Mean Shift 알고리즘과 Canny 알고리즘을 이용한 에지 검출 향상

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Using mean shift and self adaptive Canny algorithm enhance edge detection effect

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요 약

Edge detection is an important process in low level image processing. But many proposed methods for edge detection are not very robust to the image noise and are not flexible for different images. To solve the both problems, an algorithm is proposed which eliminate the noise by mean shift algorithm in advance, and then adaptively determine the double thresholds based on gradient histogram and minimum interclass variance. With this algorithm, it can fade out almost all the sensitive noise and calculate the both thresholds for different images without necessity to setup any parameter artificially, and choose edge pixels by fuzzy algorithm.

Keyword : Edge Detection, Low Level Image Processing, Mean Shift Algorithm, Threshold

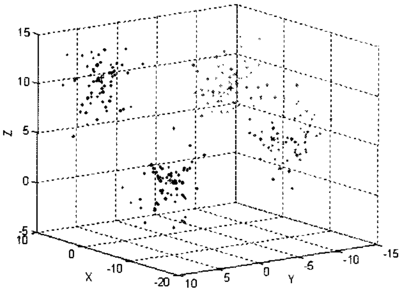
I. Introduction

In a digital image, the boundary of objects contains much information, although just include limited pixels. Therefore edge detection is the significant and hard issue in image processing, image analysis and computer vision domain. Hitherto the Canny algorithm may be the most suitable method among the other plenty methods. However, there are at least two disadvantages impact the final effect deeply, one is noise influence, the other is the both thresholds of edge point filter set artificially. For the same image, based on different circumstances, the results represent absolutely different. But for the different images, need intentionally set different thresholds almost. So that there are many masters research building thresholds method thorough the world [1][2][3], and bring the alleged self adaptive method but also need set the scale coefficient of threshold, can't shrug off the human factor.

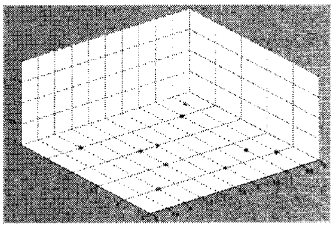
Thereby, there is an approach try to get rid of human factor influence and select the most suitable both thresholds automatically hinge on the gradient histogram and interclass variance. By besides, fade out the noise in advance by mean shift smoothing algorithm.

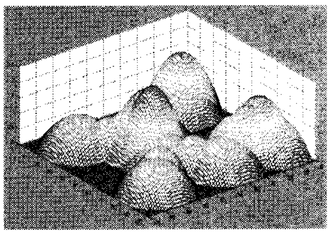
II. Edge Detection Using Mean Shift Smoothing

The mean shift algorithm is a method finds the cluster center by constantly iterating. Its basic idea is moving a shift window on the gradient direction of the feature space. Take briefly explanation of clustering problem. Given a set of data points $\{x_i\}$ in a d-dimensional Euclidean space R^d, assign a label l_i to each point x_i based on proximity to high density regions in the space, see the following diagram



The multivariate kernel density estimate is defined as: $f(x)=\frac{1}{nh^d}\sum_{i=1}^{n}K(\frac{x-x_i}{h})$, using the Epanechnikov kernel: $K_E(x)=\begin{cases}(2c_d)^{-1}(d+2)(1-x^Tx) & x^Tx<1\\ 0 & otherwise\end{cases}$, and we obtain the mean shift vector as: $M_h(x)=\frac{h^2}{d+2}\frac{\nabla f(x)}{f(x)}=\frac{1}{n_x}\sum_{x_i\in S_h(x)}x_i-x$, and the mean shift iteration, derived from the mean shift vector $M(x)$: $y_{k+1}=\frac{1}{n_k}\sum_{x_i\in S_h(y_k)}x_i$, where n_k is the number of points in a sphere of radius h, and h is the window radius [4]. The following diagrams show the multivariate kernel density estimate:





Example Data Set $\{x_i\}$

$$f(x)=\sum_{i=1}^{n}K(x-x_i)$$

$$K_E(x)=\begin{cases}(1-x^Tx) & x^Tx<1\\ 0 & otherwise\end{cases}$$

The mean shift procedure smoothes the image while preserving and sharpening its discontinuities. It should be recalled that smoothing has a positive effect to reduce noise and to ensure robust edge detection; and a negative effect on information loss. Clearly, a fundamental tradeoff between loss of information and noise reduction is crucial [5].

This procedure make true on computer like the following steps:

Initialize data set: $I(i,j)\rightarrow(i,j,I(i,j)*C)$

For each $j=1\ldots n$

Initialize $k=1$ and $y_k=x_j$.

Repeat: Compute y_{k+1} using the mean shift iteration; $k\leftarrow k+1$

Until convergence

$(y_{k+1}-y_k<\varepsilon)$.

Assign $I_{smoothed}(x_j(1),x_j(2))=y_k(3)$.

III. Edge Detection After Smooth Formality

The original Canny algorithm adopt the finite differential of adjacent area's first partial derivate to calculate the data matrix $I(x,y)$'s gradient amplitude and orientation. The partial derivate of x and y's 2 matrixes, which are $P_x[i,j]$ and $P_y[i,j]$:

$$P_x[i,j]=(I[i,j+1]-I[i,j]+I[i+1,j+1]-I[i+1,j])/2,$$

$$P_y[i,j]=(I[i,j]-I[i+1,j]+I[i,j+1]-I[i+1,j+1])/2.$$

Pixel's gradient amplitude and orientation use convert formula rectangular to polar to figure out: the gradient amplitude is $M[i,j]=\sqrt{(P_x[i,j])^2+(P_y[i,j])^2}$, and the gradient orientation is $\theta[i,j]=\arctan(P_y[i,j]/P_x[i,j])$. Then in order to extract the single pixel thick edge, we have to make out thinned amplitude image. However, near the position of maxima $M[i,j]$ will appear ridge; maintaining the maxima regional change point of amplitude can determine the edge position precisely, and this procedure is the alleged non-maxima suppression. In this section, the Canny algorithm use the magnitude of 3×3, 8 directions adjacent area interpolate all pixels of amplitude matrix $M[i,j]$ along the gradient direction. On every point, compare the adjacent area center pixel $m[i,j]$ with the two interpolation result along the gradient direction. If adjacent area center point' amplitude $M[i,j]$ is not large than both interpolation results, assign the edge sing corresponding to $m[i,j]$. This procedure details the ridge into one pixel magnitude, and maintains the gradient amplitude at the same time.

After the above steps, we have to determine the double thresholds and connect the edge. Undergone the non-maxima suppression and set both high threshold H_{T_H} and low threshold H_{T_L} for the sub-image $N[i,j]$ of gradient histogram, assign zero to the pixel whose gray vale is less than the threshold, then get two edge images $T_h[i,j]$ and $T_l[i,j]$. The $T_h[i,j]$ who through high threshold include very few fake edges, while $T_l[i,j]$ is opposition, consist of detail information but many more fake edges. Therefore combine both of them can get plausible edge [7].

According to these descriptions, the both thresholds determination can't refrain from the effect of personal factor, so need some method can absolutely exclude the personal factor and automatically determinate the thresholds hinge on different images. Inspirited by the Otsu's method [6], adopt the improved approach which based on gradient amplitude histogram and interclass variance to make out the both thresholds and then undertake non-maxima suppression to select the proper points, accomplish edge detection finally.

The gradient amplitude through non-maxima suppression is compose of L level, modulus maxima separate into three classes: C_0, C_1, C_2, C_0 class is the pixel that didn't belong to edge, C_2 class is the pixel belong to edge, C_1 class include the rest limbo pixels. Assume n_i is the amount of pixels whose modulus is i, P_i is the ratio of this kind of pixel to the whole pixels: $P_i = \frac{n_i}{N}, p_i \geq 0, \sum_{i=0}^{l-1} P_i = 1$, let C_0 include the pixels whose modulus is $[0,1,\cdots,k]$, C_1 include the pixels whose modulus is $[k+1,k+2,\cdots,m]$, C_2 include the pixels whose modulus is $[m+1,m+2,\cdots,l-1]$: $\mu_T = \mu(l-1) = \sum_{i=0}^{l-1} ip_i$,

$$\begin{cases} \omega_0(k) = \sum_{i=0}^{k} P_i, \omega_1(k,m) = \sum_{k+1}^{m} p_i, \\ \omega_2(m) = \sum_{m+1}^{l-1} p_i, \mu_0(k) = \frac{\sum_{i=0}^{k} ip_i}{\omega_0}, \\ \mu_1(k,m) = \frac{\sum_{i=k+1}^{m} ip_i}{\omega_1}, \mu_2(m) = \frac{\sum_{i=m+1}^{l-1} ip_i}{\omega_2}, \end{cases}$$

$$\begin{cases} \sigma_0^2 = \frac{\sum_{i=0}^{k} (i-\mu_0)^2 p_i}{\omega_0}, \\ \sigma_1^2 = \frac{\sum_{i=k+1}^{m} (i-\mu_1)^2 p_i}{\omega_1}, \\ \sigma_2^2 = \frac{\sum_{i=m+1}^{l-1} (i-\mu_2)^2 p_i}{\omega_2} \end{cases}$$

Propose the evaluate function "based on gradient amplitude histogram and minimized interclass variance determine the two thresholds":

$$J(k,u) = Arg\min(\sigma_w^2) = Arg\min(\omega_0\sigma_0^2 + \omega_1\sigma_1^2 + \omega_2\sigma_2^2).$$

Minimized interclass variance reflects the difference between the different classes should be minima. Through thisprocedure convert itself into first order statistical data, get the result has the advantages that easy to figure out and code out. There is the inference:

$$J(k,m) = \int_0^k (i-\mu_0(k))^2 p_i di + \int_{k+1}^{m} (i-\mu_1(k,m))^2 p_i di + \int_{m+1}^{l-1} (i-\mu_2(m))^2 p_i di$$

$$, \frac{\partial J(k,m)}{\partial k} = (k-\mu_0(k))^2 p_k - 2\mu_0^{(1)}(k) \int_0^k (g-\mu_0(k)) p_i di - (k-\mu_1(k,m))^2 p_k - 2\mu_1^{(1)}(k,m) \int_m^{k+1} (g-\mu_1(k,m)) p_i di.$$

From mathematical statistics we know that: if $\int_0^k (g-\mu_0(k)) p_i di = 0$, than

$$\frac{\partial j(k,m)}{\partial k} = [k-\mu_0(k)]^2 p_k - [k-\mu_1(k,m)]^2 p_k.$$

Let $\frac{\partial J(k,m)}{\partial k} = 0$, and simplify the equation than get $2k - \mu_0(k) - \mu_1(k,m) = 0$. In a similar way: $2m - \mu_1(k,m) - \mu_2(m) = 0$ [8].

From the above proof process, get the results that m,k are the most suitable extreme points for split. After that use fuzzy control method filter the pixel between the both thresholds.

When adopting both thresholds to filter the maximum modulus undergone the non-maxima suppression, fade out the point whose modulus is less than the low threshold as the non boundary point, while maintain the point that is large than the high threshold as the boundary point. But the pixel between the both thresholds can't decide. Because there is one regional peak in any boundary and its vertical direction, hence decide whether the maximum modulus between both thresholds is the boundary or not. According to some point maximum modulus'direction, determine the direction of boundary, and select its line adjacent area at boundary vertical direction, there are two pixels on this point's every side. If its maximum modulus is the most among its adjacent area, it is boundary point, otherwise is not. Using fuzzy control algorithm extract the pixel between the thresholds, set up membership function depending on maximum modulus $Mf_{2^j}(x,y)$, and undertake edge extraction and connection:

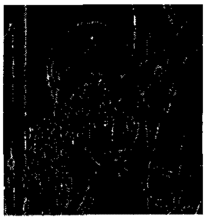
$$\mu(Mf_{2^j}(x,y)) = \begin{cases} 1, Mf_{2^j}(x,y) \geq m, \\ 0, Mf_{2^j}(x,y) \leq k, \\ \{1+[q_{\max} - Mf_{2^j}(x,y)]^2\}^{-1}, k < Mf_{2^j}(x,y) < m. \end{cases}$$

The $q_{\max}$ is the largest one among the 5 pixels which perpendicular to edge direction. And the membership show that, if the maximum modulus of decision point is not the largest among the adjacent area, this point must not belong to the edge; if it is, it belongs to the edge definitely [9].

IV. Conclusion

Take experiment to compare the original Canny method with the enhanced method, the different between results are absolutely obvious.

The original image The original Canny method with scale coefficient 0.5, 0.8 set by human.



Then enhanced Canny method with mean shift smoothing and self adaptive thresholds selection.

The edge extraction method mentioned in this paper is better depicting the contour of the main objects, and the automatically selected thresholds are suitable for human vision system.

Reference

[1] R.S.Anand, Pradeep Kumar, "Flaw detection in radiographic weld images using morphological approach", NDT&E International, 2006.

[2] Kiranyaz S, Ferreira M, Gabbouj M, "Automatic object extraction over multi scale edge field for multimedia retrieval", IEEE Trans Image Processing, 2006.

[3] Hongshan Yu, Yaonan Wang, "An improved Canny edge detection algorithm", Engineering and Application of Computer, 2004.

[4] D. Comaniciu, P. Meer, "Mean Shift: A Robust Approach towards Feature Space Analysis", IEEE Trans on Pattern Analysis and Machine Intelligence, Vol.24, No.5, May 2002.

[5] Huimin Guo, Ping Guo, Qingshan Liu, "Mean Shift-Based Edge Detection for color image", Department of Computer Science, Beijing Normal University, National Laboratory of Pattern Recognition Institute of Automation, CAS, Beijing.

[6] Otsu N. "A threshold selection method from gray-level histograms", IEEE Trans on Systems, Man, and Cybernetics, 1979,9(1):62-66.

[7] J.R.Parker, 《Algorithms for Image Processing and Computer Vision》, P23~P29.

[8] Mu Kang, Qinggong Xu, Baoshu Wang, "A Roberts' Adaptive Edge Detection Method", Academy of Information Technology, Xidian University, Xi'an.

[9] Ye Yuan, Zongying Ou, "Method of edge detection based on wavelet transform and fuzzy algorithm", Journal of Dalian University of Technology, 2004,42(4).