Contour Extraction Based on Human Visual System

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Abstract. The contour extraction in image processing and computer vision is extremely an important image analysis method. On the basis of features of the primary visual cortex (V1 area) neurons which will inhibit or enhance the response to the specific area of the visual field, this paper improves the traditional Gabor function, establishes more effective mathematical models of visual receptive field and proposes an algorithm based on visual perception mechanism. Experiments demonstrate that the algorithm can extract the image contour efficiently.

Keywords: Contour extraction · Primary visual cortex · Gabor function · Mathematical models

1 Introduction

For humans, visual system is the most important and direct way to acknowledge the world, analyze the external environment and respond accordingly. With the development of computer performance and functionality, how to reveal and simulate the human visual system has been a research focus. A complex natural scene image contains a wealth of information and it's impossible for sight to give the same level of attention to every point in space. The human visual system experiments [1-4] demonstrate that the contour feature in images is particularly important. They retain the border (useful structure information) about the object, while greatly reducing the amount of data, thereby simplifying the forms of expression, so that the visual can handle the ever-changing inputs in a timely and effective manner. In many cases, the object can be identified according to the outline of objects. In the past few years, researches [5-6] on contour extraction based on visual attention mechanism have made tremendous progress, but how to extract significant contour features of complex images is still a pressing problem quickly and accurately.

The traditional edge detection method is the classical operator method, namely by means of a spatial difference operator, convolve the image with the template such as Gradient operator, Laplace operator, Canny operator and so on. In early 1980, Canny presented the canny edge detection operator from the point of signal processing, which is theoretically a relatively complete edge detection operator. Although the several operators are simple to achieve and fast to operate, they both failed to properly

H. Zha et al. (Eds.): CCCV 2015, Part II, CCIS 547, pp. 394–405, 2015.
DOI: 10.1007/978-3-662-48570-5_38

deal with an edge noise interference brought by an actual image texture, which leads to precisely a result that extracted contour accuracy can't be guaranteed. Based on this, we need to address two problems existing in the traditional edge detection methods: firstly, inhibit the noise brought by the texture information; secondly, make the discrete edge pixels continuous.

Studies on the optic nerve [7-10] showed that: the retinal process includes forming the central- peripheral receptive field of the bipolar cells and ganglion cells. Other cells in the retina, particularly horizontal cells and amacrine cells transfer lateral information (transfer from one neuron to the same layer adjacent neurons) to form a more complex receptive fields, such as motion sensitive and color insensitive receptive field or color sensitive and motion insensitive receptive field. Related experiments [8, 10-13] demonstrated that when neurons in the visual cortex respond to stimulation with a specific space, receptive field plays an important role in combing and organizing the contour. Various representative models have been established based on this feature. Grossberg [14] et al proposed a boundary contour system to detect some false contour generated by the visual illusion. Li [15] proposed a significant edge detection method to locate edge information by detecting the edge orientation and homogeneous boundary point. These visual models are mainly used to explain how the human visual system to achieve a combination of contour and segmentation of boundary, mainly for processing synthetic images instead of natural images.

Knierim [16] et al, proposed environment suppression domain applied to the contour extraction of natural scenes, but the environment suppression domain is isotropic. On the basis of the properties of non-classical receptive field in the primary visual cortex, Cosmin Grigorescu [17] et al made comprehensive consideration of isotropic and anisotropic suppression, and proposed an effective algorithm to outstand the boundary and save the orphaned contour.

Environment suppression can reduce some edge-texture noise but leave behind many discrete and fracture edge segments. In order to detect a more complete edge of objectives, we also need to further combine and connect the edge segments. Geisler et al [18] thought that the visual cortex's stimulation response to the components possessing a consistent space agencies will be strengthened. And it has two characteristics: if local ingredients are smoother and closer, there will be a greater probability of being aggregated into global contours; if two local ingredients are close and touch the same circle, then this local contour will have a higher significance, which is e well applied to the algorithms for making the edge segments continuous.

According to problems existing in the traditional edge detection methods, basing on the physiological mechanism of visual saliency, combining with significant computer calculations, the paper presents an algorithm based on visual perception mechanism. The basic flow chart of the algorithm is shown below.

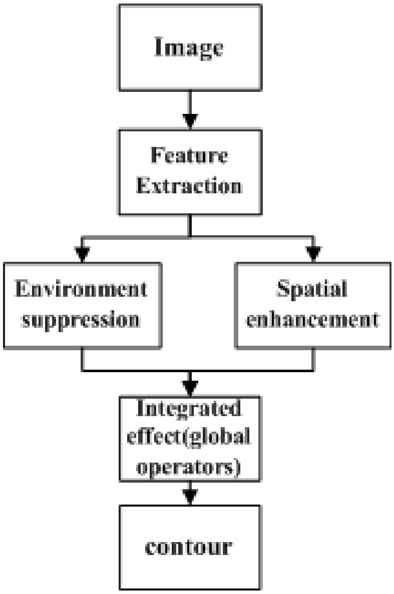


Fig. 1. The Basic Flow Chart of the algorithm

This paper will establish a more effective mathematical model (improved Gabor function) to describe human visual system in the feature extraction Module, and then use improved Gabor energy based on human visual system to achieve effects of environment suppression and spatial enhancement, finally use a global operator to obtain the goal of extracting the contour. Experiments demonstrate that this method has strong anti-interference, high precision and can meet the actual needs of the engineering survey compared with classical contour extraction methods.

2 Feature Extraction

Gabor function can simulate the structure of receptive field. It is possible to simulate the response to complex cellular by Gabor energy function to obtain the energy diagram of the visual characteristics.

However, studies [19-22] showed that in the process of the receptive field structure predicted by Gabor function gradually increasing as the center frequency of visual pathways, the receptive field center and the periphery will generate the phenomenon of alternate oscillation, which is inconsistent with most of the neurons well-known to us in the visual receptive field structure.

Longxiang You [23] et al thought that owing to the spectral distribution of each spatial frequency of the visual pathway channel having a certain overlap, the visual system information processing can't be equivalent to the compression and recovery process of the spectrum. Thus, Gabor function cannot predict the complex structure of receptive fields and the corresponding mathematical description of it as a visual receptive fields of neurons need to be improved.

Longxiang You [23] et al presented mathematical description of mathematical models of isotropic and anisotropic visual receptive fields under the premise of analyzing shortages of the existing mathematical models of visual information processing neuron receptive field. In addition to the relationship with the distribution parameters of receptive field models, they also studied its response to spatial frequency domain.

In this paper, learning from their models, we improve the Gabor function, which uses the Laplace transform of Gaussian function to optic spatial distribution model of nerves receptive fields, so as to achieve the purpose of extracting the contour of the target.

The calculation process is as follows:

For the human visual system, the process of extracting feature edges in spatial domain and spatial frequency spectrum can be expressed as following:

$$\mathrm{f}_{\sigma}(\mathrm{x}',\mathrm{y}') = \iint_{s_1} \mathrm{f}(\mathrm{x},\mathrm{y}) \times \mathrm{h}(\mathrm{x}' - x, \mathrm{y}' - y)dxdy \tag{1}$$

$$\mathrm{F}_{\sigma}(\mathrm{u},\mathrm{v}) = \mathrm{F}(\mathrm{u},\mathrm{v}) \times H(u,v) \tag{2}$$

Where $\mathrm{h}(\mathrm{x},\mathrm{y})$ is the system kernel, s_1 is the spatial domain, $\mathrm{f}(\mathrm{x},\mathrm{y})$ is the input, $\mathrm{f}_{\sigma}(\mathrm{x},\mathrm{y})$ is the output.

Depending on the difference of treatments, treatments will be divided into mathematical description to isotropic neurons and anisotropic neurons.

Laplace transform expression of Gaussian function is as follows:

$$\nabla^2 G(x,y) = \frac{-1}{\pi\sigma^4}\left(1 - \frac{x^2+y^2}{2\sigma^2}\right) \exp\left(-\frac{(x^2+y^2)}{2\sigma^2}\right. \tag{3}$$

In engineering applications, we use the difference between different spatial distributions of two Gaussian functions to approximate. Expression is shown below.

$$\mathrm{h}(\mathrm{x},\ \mathrm{y}) = \frac{1}{2\pi\sigma_1^2} e\,\mathrm{xp}\left(-\frac{(x^2+y^2)}{2\sigma_1^2}\right) - \frac{1}{2\pi\sigma_2^2} e\,\mathrm{xp}\left(-\frac{(x^2+y^2)}{2\sigma_2^2}\right) \tag{4}$$

The system kernel is as follows:

$$\mathrm{h}(\mathrm{x},\mathrm{y}) = \mathrm{g}(\mathrm{x},\ \mathrm{y})\exp(j2\pi f x) \tag{5}$$

Gaussian function has good smoothness and locality in space domain and spatial frequency, so the Laplace transform is suitable as kernel function of neuronal receptive field. We will name the response to image by the system kernel as the improved Gabor energy, the expression is as follows:

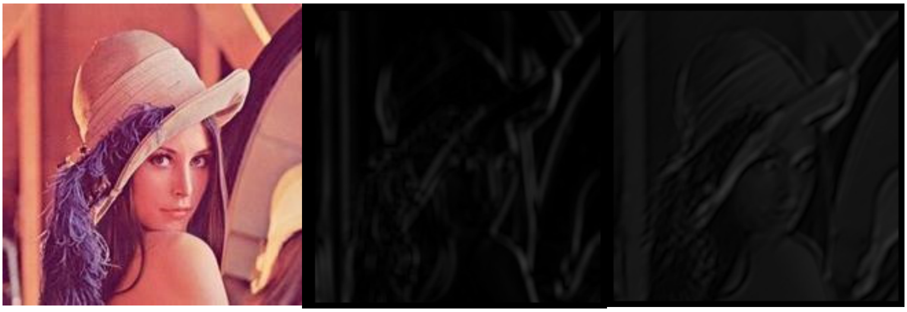
$$\mathrm{E}_{\sigma}(\mathrm{x},\mathrm{y}) = \sqrt{\mathrm{E}_e(\mathrm{x},\mathrm{y})^2 + \mathrm{E}_o(\mathrm{x},\mathrm{y})^2} \tag{6}$$

$$\mathrm{E}_e(\mathrm{x},\mathrm{y}) = \mathrm{f}(\mathrm{x},\mathrm{y}) * \mathrm{h}_e(x,y) \tag{7}$$

$$\mathrm{E}_o(\mathrm{x},\mathrm{y}) = \mathrm{f}(\mathrm{x},\mathrm{y}) * \mathrm{h}_o(x,y) \tag{8}$$

Where $\mathrm{h}_e(x,y)$, is the real part and $\mathrm{h}_o(x,y)$ is the imaginary parts.

We use the improved the Gabor filter in four directions to operate the Lena. The results are shown below.



(a) Original image (b) Theta 0 (c) Theta pi/4

(d) Theta pi/2 (e) Theta pi*3/4

Fig. 2. The Improved Gabor Filter

The improved Gabor energy can identify the chaotic texture the chaotic texture. However, the response of improved Gabor energy function is only partial orientation information. So to achieve effects of environmental suppression and spatial enhancement, we also need to design a global operator on the basis of the improved Gabor energy function.

3 Environment Suppression

Neurons in the primary visual cortex preferentially respond to stimulation with particular space. When the stimulation is larger than the area they feel, these neurons will be suppressed and have effects on aggregate perception of contours and lines. Studies [24-27] have shown that modulation of environment on neural response is considered to be the basis of many sensory phenomena.

Due to neurons possessing direction selectivity in the human primary visual cortex, these cells suppress non-classical receptive field around the area, and have the impact on aggregate perception of contours and lines. Cosmin Grigorescu [17], who was inspired to propose a significant computing model called the environment suppression in order to improve the detection of contours and boundaries of the target area of a natural scene image. It is calculated as follows:

(1) Environment suppression
Cosmin Grigorescu [21] operated the Gauss difference to simulate human primary visual cortex's suppression on the environment. DoG expression is shown below.

$$\mathrm{DoG}\sigma(\mathrm{x},\mathrm{y}) = \frac{1}{2\pi(4\sigma)^2}\exp\left(-\frac{\mathrm{x}^2+\mathrm{y}^2}{2(4\sigma)^2}\right) - \frac{1}{2\pi\sigma^2}\exp\left(-\frac{\mathrm{x}^2+\mathrm{y}^2}{2\sigma^2}\right) \tag{9}$$

Custom expression of weighting function is shown below.

$$\mathcal{W}\sigma(\mathrm{x},\mathrm{y}) = \frac{\mathrm{H}(\mathrm{DOG}\sigma(\mathrm{x},\mathrm{y}))}{\|\mathrm{H}(\mathrm{DOG}\sigma)\|1} \tag{10}$$

$$\mathrm{H}(\mathrm{z}) = \begin{cases} 0 & z < 0 \\ z & z \geq 0 \end{cases} \tag{11}$$

$\|*\|\ 1$ represents the norm of L1.

(2) Isotropic and anisotropic suppression
The effect of isotropic suppression only considers the distance factor. The expression is shown below.

$$F_{env}(x,y) = \iint_{\Omega} \mathrm{E}_{\sigma}(\mathrm{x}-\mathrm{u},\mathrm{y}-\mathrm{v})\,\mathcal{W}_{\sigma}(\mathrm{u},\mathrm{v})dudv \tag{12}$$

Where $\mathrm{E}_{\sigma}(\mathrm{x},\mathrm{y})$ is the improved Gabor energy response, Ω is the spatial domain.

Compared to the isotropic suppression, the anisotropic suppression adds a suppression factor namely the direction factor. There are two points (x, y) and (x-u, y-v) and the expression of the direction factor is shown below.

$$\Delta_{\Theta,\sigma}(\mathrm{x},\mathrm{y},\mathrm{x}-\mathrm{u},\mathrm{x}-\mathrm{v}) = |\cos(\Theta_{\sigma}(\mathrm{x},\mathrm{y}) - \Theta_{\sigma}(\mathrm{x}-\mathrm{u},\mathrm{y}-\mathrm{v}))| \tag{13}$$

According to the above equation, if these two points are in the same direction and then the suppression is greatest. When the angle increases, the inhibition is reduced because of cos (0) = 1, When the two points are perpendicular to each other, the inhibitory will have minimum effects (cos (π / 2) = 0).

After adding the direction factor, the expression is shown below.

$$F_{env}(x,y) = \iint_{\Omega} \mathrm{E}_{\sigma}(\mathrm{x}-\mathrm{u},\mathrm{y}-\mathrm{v})\,\mathcal{W}_{\sigma}(\mathrm{u},\mathrm{v}) \times |\cos(\Theta_{\sigma}(\mathrm{x},\mathrm{y}) - \Theta_{\sigma}(\mathrm{x}-\mathrm{u},\mathrm{y}-\mathrm{v}))|dudv \tag{14}$$

4 Spatial Enhancement

Geisler et al [18] thought that the visual cortex's stimulation response to the components possessing a consistent space agencies will be strengthened. And it has two characteristics: if local ingredients are smoother and closer, there will be a greater probability of being aggregated into global contours; if two local ingredients are close and touch the same circle, then this local contour will have a higher significance, which is known as co-circular rules. Concyclic geometric relationship is shown in Figure 2. If an azimuth of the center position is α ($0 \leqslant \alpha < \pi$), then the azimuth of co-circular geometry β will satisfy:

$$\beta = \begin{cases} 2\gamma - \alpha + \pi, & 2\gamma - < 0 \\ 2\gamma - \alpha, & 0 \le 2\gamma - \alpha < \pi \\ 2\gamma - \alpha - \pi, & \pi \le 2\gamma - \alpha \end{cases} \tag{15}$$

γ is the orientation of the connection of center and the ambient component ($0 \le \gamma < \pi$).

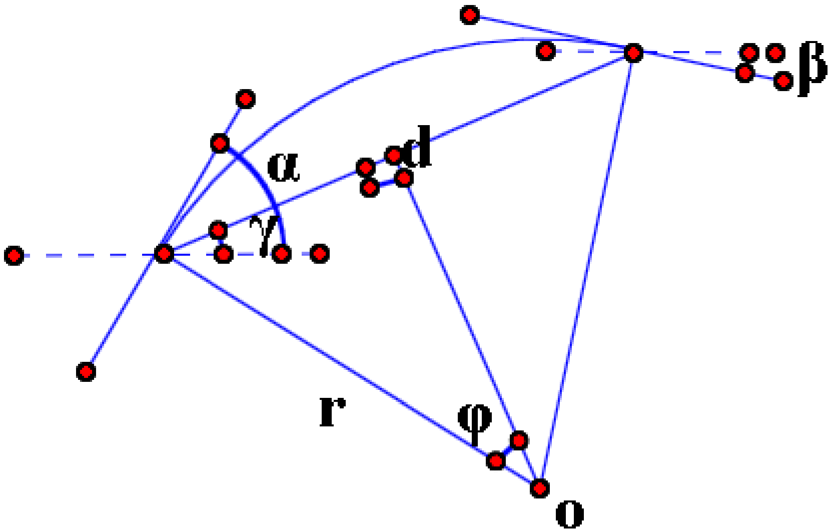


Fig. 3. Concyclic Geometric Diagrams

The curvature is an important factor to determine the detectability of the natural contours, and concyclic curvature k is calculated as follows:

$$k = \frac{1}{\gamma} = \frac{2}{d}\sin(\theta) = \begin{cases} \frac{2}{d}\sin\left|\frac{\beta-\alpha}{2}\right|, & 0 \le 2\gamma - \alpha < \pi \\ \frac{2}{d}\sin\left|\frac{\beta-\alpha}{2}\right|, & 2\gamma - \alpha < 0\ or 2\gamma - \alpha > \pi \end{cases} \tag{16}$$

α, β are the optimal orientation of the reference point of the center-periphery receptive field. You can get the weighting function according to the curvature and distance decay function, which is calculated as follows (D is a normalization constant):

$$W_c(x, y, \alpha; x', y', \beta) = \exp\left(-\frac{k^2}{2{\sigma_c}^2}\right) \tag{17}$$

$$W_d(d) = \frac{1}{D}\exp\left(-\frac{d^2}{2{\sigma_d}^2}\right) \tag{18}$$

The expression of spatial enhancement is as follows:

$$F_{\mathrm{air}}(x,y,\alpha) = \sum_{d\in R}\sum_{\beta} W_c(x,y,\alpha;x',y',\beta)\, W_d(d) \times \mathrm{E}_{\sigma}(x',y',\beta) \tag{19}$$

Where $\mathrm{E}_{\sigma}(x,y,\beta)$ is the best improved Gabor energy response in the direction of β .

5 Integrated Model

Environment suppression can suppress texture contour noise, spatial enhancement can combine discrete significant contour and the property model can highlight significant contours. Then use the property model to integrate these mechanisms, and achieve the goal of extracting significant goal contour ultimately. Comprehensive formula is as follows:

$$F_{\mathrm{n+1}}(x,y,\alpha_i) = \mathrm{F}(x,y,\alpha_i) + \eta(n)\big(F_{\mathrm{air}}(x,y,\alpha_i) - c\cdot F_{\mathrm{env}}(x,y)\big) \tag{20}$$

$$\mathrm{F(x,y)} = \underset{i}{MAX}\big(F_{\mathrm{n+1}}(x,y,\alpha_i)\big) \tag{21}$$

$$F_{\mathrm{com}}(x,\ y) = \sum_{x,y\in n}\mathrm{E(x,y)} \tag{22}$$

Where $\eta(n)$ the iteration parameter and c is enhanced suppression coefficient determining the degree of the inhibition and enhanced in the model.

$\mathrm{i} = 1,2,3,\ldots,\mathrm{k}$ represents the number of directions of the improved Gabor energy function. $F_{\mathrm{com}}(x,\ y)$ is the comprehensive effects.

6 Global Operator

We use the non-maximal suppression and hysteresis thresholding that Canny used in his classic paper [28] to obtain the results of the binary processing. The specific algorithm process is as follows:

(1) Calculate the gradient

Firstly, convolute the artwork with Gaussian function, then smooth and filter the image, finally perform the finite difference operation on the filtered image. In Canny operator, the expression is given below.

$$\mathcal{F}\sigma(\mathrm{x,y}) = (\mathcal{F} * \mathcal{G}\sigma)(\mathrm{x,y}) \tag{23}$$

$$\mathcal{G}\sigma(\mathrm{x,y}) = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{\mathrm{x}^2+\mathrm{y}^2}{2\sigma^2}\right) \tag{24}$$

$$\nabla\mathcal{F}\sigma(\mathrm{x,y}) = \left(\frac{\partial\mathcal{F}\sigma(\mathrm{x,y})}{\partial x},\frac{\partial\mathcal{F}\sigma(\mathrm{x,y})}{\partial y}\right) \tag{25}$$

However, the study concluded that using the above expression to calculate is ill-posed. Therefore, use the following expression to calculate the gradient.

$$\mathcal{F}\sigma(\mathrm{x,y}) = (\mathcal{F} * \mathrm{h})(\mathrm{x,y}) \tag{26}$$

$$\mathrm{h}(\mathrm{x}, \mathrm{y}) = \frac{1}{2\pi\sigma_1^2} e\,\mathrm{xp}\left(-\frac{(x^2+y^2)}{2\sigma_1^2}\right) - \frac{1}{2\pi\sigma_2^2} e\,\mathrm{xp}\left(-\frac{(x^2+y^2)}{2\sigma_2^2}\right) \tag{27}$$

$$\nabla\mathcal{F}\sigma(\mathrm{x,y}) = (\mathcal{F} * \nabla\mathrm{h})(x,y) \tag{28}$$

Wherein, ∇h (x, y) is the first derivative of the Gaussian function. Then have further to calculate the gradient along the X, Y directions and the expression is shown below.

$$\nabla x\mathcal{F}\sigma(\mathrm{x,y}) = \left(\mathcal{F} * \nabla\frac{\partial \mathrm{h}}{\partial x}\right)(\mathrm{x,y}) \tag{29}$$

$$\nabla y\mathcal{F}\sigma(\mathrm{x,y}) = \left(\mathcal{F} * \nabla\frac{\partial \mathrm{h}}{\partial y}\right)(\mathrm{x,y}) \tag{30}$$

Calculate the gradient and then get the magnitude and direction. The expression is shown below.

$$\mathrm{M}_\sigma(\mathrm{x,y}) = \sqrt{\nabla x\mathcal{F}\sigma(\mathrm{x,y})^2 + \nabla y\mathcal{F}\sigma(\mathrm{x,y})^2} \tag{31}$$

$$\Theta_\sigma(\mathrm{x,y}) = \tan^{-1}\frac{\nabla y\mathcal{F}\sigma(\mathrm{x,y})}{\nabla x\mathcal{F}\sigma(\mathrm{x,y})} \tag{32}$$

(2) Combine effects

After the first step of the calculation, using the non-maxima suppression along the direction of gradient to locate the contour pixels of the image can obtain the contour image. In this step, we need to suppress background texture and noise of contour images and enhance the spatial.

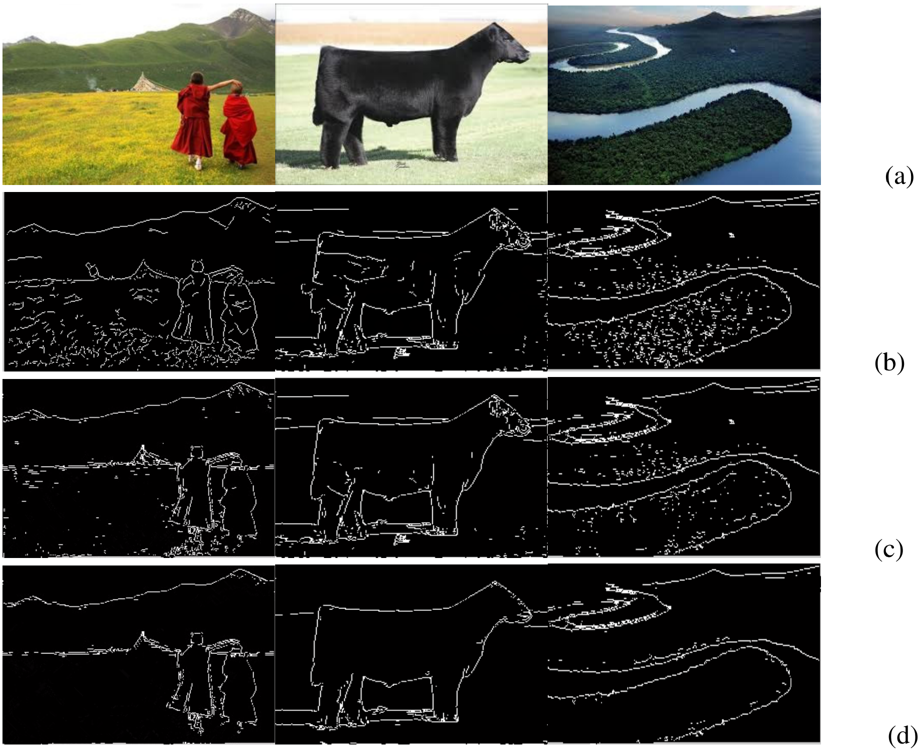
Finally, get the contour extraction operator and its expression is shown below.

$$C_\sigma^f(x, y) = H(\mathrm{M}_\sigma(\mathrm{x,y}) - \alpha F_{\mathrm{com}}(x, y)) \tag{33}$$

H (*) is operating operator involving the refinement of contours, hysteresis thresholding and contour connections. The specific operation can refer canny operator [28].

7 Results and Analysis

In order to test the effect of contour extraction, select a number of images from the library Pinterest. Furthermore, do an experiment and compare it with other algorithms. Results are as follows:



(a) Original Image (b) Canny Contour Extraction
(c) Traditional Detection Algorithm (d) the Proposed Algorithm

Fig. 4. Image Contour extraction Result

According to the performance criteria of the contour extraction:

$$P = \frac{card(E)}{card(E)+card(E_{fP})+card(E_{fN})} \tag{34}$$

Wherein card (E) represents the number of members in the set E; E, E_{fP}, E_{fN} represent the correct contour, false contour and omissions contour respectively. Performance testing index of Figure 3 is shown in the following table (frequency of bandwidth B_f = 1.5, the number of samples k=12, orientation bandwidth B_θ =-r / 6, variance of DoG σ=3, variance of weighting function=-r / 6):

Table 1.

Algorithm	Performance P	Performance P	Performance P
	Group1	Group2	Group3
Canny	0.20	0.15	0.15
Represent	0.30	0.30	0.27
The paper	0.32	0.33	0.31

Through the above performance comparison, this algorithm is significantly better than the canny algorithm and better than the representative detection algorithm.

8 Conclusion

In computer vision, the image contour extraction is a necessary link. Selecting the appropriate image contour extraction method is undoubtedly very important. According to traditional contour extraction methods' problems, the paper improves the Gabor function model and proposes the idea of using the Gaussian function Laplace transform as the mathematical description of receptive fields. In addition, the paper learns from the Gabor function's suppression effect on the environment and spatial enhancement of the integrated mechanism in order to establish the visual fusion model. Experiments show that this method has a continuous contour extraction, high precision, single-pixel width and other characteristics. When as compared with classical edge detection, contour extraction method given herein is of strong anti-interference, good stability and can meet on computer vision measurement requirements.

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