A new edge detection method based on probability density gradient and fuzzy inference

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Abstract

Edge detection is an important research content in image processing. In this paper,an edge detection method based on probability density gradient and fuzzy reasoning is proposed to solve the problem of low accuracy of edge detection. the probability density gradient direction is first used to divide the regional points from the non-regional points, which reduces the computational complexity of the algorithm. Then, a new membership function is constructed by using the local consistency of the image. The Sugeno model, which can be output accurately, is used to define the effective fuzzy rules for fuzzy reasoning. Finally, the final binary edge image is obtained by using the threshold surface method of dynamic ordered change. The experimental results show that the proposed method can effectively extract the edges of gray images, and the extracted edges have good continuity and larger information entropy.

Keywords

Image processing, Fuzzy inference, Edge detection.

1. Introduction

As one of the basic features of the image, image edge is usually used in higher level image processing and analysis. So edge detection is an important research content in image processing. The edge detection method commonly used by a variety of differential operator detection[1-3]. In recent years, some better edge detection methods have emerged, including probability density gradient method[4-6] and fuzzy logic reasoning method[7-9].

One of the most commonly used image segmentation techniques is to cluster pixels based on color (or brightness) information, and then divide the contiguous pixels into the same region. Fukunaga [10] points out that the probability density gradient of the sample point always points to the central direction of the class to which the sample point belongs. According to this property, the probability density gradient can be used to complete the self-clustering of the sample points. According to the clustering ability of the probability density gradient, Comaniciu [11] adopts the normalized probability density gradient to smooth and segment the image, and good results are obtained. Because the pixel points on both sides of the image edge belong to different categories, the pixel points on both sides of the edge move in the opposite direction during the MeanShift clustering process. According to this property, the distinction between the edge point and the non- edge point can be realized by comparing the probability density gradient direction of the adjacent points.

Fuzzy edge detection algorithm [12, 13] proposed by Pal and King is introduced into the image edge detection algorithm for the first time. Because the uncertainty of object boundary in image is usually fuzzy, this method can effectively separate objects from background, especially in the field of medical image processing and pattern recognition. The Pal and King algorithms are better than the traditional methods because of the introduction of fuzzy idea.

In this paper, the probability density gradient and fuzzy theory are combined, the edge extraction method based on probability density gradient and fuzzy reasoning is proposed, and the edge feature of gray image is extracted by using the advantages of two methods. Finally, the performance of the new algorithm is compared with the traditional Canny algorithm and the Pal and King algorithm.

2. The distinction between regional points and non-regional points of image

In this section, we first give the estimation of the probability density gradient of each pixel in the image, and propose a method to distinguish the regional point from the non-regional point based on the direction of the probability density gradient.

2.1 Probability density gradient direction

The image is the distribution of pixels in the image space, where the probability density of each point can be estimated by kernel function [10]. The kernel function of the probability density of the pixel point $M(x,y)$ of the color C in the image is estimated to be

$$P(M)=\sum_{w}\frac{C}{h_s^2 h_f^p}k\left(\left\|\frac{x-x_j}{h_s}\right\|\right)k\left(\left\|\frac{c_j-c}{h_f}\right\|\right) \tag{1}$$

Among them, C is a constant; X is the plane coordinate of point $M(x,y)$; x_j is a point in a window w centered on x; c_j is the color of x_j points in the image; k is kernel function and usually as Gaussian function; h_s is the bandwidth in the image plane space, h_f is the bandwidth in the attribute (color) space, and p is the dimension of the attribute space. According to formula (1), the estimation formula of the probability density of each pixel in the image plane space gradient $G(x,y)$ can be derived.

$$G(x,y)=\nabla_s P(x,y)=(P_x,P_y) \tag{2}$$

$$P_x=\sum_{w}\frac{C}{h_s^2 h_f^p}k_x^{'}\left(\left\|\frac{x-x_j}{h_s}\right\|\right)k\left(\left\|\frac{c_j-c}{h_f}\right\|\right) \tag{3}$$

$$P_y=\sum_{w}\frac{C}{h_s^2 h_f^p}k_y^{'}\left(\left\|\frac{x-x_j}{h_s}\right\|\right)k\left(\left\|\frac{c_j-c}{h_f}\right\|\right) \tag{4}$$

Then the probability density gradient direction of the pixel point $M(x,y)$ is

$$\theta=\arctan\left(\frac{P_y}{P_x}\right) \tag{5}$$

2.2 Division of regional and non-regional points in image

Based on the fact that the probability density gradient of the sample point always points to the central direction of the class to which the sample point belongs. According to this property, the probability density gradient can be used to complete the self-clustering of the sample points. So we can use the direction of probability density gradient to realize the division of regional and non-regional points. The specific steps are given as follows:

Calculating the direction of probability density gradient of filtered image;

Judging the angle between the direction of probability density gradient of each pixel $\theta_i(i=1,2,...,n^2-1)$ and the direction of probability density gradient of central pixel θ in $n*n$ mask window.

$$\begin{cases}|\theta_i-\theta|\le 90^\circ, \textit{marking the pixel } i \textit{ as } -1\\ |\theta_i-\theta|>90^\circ, \textit{marking the pixel } i \textit{ as } 1\end{cases} \tag{6}$$

(1) Determine whether all of the marked points in the window are -1 or 1 or both.

If the marking points in the window are all -1 or 1, the probability density gradient of the window pixels is set to zero. If the marking points in the window are -1 and 1, the probability density gradient values of the window pixels remain unchanged.

3. Improved fuzzy reasoning method

In the previous section, probability density gradient direction has used to divide the non-regional points of the image, the computational complexity of the subsequent algorithm can be effectively reduced. This section will improve the fuzzy logic reasoning algorithm from two aspects: improve the membership function and improve the fuzzy reasoning rules.

3.1 Improved membership function

In order to process the image in the fuzzy domain, it is necessary to transform the image from the spatial domain to the fuzzy domain. The local consistency of image is the inherent attribute of the image. In this paper, by analyzing the neighboring pixels, we define the degree to which the new pixel belongs to the edge point, that is, the membership function, as shown in formula 7.

$$\mu = \frac{2F * \overline{F}}{F^2 + \overline{F}^2} \tag{7}$$

Where F is the probability density gradient value of the center pixel of the 3*3 window and $\overline{F}$ is the mean value of the probability density gradient of all the pixels in the 3*3 window. The ideal range of μ is $[0,1]$.

It can be seen from formula 7 that if the pixel point belongs to the edge point, the difference between the pixel point and its neighborhood mean value is larger, so the value of μ will also be larger. If the pixel is not an edge point, the difference between the pixel and its neighborhood mean is smaller. The corresponding μ will also be smaller. Therefore, the value of μ in formula 7 reflects the degree of the pixel belonging to the edge point.

3.2 Improved fuzzy inference rules

In order to avoid the huge rule base, in this paper, Sugeno fuzzy model[14] is adopted to get the exact output and define the new fuzzy inference rules as follows:

$$\text{Rule 1: If } x \text{ is edge point,then } \mu' = \mu^{0.1} \tag{8}$$

$$\text{Rule 2: If } x \text{ is area point,then } \mu' = \mu^{0.8} \tag{9}$$

$$\text{Rule 3: If } x \text{ is noise point,then } \mu' = \mu^{0.9} \tag{10}$$

These three fuzzy inference rules can effectively extend the difference of membership degree between edge points and non-edge points (regional points and noise points).

3.3 Threshold surface method for dynamic ordered variation

The threshold surface method of dynamic order change is used to segment the edge point and non-edge point after fuzzy reasoning, the final binary edge graph is obtained by eliminating non-edge points and preserving edge points.

4. Experimental results and analysis

In order to verify the superiority of this method. The results are evaluated from two aspects： subjective evaluation and objective evaluation. The continuity of human visual perception is taken as the subjective evaluation result. The information entropy is used to objectively reflect the edge detection effect. The following two evaluation methods are used to evaluate the processing effect of the algorithm.

4.1 Subjective evaluation of edge detection

In order to compare the advantages of the algorithm, this method is compared with the traditional Canny edge detection algorithm and Pal and King (PK) edge detection algorithm. In this paper, we give three result graphs , see Fig. 1, Fig. 2, Fig. 3.

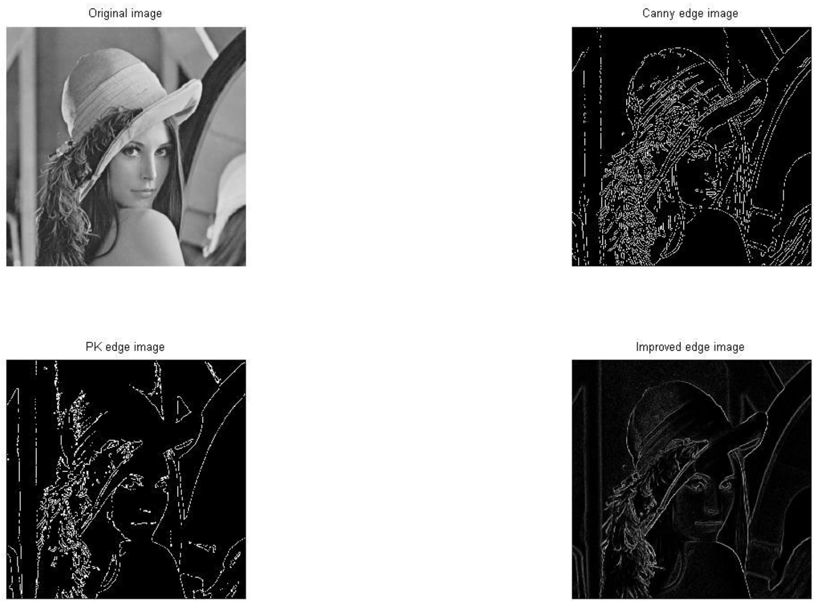

Fig.1 Three methods for edge detection of image Lena.

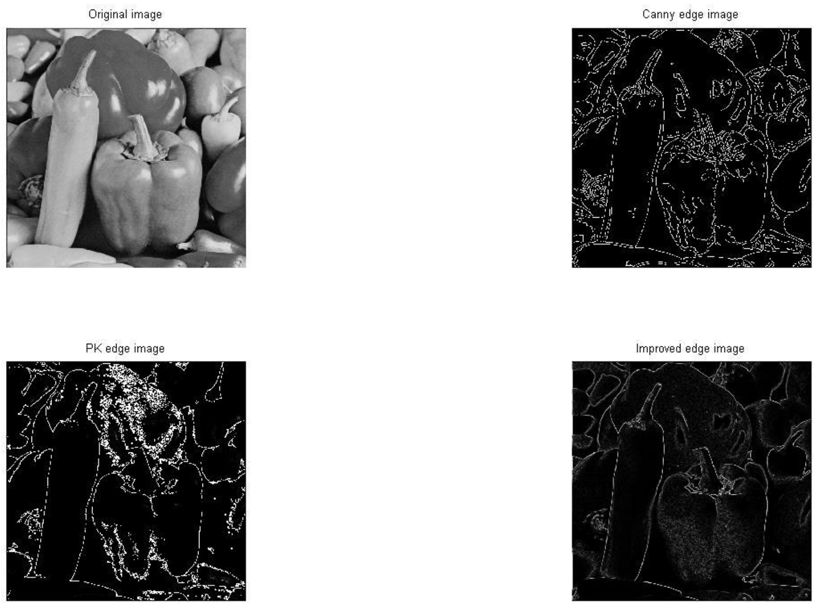

Fig.2 Three methods for edge detection of image Peppers.

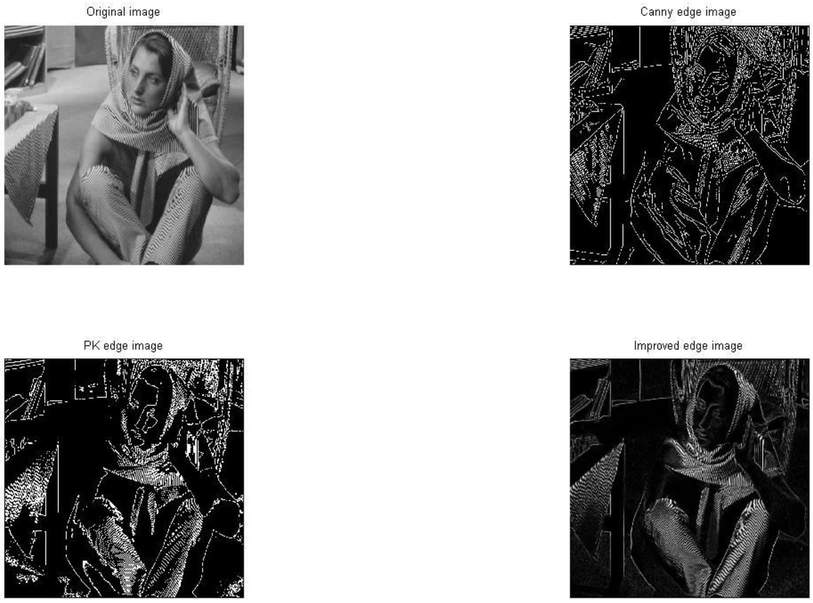

Fig.3 Three methods for edge detection of image Barbara.

It can be seen from the above three groups that the algorithm proposed in this paper has better edge detection continuity and higher detection accuracy. It avoids a lot of trivial details and is obviously superior to the contrast algorithms.

4.2 Objective evaluation of edge detection

Information entropy is an index to measure the amount of information. In image edge detection, it is often used to express the advantages and disadvantages of edge detection algorithm[15,16]. The bigger the information entropy is, the better the edge detection effect of the algorithm is. The calculation formula of information entropy is as follows:

$$H(x) = -\sum_{i=1}^{n} P_i(x)\log_2 P_i(x) \tag{11}$$

where $H(x)$ is the information entropy and P_i is the probability of pixels with a probability density gradient of i.

Table 1 shows the information entropy values of the results of three algorithms for edge detection of 6 images(Lena, Peppers, Barbara, Columbia, Cameraman, Boats), which IFM represents the improved fussy method and OI represents original image.

Table 1 Information entropy of different images with different algorithms

Method	Information entropy					
	Lena	Peppers	Barbara	Columbia	Cameraman	Boats
Canny	0.3640	0.4203	0.4927	0.4074	0.4484	0.4687
PK	0.9662	0.5437	0.8595	0.6311	1.2296	0.5303
IFM	4.9418	4.9292	5.8159	4.6219	3.9801	4.9433
OI	7.5925	7.4372	7.4664	7.2736	6.9046	7.0881

5. Conclusion

In this paper, the probability density gradient direction is first used to divide the regional points from the non-regional points, which reduces the computational complexity of the algorithm. Then, a new membership function is constructed by using the local consistency of the image. The Sugeno model, which can be output accurately, is used to define the effective fuzzy rules for fuzzy reasoning. Finally, the final binary edge image is obtained by using the threshold surface method of dynamic ordered change. The experimental results show that the proposed method can effectively extract gray image edges and the extracted edges are smoother. It effectively avoids a lot of trivial details and has a larger information entropy.

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