gravitational field intensity produced by pixels further away is negligible) can be calculated by the following formulas.

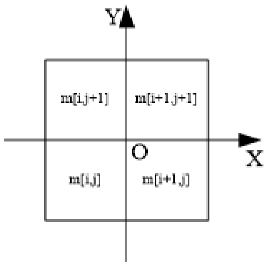


Fig.1 2×2 neighbouring area pixels' position

The gradient component on the X direction is:

$$\vec{E}_x = \sqrt{2}G(m[i+1,j+1] - m[i,j+1] + m[i+1,j] - m[i,j])\,\vec{i} \tag{11}$$

and the gradient component on the Y direction is:

$$\vec{E}_y = \sqrt{2}G(m[i+1,j+1] - m[i+1,j] + m[i,j+1] - m[i,j])\,\vec{j} \tag{12}$$

Therefore, the gradient magnitude is:

$$E = \sqrt{E_x{}^2 + E_y{}^2} \tag{13}$$

and the azimuth of gradient is:

$$\theta = \arctan\left(E_y / E_x\right) \tag{14}$$

Where $\vec{i}$ and $\vec{j}$ are the unit vectors on the horizontal and vertical direction respectively. θ is the direction of the gravitational field intensity.

In practice, the G can be set to other value to act at some special circumstances. If let G= $\sqrt{2}/2$, it can be seen from (11) that the gravitational field intensity calculation template is the same to the traditional Canny gradient calculate operator for the 2×2 neighbouring area. In order to retain more edge information, this paper extend the neighbouring area form 2×2 to 3×3 window. Table *I* shows the pixels' position of 3×3 window.

TABLE *I*
PIXELS' POSITION

I[i-1,j+1]	I[i,j+1]	I[i+1,j+1]
I[i-1,j]	I[i,j]	I[i+1,j]
I[i-1,j-1]	I[i,j-1]	I[i+1,j-1]

Assume that the gray value of the pixel which is on the top left corner of the center pixel I[i,j] is m1, and clockwise around it are m2,m3,…m8.The Equation(10) can be applied to calculate the resulting total intensity of the center point.The gradient component on the X direction is:

$$\vec{E}_x[i,j] = G[(m4-m8)+\sqrt{2}(m5-m1+m3-m7)/4]\,\vec{i} \tag{15}$$

and the gradient component on the Y direction is:

$$\vec{E}_y[i,j] = G[(m2-m6)+\sqrt{2}(m1-m5+m3-m7)/4]\,\vec{j} \tag{16}$$

Therefore, the gradient magnitude is:

$$\|\vec{E}(i,j)\| = \sqrt{\vec{E}_x[i,j]^2 + \vec{E}_y[i,j]^2} \tag{17}$$

and the azimuth of gradient is:

$$\theta = \arctan\left(\|\vec{E}_y[i,j]\| \;/\; \|\vec{E}_x[i,j]\|\right) \tag{18}$$

Make the constant G=1, it's easy to obtain the 3 × 3 neighbouring area operator:

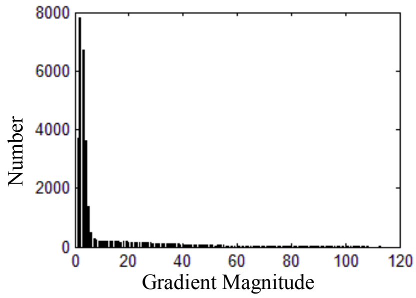
$$G_x = \begin{pmatrix} -\frac{\sqrt{2}}{4} & 0 & \frac{\sqrt{2}}{4} \\ -1 & 0 & 1 \\ -\frac{\sqrt{2}}{4} & 0 & \frac{\sqrt{2}}{4} \end{pmatrix} \tag{19}$$

$$G_y = \begin{pmatrix} \frac{\sqrt{2}}{4} & 1 & \frac{\sqrt{2}}{4} \\ 0 & 0 & 0 \\ -\frac{\sqrt{2}}{4} & -1 & -\frac{\sqrt{2}}{4} \end{pmatrix} \tag{20}$$

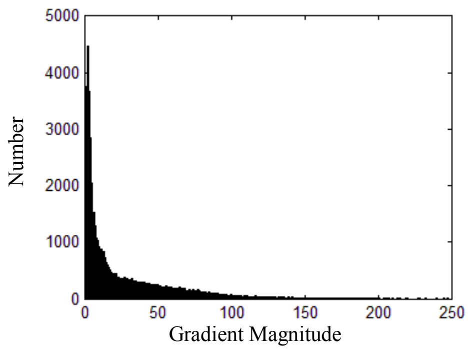
B. *Adaptive Threshold Selection*

Since the parameters of the traditional Canny algorithm are fixed, which leads to the algorithm can't adapt to different situations, two adaptive threshold selection methods were introduced for two kinds of typical images respectively. The improved algorithm can obtain thresholds automatically in the process of edge detection.

Edges are the regions with large magnitude variation, i.e. the pixels of the edge area have large gradient magnitude. The gradient histogram can describe the intensity information of edges. In practical engineering, there are two typical situations involving image edge detection: (1) less edge information, mostly occurred in microscopic vision; (2) a large field of view and rich edge information, in which the edge pixels occupy a relatively larger proportion and the local image contrast is inconsistent. After obtained the image gradient as the section 2.1, integer conversion was needed, and then the image gradient histograms can be drawn. Fig. 2 shows two typical kinds of image's gradient histogram, Fig.2(a) shows the gradient histogram of *cell* image in the microscopic view, and Fig.2(b) shows the gradient histogram of *tire* image in the large view scope.



(a) *cell* image



(b) *tire* image

Fig. 2. Gradient magnitude histogram for two typical images

Generally the edges in image only occupy a little part, therefore in the image gradient histogram, the majority of pixels within a small gradient magnitude range are non-edge pixels. The gradient magnitude of the edge pixels is large, and the number of edge pixels is quite small. The number of pixels decreases with the increasing of the gradient magnitude. For these two typical images edge extraction, this paper proposes two adaptive threshold selection methods respectively. The selection of threshold has great relationship with the mean of gradient magnitude and standard deviation. The mean of gradient magnitude response the distribution center location of gradient magnitude, and the standard deviation reflects the discrete degree of gradient magnitude distribution.

(1) Method for image with less edge information

The gradient magnitude of majority of the pixels is located in a small range in images with less edge information. The mean of gradient magnitude and the standard deviation of this kind of images is small relatively. Images in the field of micro-vision always have less edge information. The distribution of the gradient magnitude of those non-edge pixels is con-centrated, therefore, a proper double-threshold can help select edge pixels out. The double-threshold selection method for images with less edge information is shown as follows:

$$E_{ave} = \sum_{i=1}^{m}\sum_{j=1}^{n} \left| E[i,j] \right| / (m*n) \tag{21}$$

$$\sigma = \left(\sum_{i=1}^{m}\sum_{j=1}^{n} \left| E[i,j] - E_{ave} \right|^2 / (m*n) \right)^{1/2} \tag{22}$$

$$T_h = E_{ave} + k \cdot \sigma \tag{23}$$

$$T_1 = T_h / 2 \tag{24}$$

where E_{ave} stands for the mean of gradient magnitude, *m* and *n* are the number of pixels on the image width direction and height direction respectively, E[i, j] stands for the image gradient magnitude, i.e., the gravitational field intensity mentioned in section 3.1, T_h and T_l stand for high threshold and low threshold respectively, σ is image standard deviation, and *k* is its coefficient. The value range of *k* can be obtained through experiment, and $k \in (1.2,1.6)$. When image edge information is rich relatively and the gradient magnitude distribution is scattered, the value of σ will be larger, in order to keep more edge information the value of *k* should be smaller. Otherwise, the value of σ is smaller, and the value of *k* is bigger.

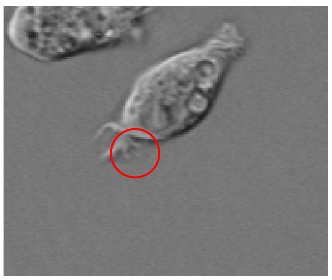
(2) Method for image with rich edge information

In images with a large field of view, rich edge information and scattered gradient magnitude distribution, the contrast of each part of the entire image is inconsistent, and the image gradient's standard deviation is large relatively. Selecting a double-threshold for the whole image can not help accomplish edge detection, since the selected threshold will be too high for some edge regions with small gradient magnitude, which will lead to the loss of detail edges. For this kind of images, this paper proposed a method to select a double-threshold for each pixel. Firstly, the mean of gradient magnitude of the whole image E_{ave} is calculated by (21). If the gradient magnitude of pixel I[i,j] is smaller than 15%~20% of the E_{ave} ,it will be marked as non-edge point directly. This process contributes to guarantee that for image with large field of view and rich edge information, the improved algorithm won't introduce more noise in areas where there are few edges, that is, the mean of gradient magnitude and standard deviation of these areas are very small. The threshold for pixel I[i,j] is calculated based on the mean of the gradient magnitude and standard deviation of the elements in the N×N matrix image gradient, whose center is the pixel I[i,j] (N is an odd number, generally larger than 20). Then, the threshold value of the pixel can be obtained by (23). When the pixel I [i, j] is located in the border area of the image and the matrix is less than N×N, the insufficient parts were set null, then calculate the mean and standard deviation of this matrix to obtain the threshold. Therefore, every pixel has its corresponding double-threshold, and the whole image's edge information can be obtained through detecting and connecting edges.

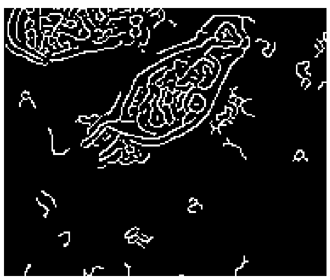
IV. Experiments and Analysis

In the experiments, this paper used *MATLAB* to test the performance of the improved Canny algorithm, and carried out the research experiments on the *cell* image, *liftingbody* image and *tire* image which are 256-level gray, using the traditional Canny edge detection algorithm and the improved algorithm respectively.

Since the *cell* image which is in the microscopic view has a little of edge information, the mean of gradient magnitude and standard deviation σ are small, k was made to be 1.6 , and selecting a double-threshold for the whole image is practicable to achieve the goal of edge detection. Fig. 3 shows the detection results of the *cell* image. It can be seen from the Fig.3(b) that the traditional Canny algorithm is sensitive to noisy. Fig.3(e) shows the detection result of the improved method. The differences among Fig.3(e), Fig.3(c) and Fig.3(d) are that in Fig.3(e) it used the gravitational field intensity operator to calculate the gradient magnitude, and the latter two used Sobel operator and Prewitt operator respectively. Fig.3(e) preserved more useful edges than Fig.3(c) and Fig.3(d), which demonstrates that the gravitational field intensity operator perform better than Sobel and Prewitt operators. Compared with traditional method, the improved algorithm presented is more robust to noise and it can preserve more useful edge information. The improved algorithm has a better edge detection result than the traditional Canny algorithm, so it's more competitive. The improved algorithm has great practical value in microscopic visual edge detection engineering.



(a)



(b)

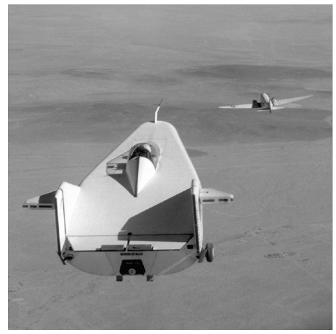
(c)

(d)

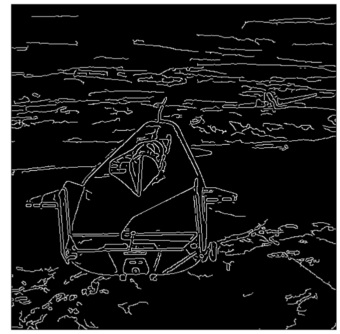
(e)

Fig 3. Experiments for *cell* image:(a) *cell* image,(b) traditional method,(c) and (d) are Canny method whose gradient calculation used Sobel operator and Prewitt operator respectively,(e) method for images with less edges in this paper

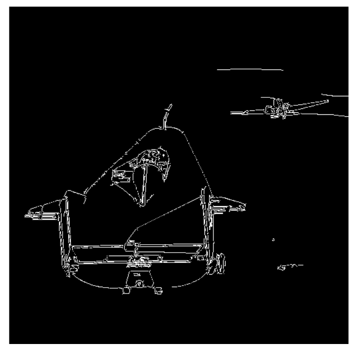
In some particular situations, although images have a large field of view, the mean of gradient magnitude and the standard deviation of the whole image are small. For this kind of image, this paper used the method for images with less edges to detect edge information. Fig.4 shows the edge detection results of the *liftingbody* image. Compared with traditional Canny algorithm, the improved method is more robust to noise, and it has higher SNR.



(a) *liftingbody* image



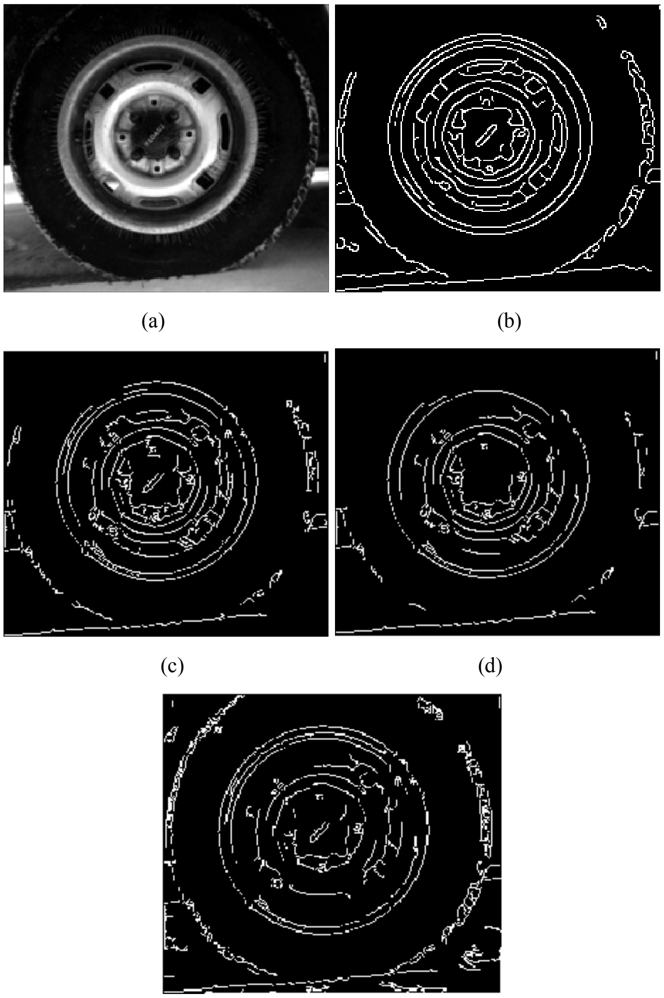
(b) Traditional method



(c)Method for images with less edges, k=1.2

Fig.3 Experiments for *tire* image

The *tire* image has a large field of view and rich edge information. Fig. 5 shows the edge detection results of the *tire* image. The result of traditional Canny algorithm is shown Fig.5(b). Fig.5(c) and Fig.5(d) show the results of the improved algorithm for images with less edge information, which is used in the *cell* image edge detection process. The difference between them is that in former image the value of k is 1.6,and the latter k is 1.2. It's clear to find that a double-threshold for images with large field of view and rich edge information can not help to achieve detail edge extraction. The standard deviation σ of this kind of images is large, so when k is small, it can preserve more edge information. However, if k is too small, it will be sensitive to noise and easy to bring in fake edges. Fig.5(e) shows the edge detection results of the improved algorithm for images with rich edge information, in which every pixel has its own double-threshold, and N=21, k=1.2. Compared with traditional Canny algorithm, the method in this paper for this kind of image can preserve more local edge information.



(a) (b)

(c) (d)

(e)

Fig.5. Experiments for *tire* image:(a)*tire* image,(b) traditional method,(c) and (d) are obtained by method for images with less information, the former k=1.2,and the latter k=1.6 ,(e)the improved Canny algorithm for images with rich edge information, 21×21 neighbouring area, k=1.2

V. CONCLUSION

The gravitational field intensity was introduced in this paper to replace image gradient, and the 2×2 operator was extended to 3×3 operator. This paper put forward two adaptive double-threshold selection methods for two kinds of typical images based on the mean and standard deviation of image gradient. The improved algorithm not only keeps the advantages of the traditional Canny algorithm, but also it enhances the ability of noise suppression and keeps more edge information, i.e. it has higher SNR. This algorithm can obtain threshold automatically, which has higher practical value in the practical engineering application. The detection results of algorithm are superior to the ordinary first-order, second-order edge detection algorithm (Roberts, Sobel, Laplacian, etc.) and the traditional Canny algorithms, but its computing speed is relatively slow, which need to be further improved.

ACKNOWLEDGMENT

This research was supported by Self-Planned Task of State Key Laboratory of Robotics and System (SKLRS201301A01) and Program for Changjiang Scholars and Innovative Research Team in University (IRT0915).

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