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Edge Extraction Method Based on Separability of Image Features

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Abstract

This paper proposes a new robust method for detecting step and ramp edges. In our method, an edge is defined not as *a point* where the intensity changes largely, but as *a region boundary* based on separability of image features which can be calculated by linear discriminant analysis. Based on this definition of an edge, the intensity of an edge is obtained from the separability, which depends only on the shape of an edge. This feature enables us to easily select the best threshold value for the extraction of an edge, our method can be applied to color, and texture edge extraction. Experimental results have shown that this proposed method is powerful enough to extract weak edges.

1 Introduction

Edges are primitive features of an image for high level image processing. Many edge extraction methods have been proposed, most of which are mainly based on the gradient of image intensity. These gradient-based methods use the smoothing filter such as a Gaussian filter for suppression of noise[1, 2]. Since they blur edges, the precision for edge localization degrades.

Recently others type of edge extraction method without smoothing are proposed, which are based on the moment-based method[6, 7] and robust to noise. The process of this method however becomes very complex to improve that performance. Some are based on the statistical analysis of the distribution of image features, such as an image intensity[8] and a gradient of an image intensity[9] inside a local region. Since they partially use the gradient value of an image intensity, they are sensitive to the selection of a thresholding parameter for a gradient value. And others model-based methods such as [4] are also developed, which need to determine many parameters. To study a better edge extraction method, we have considered the following characteristics.

1. Robustness to noise and diffuse edges.
2. Easy selection of the best parameters, such as the threshold value for an edge intensity.

In our new method, an edge is defined not as *a point* where the intensity changes rapidly, but as *a region boundary* where the features (such as an image intensity) of a local region are separated well as shown in Fig.1. Based on this definition of an edge, an edge intensity is obtained from *Separability* value which shows a degree of separation of the features. *Separability* depends only on the shape of an edge. This characteristic gives our method easy selection of the threshold parameters. Moreover our method is robust to noise, since it is based on the statistical analysis in a local region.

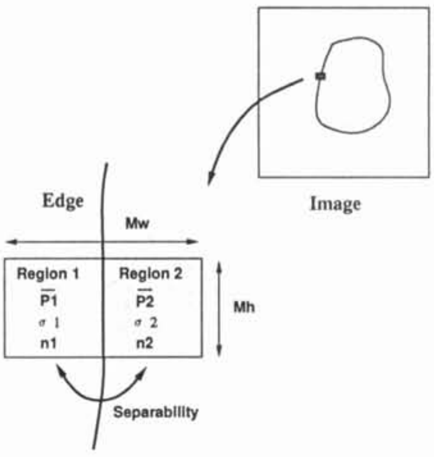

Figure 1: Definition an edge based on separability in a local mask region Mw×Mh.

This paper is organized as follows. Section 2 presents the definition of *Separability* and the characteristic of *Separability* in detail. Section 3 describes an algorithm of edge extraction. In Section 4 the quality evaluation of the performance of our method is compared with the conventional methods in terms of FOM (Figure Of Merit[3]). The experimental results for the real images are presented.

2 Basic Concepts

2.1 Definition of Separability

As shown in Fig.1 a local Mw×Mh region which consists of two small regions 1 and 2. *Separability* η can be calculated by linear discriminant analysis with information from

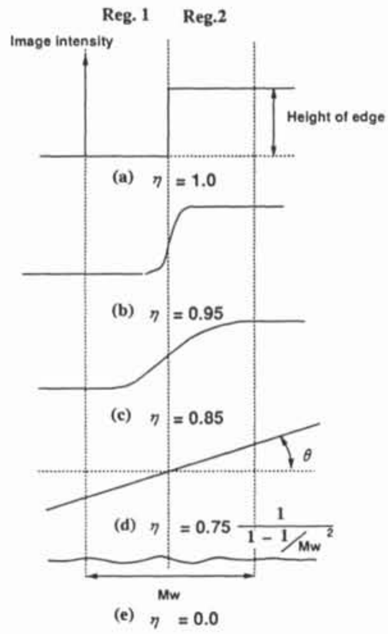

Figure 2: Changes of Separability η

regions 1 and 2 using the following Eqs.1-3,

$$\eta = \frac{{\sigma_b}^2}{{\sigma_T}^2} \tag{1}$$

$$ {\sigma_b}^2 = n_1(\overline{P_1} - \overline{P})^2 + n_2(\overline{P_2} - \overline{P})^2 \tag{2}$$

$$ {\sigma_T}^2 = \sum_{i=1}^{N} (P_i - \overline{P})^2 \tag{3}$$

Where P_i is a feature(for example, the intensity of an image) of an image at a pixel i. $\overline{P_1}$ and $\overline{P_2}$ are the means of the image features in regions 1 and 2 respectively. $\overline{P}$ is the mean of features for the combined local region, where n1 and n2 are the number of pixels in region 1 and 2 respectively. N is the number of pixels in the combined region(n1 + n2). When σ_T is smaller than σ_L, η is set at zero, where σ_L limits the height of a step edge to be extracted.

The concept of separability can be applied to multiple features (such as hue,saturation, statistical features of a region,etc.) by using the following Eqs.4-6.

$$\eta = \frac{\sum_{k=1}^{k=L} {\sigma_{bk}}^2}{\sum_{k=1}^{k=L} {\sigma_{Tk}}^2} \tag{4}$$

$$ {\sigma_{bk}}^2 = n_1(\overline{P_{k1}} - \overline{P_k})^2 + n_2(\overline{P_{k2}} - \overline{P_k})^2 \tag{5}$$

$$ {\sigma_{Tk}}^2 = \sum_{i=1}^{N} (P_{ki} - \overline{P_k}) \tag{6}$$

where L is the number of features. $\overline{P_k}$ is the mean of the image features k in the combined region. $\overline{P_{k1}}$ and $\overline{P_{k2}}$ are the mean of the image features k in regions 1 and 2.

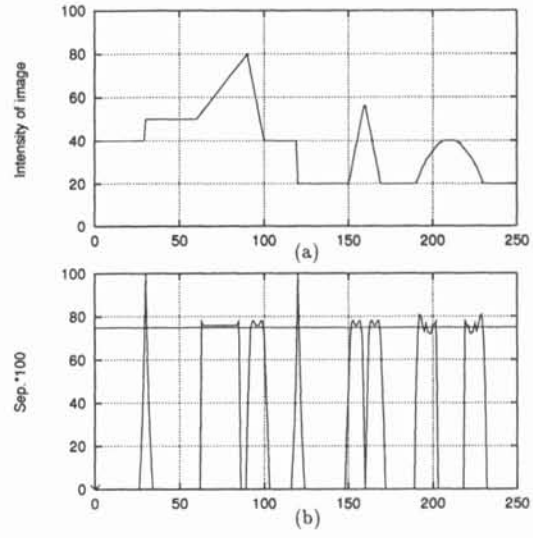

Figure 3: (a) Profile of an image intensity (b) Profile of Separability for (a) (Mw=6,Mh=1)

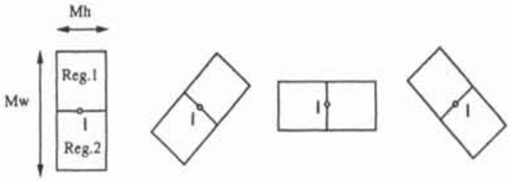

Figure 4: Example of a mask configuration for pixel i

2.2 Characteristics of Separability

Figs.2 shows such *Separability* η value for various intensity profiles. At an ideal step edge η is equal to 1.0, independent of the height of the step edge (Fig.2(a)). As the shape of an edge becomes smooth, η decreases as in Figs.2(b)-(c). In the region where thex intensity changes linearly, η is always about 0.75 (Fig.2-(d)), independent of the gradient θ of the region. In the region where there is little change of intensity, η is close to zero (Fig.2-(e)). Thus *Separability* η depends only on the edge shape. Fig.3 shows the image intensity which our method outputs for a test profile. This figure shows that the threshold value T_r for extraction edge can be set at a fixed value (above 0.75) for the whole pixel. If the image has some noise, it may be smoothed by such as a 3×3 Median filter or T_r should be set at a lower value (for example 0.65).

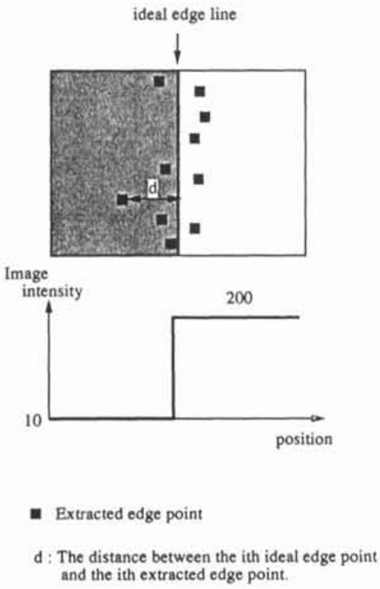

Figure 5: Test edge for FOM

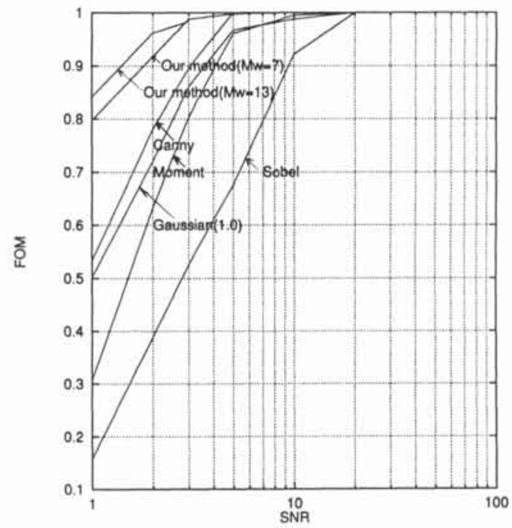

Figure 6: Characteristics of FOM to SNR

3 Algorithm of Edge Extraction

In order to extract an edge from a given image for a pixel i, our method uses a set different masks as shown in Fig.4 which consists of four masks (for 0,45,90,135 deg.). The mask size (Mw×Mh) could be determined in the following experiments. The main steps for edge extraction are outlined below.

1. Set four masks at a pixel i.
2. Calculate η value for each mask by using Eqs.1-3. When σ_T is smaller than σ_L, η is set at zero.
3. Determine the intensity and the direction of an edge by the mask which outputs the largest η among the four masks.
4. Move the mask to the next pixel.
5. Threshold the edge intensity by a given threshold value (for example 0.75) to obtain an edge image.

4 Experimental Results

4.1 Quality Evaluation of Robustness

The quality of our method's robustness to noise and a diffuse edge are compared with the various conventional methods in terms of FOM (figure of merit rating factor) introduced by Pratt[3]. FOM is obtained from the edge extraction result for the simulated test edge image which consists of two regions as shown in Fig.5.

$$FOM = \frac{1}{max(I_I, I_E)} \sum_{i=1}^{I_E} \frac{1}{1+\frac{1}{9}d^2(i)} \tag{7}$$

where I_I, I_E are the number of ideal and extracted edge points, $d(i)$ is the pixel miss distance of the ith edge detected. When the method detects all the edge points perfectly, FOM is equal to 1.0.

Fig.6 shows the variation of FOMs as a function of SNR for our method (Mw=7 and 13, Mh=7, ${\sigma_L}^2 = 30$) and the various conventional such as Sobel, Canny(Deriche's method[5], α=1.2),the moment-based method(5×5)[7] and the first derivative of a Gaussian(7×7) with σ=1.0. SNR is defined as $\left(\frac{k}{\sigma_n}\right)^2$ where σ_n is standard deviation of noise and k is the height of a step edge.

In this case, FOM is the largest value obtained from edge points extracted by nonmaxima suppression in the perpendicular direction to the extracted edge and thresholding with the best threshold value. When SNR is higher than 10, there is little difference in FOM. However, when SNR is lower than 10, our method has a high FOM value compared with the other methods. This means that our method is more robust to noise than the others. Fig.7 shows the variation of FOM to diffuse edges for our method (Mw=7,Mh=7,${\sigma_L}^2 = 30$) and the conventional methods. The test images with noise (SNR=20) are dulled by a Gaussian filter of which the standard deviation is Sigma. When Sigma is higher than 3, only the proposed method maintains a high FOM value and more robustness compared with the others.

4.2 Threshold selection

Fig.8(a) shows the image profile at the broken line shown in Fig.10. Fig.8(b) shows the edge intensity which the proposed method (Mw=8,Mh=1) outputs. Fig.8(c) shows the edge intensity which the conventional methods(the first derivative of a Gaussian with σ=1.0, Sobel) output. Note the proposed method obtains an equal intensity for the step

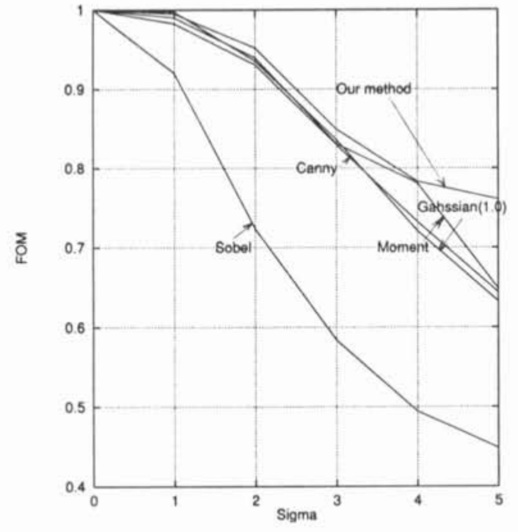

Figure 7: Characteristics of FOM to diffuse edges

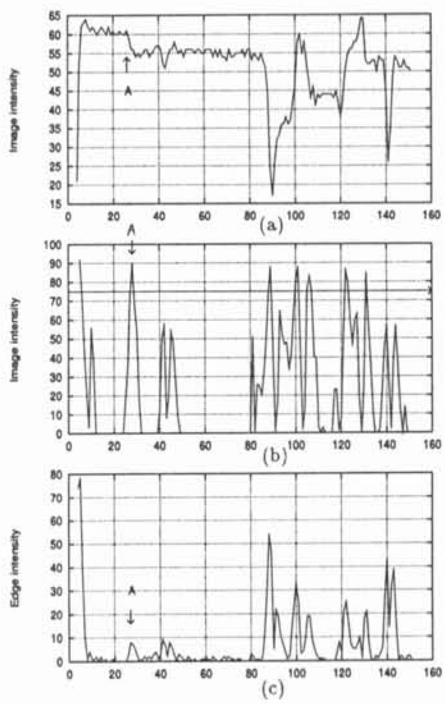

Figure 8: (a) The 1D intensity distribution at the broken line in fig.10. (b) The output of our method for (a) (Mw=8,Mh=1). (c) The output of the first derivative of a Gaussian withσ = 1.0 for (a).

and ramp edges and obtains a strong intensity for edge A (indicated by the arrow in Fig.8(a)). This guarantees the the performance of the proposed method is not affected by choice of the threshold value. On the other hand, the other method obtain a different intensity for the edges and obtains a weak intensity for edge$A$. Thus it requires to select dynamically the best threshold value for each pixel. In the worst case, it is impossible to extract weak edges if a very low threshold value is used.

Figs.9-10 show the two different test images 512 × 512 with the iris control. Figs.11-12 show the edge intensity images which our method (6×3) outputs. Although the gray level distributions are very different, our method can output the fixed intensity of the edges. Fig.13 shows the histogram of image intensity. Figs.14-15 show the histograms of edge intensity for our method and the first derivative of a Gaussian with σ=1.0 respectivley. These results mean that the best threshold value for edge extraction is not influenced by the change of gray level due to such as a change of an illumination and an iris value. If the best threshold value is determined once, it does not need to be changed.

4.3 Extraction of Weak Edges

Fig.16 shows a test image which has a object with low contrast and many texture edges. It is very difficult to extract the weak contour edges alone without any noise and small texture edges. Figs.17-19 show the edges extracted from the edge intensity image which the proposed method(Mw=14,Mh=7,$\sigma_L{}^2 = 30$), and the first derivative of a Gaussian with σ=2.0 output for the image shown in Fig.15. In this case, the edge extraction consists of thresholding by Tr and thinning by nonmaxima suppression in the perpendicular direction to the direction of the extracted edge. Our method obtains the excellent contour edges without excessive edges. On the other hand, when Tr is low (20), the first derivative of a Gaussian obtains many texture edges and noise. When Tr is high (50), it removes the texture edges and noise, but in turn does not obtain the contour edges.

5 Conclusion

We have proposed a new robust method for extracting step and ramp edges. In our method an edge is defined not as *a point* where the intensity changes rapidly, but as *a region boundary* based on ***separability*** of image features which can be calculated by linear discriminant analysis. Based on this definition, the edge intensity is obtained from ***separability***, which depends only on the shape of an edge. Experimental results have demonstrated the efficacy of the proposed method. The merits of the proposed method can be summarized:

1. Robustness to noise and a diffuse edge.
2. Easy selection of a best threshold value for edge extraction.
3. Ability to extract weak edges.
4. Applicability to obtain color edges, texture edge, etc.

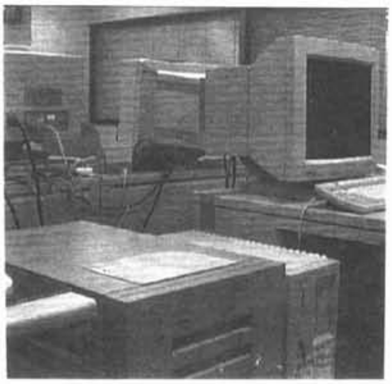

Figure 9: Original image 512×512 pixels (F10)

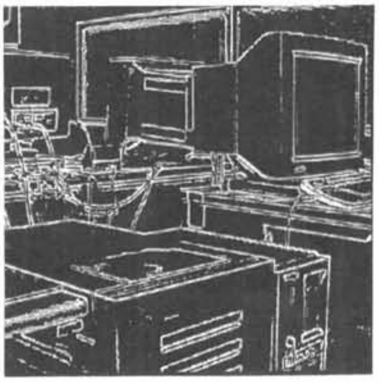

Figure 11: Edge intensity image for Fig.9 (Mw=6, Mh=3, ${\sigma_L}^2 = 30$))

Figure 10: Original image 512×512 pixels (F5.6)

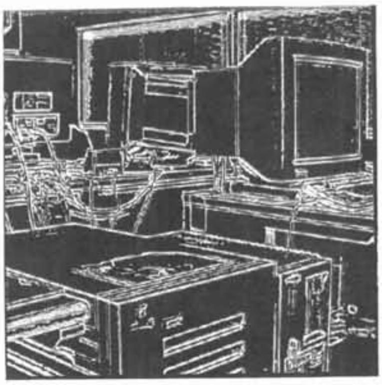

Figure 12: Edge intensity image for Fig.10 (using the same parameters as in Fig.11)

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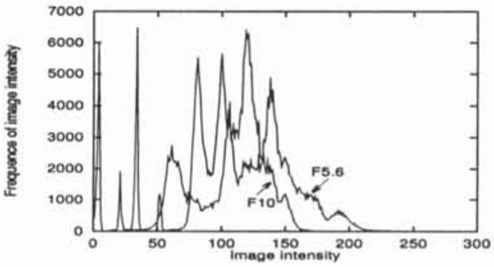

Figure 13: Histogram of image intensity

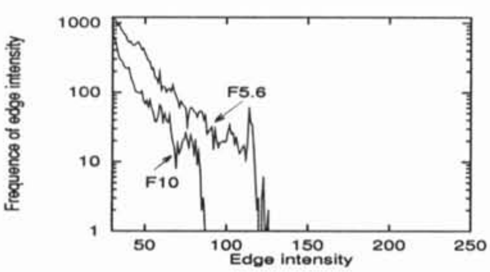

Figure 14: Histogram of edge intensity by the first derivative of a Gaussian with σ=1

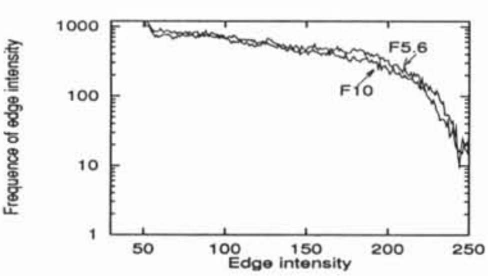

Figure 15: Histogram of edge intensity by our method

Figure 16: Original image 512×512 pixels

Figure 17: Edge image by our method (Mw=14, Mh=7, ${\sigma_L}^2$=30, Tr=0.65)

Figure 18: Edge image by the first derivative of a Gaussian with σ=2, (Tr=20)

Figure 19: Edge intesity image by the first derivative of a Gaussian with σ=2, (Tr=50)