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Edge Extraction Method Based on Separability of Image Features

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SUMMARY This paper proposes a robust method for detecting step and ramp edges. In this method, an edge is defined *not as a point* where there is a large change in intensity, *but as a region boundary* based on the separability of image features which can be calculated by linear discriminant analysis. Based on this definition of an edge, its intensity can be obtained from the separability, which depends only on the shape of an edge. This characteristic enables easy selection of the optimum threshold value for the extraction of an edge, and this method can be applied to color and texture edge extraction. Experimental results have demonstrated that this proposed method is robust to noise and dulled edges, and, in addition, allows easy selection of the optimum threshold value.

key words: *image processing, edge extraction, region-based, linear discriminant analysis, separability*

1. Introduction

Edges are primitive features of images for high level image processing. Many edge extraction methods have been proposed, mainly based on the gradient of image intensity. These gradient-based methods often require the use of smoothing filters, such as Gaussian filters for the suppression of noise [1], [2]. However, since smoothing filters tend to blur edges, one of the disadvantages of gradient-based methods is that edge localization precision is inherently low. In addition, their performance is sensitive to the selection of parameters such as the threshold value for edge extraction.

Other edge extraction methods without smoothing, which are based on the statistical analysis of the distribution of image features, such as image intensity [3], [4] and the image intensity gradient [5] within a local region. These region-based methods are robust to noise compared to gradient-based methods, since they use integrals in extracting edges. However, they require a complex process to improve performance.

Although the proposed method is region-based, its algorithm is very simple. 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 image intensity) of a local region are separated well as shown in Fig. 1. Based on this definition of an edge, an edge intensity can be obtained from the *separability* value, which is a measure of the degree of separation of the features. An edge intensity obtained using our method is a normalized value which depends only on the shape of an edge. This characteristic provides our method with the following features.

1. Robust to noisy and blurred edges.
2. Ease of selection parameters that yield the best performance, such as the threshold value for edge extraction.

In addition, the characteristic of normalization is useful for various high level image processings such as model matching, although the applications for these processings without thresholding edge intensity are not described in this paper.

This paper is organized as follows. Section 2 defines an edge and describes its characteristics in detail. In Sect. 3, the edge extraction algorithm is explained. The quality evaluation of the performance of our method is presented in Sect. 4, including a comparison with conventional methods in terms of figure of merit rating factor (FOM)[6]. Experimental results for real images are also shown.

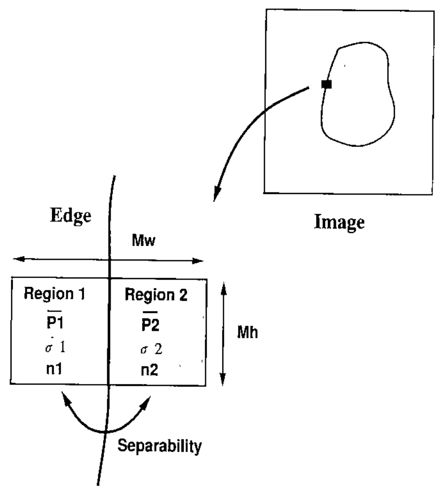

Fig. 1 Definition of an edge based on separability in a local mask region Mw × Mh.

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2. Basic Concepts

2.1 Definition of Separability

A local Mw×Mh region, which consists of two small regions 1 and 2, is shown in Fig. 1. *Separability* η can be calculated by linear discriminant analysis [7] using information from regions 1 and 2 in Eqs. (1)–(3),

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

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

$${\sigma_T}^2 = \sum_{i=1}^{n1+n2} (P_i - \overline{P})^2 \tag{3}$$

Where P_i is a feature (for example, the image intensity) of an image at a pixel i, and $\overline{P_1}$ 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, and n1 and n2 are the number of pixels in regions 1 and 2, respectively. Here, if $\frac{\sigma_T}{\sqrt{n1+n2}}$ is smaller than σ_L, η is set at zero. Thus, σ_L provides the minimum of the height of a step edge to be extracted.

The concept of separability can be applied to multiple features (such as hue, saturation, and statistical features of a region) using Eqs. (4)–(6).

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

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

$${\sigma_{Tk}}^2 = \sum_{i=1}^{n1+n2} (P_{ki} - \overline{P_k}) \tag{6}$$

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

2.2 Characteristics of Separability

Figure 2 shows *separability* η values 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 dull, η decreases as in Figs. 2 (b) and (c). In regions where the intensity changes linearly, η is always a constant value η^*, for example, 0.76 (Mw $=$ 8), as shown in Fig. 2 (d), independent of the gradient θ of the slope. In regions where there is little change of intensity, η is close to zero (Fig. 2 (e)). This figure shows that *separability* depends only on the shape of the edge. Figure 3 (b) shows the edge intensity ($\eta \times 100$) which the proposed method outputs for a profile example in Fig. 3 (a). Our method can obtain the normalized edge intensity for each edge, dependending on the shape of the edge.

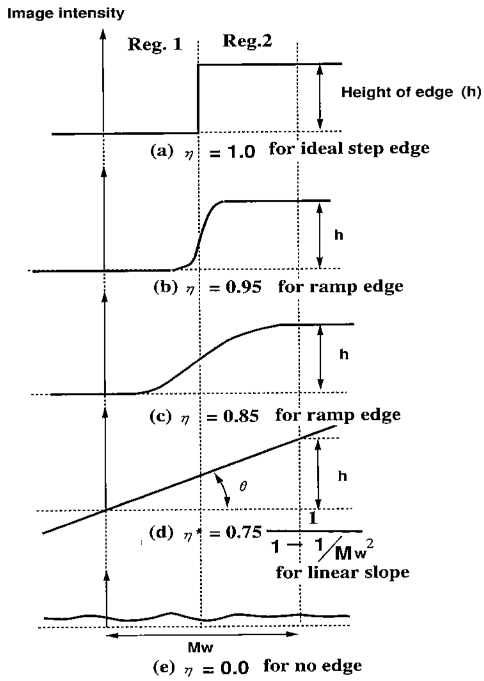


Fig. 2 Changes of separability η.

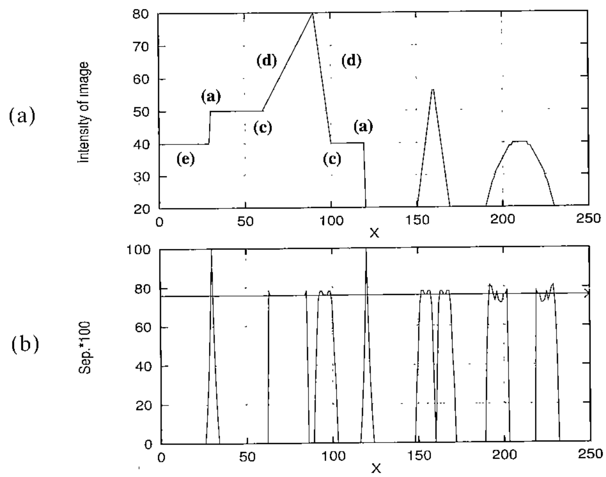


Fig. 3 (a) Profile of image intensity. (b) Profile of separability for (a) (Mw $=$ 6).

2.3 Threshold Value Selection

Figure 4 (b) shows the edge intensity ($\eta \times 100$) obtained using the proposed method with Mw $=$ 8 for the real image profile as shown in Fig. 4 (a). Likewise, Fig. 4 (c) shows the edge intensity obtained using a Gaussian method (the first derivative of a Gaussian function with σ $=$ 1.0). Note that the proposed method obtains an

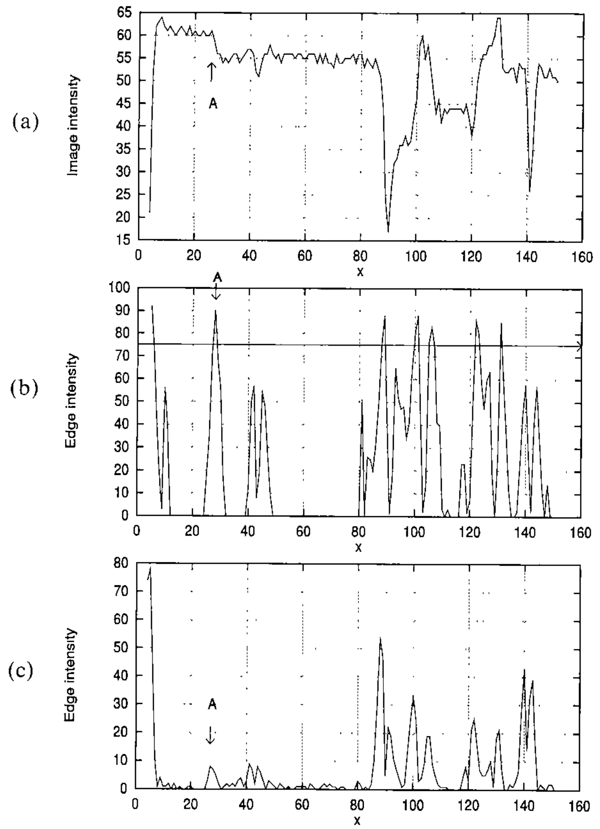


Fig. 4 (a) The 1D intensity distribution at the broken line in Fig. 14. (b) The output of our method for (a) (Mw = 8). (c) The output of the Gaussian method with $\sigma = 1.0$ for (a).

equal intensity for the step and ramp edges, and a strong intensity for weak edge A (indicated by the arrow in Fig. 4 (a)). This guarantees that the performance of the proposed method is not strongly affected by the choice of threshold value.

The Gaussian method, on the other hand, obtains a different intensity for the edges and the weak intensity for edge A. This causes a difficulty in selection of threshold value for each pixel. In the worst case, it becomes impossible to extract weak edges if a low threshold value is used, since the edge intensity cannot distinguish the weak edges from the linear slopes.

In general, edge extraction consists of thresholding edge intensity using an adequate threshold value to eliminate spurious peaks and non-maximum suppression process to search local peaks for an edge point. In the conventional gradient-based methods, it is difficult to select an adequate threshold value, since an edge intensity varies widely, dependending on the gray level in an image.

In the proposed method, on the other hand, an edge can be defined as the image profile where η value is higher than that for the linear slope (Fig. 2 (d)). In practice, since η for each edge profile in Fig. 2 decreases by the effects of the noise, T_r^* is set at a smaller value

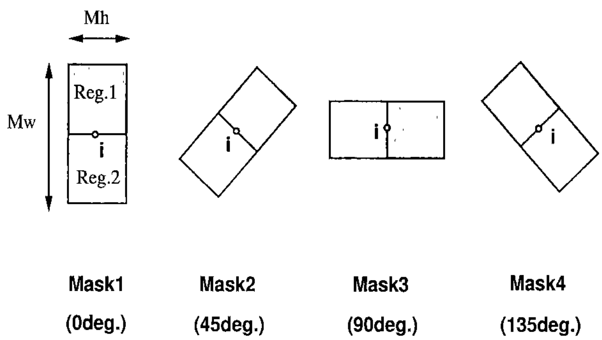


Fig. 5 Example of a mask configuration for pixel i.

(0.75–0.6) than η^*.

However, when the noise in a given image has much influence, a median filter (3×3) is used to reduce the effects of the noise in advance, or the threshold value needs to be reduced to an adequate value experimentally.

3. Algorithm of Edge Extraction

In order to extract the intensity and direction of an edge from a given image for a pixel i, our method uses a set of multiple masks. Figure 5 shows an example configuration which consists of four masks (for four directions: 0, 45, 90, 135 deg.). The main steps for edge extraction are outlined below.

1. Set the four masks at a pixel i.
2. Calculate the η value for each mask using Eqs. (1)–(3) (using Eqs. (4)–(6), if an image is color or texture).
3. Move the four masks to the next pixel.
4. Execute thresholding the edge intensity with T_r^*.
5. Smooth an edge intensity image with Gaussian filter with $\sigma = 0.5$, while the position of the local peak of the edge intensity is held and execute non-maximum suppression to obtain a final edge image.

4. Experimental Results

4.1 Quality Evaluation of Edge Localization

The precision of our method's edge localization for noisy and blurred edges is compared with various conventional methods in terms of figure of merit rating factor (FOM) introduced by Pratt [6]. FOM is obtained from the edge extraction result for the simulated test edge image which consists of two regions as shown in Fig. 6.

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

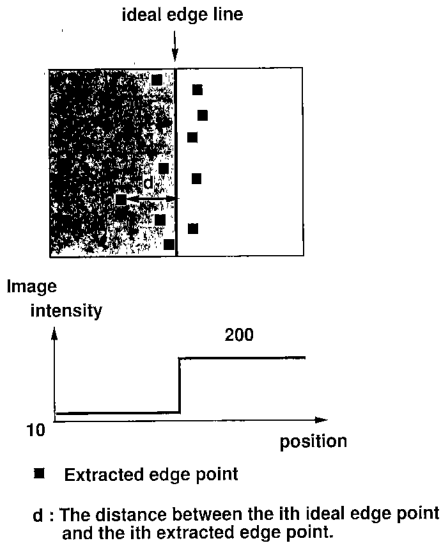


Fig. 6 Test edge for FOM.

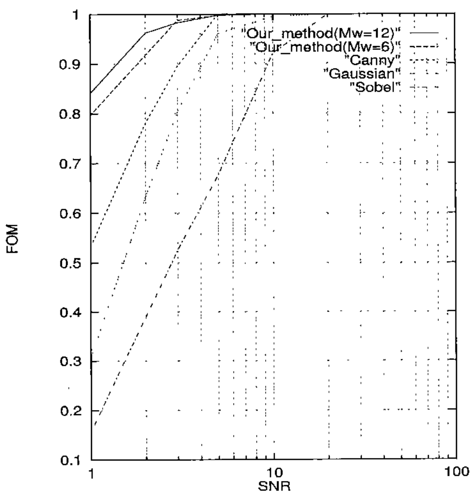


Fig. 7 Variation of FOM as a function of SNR.

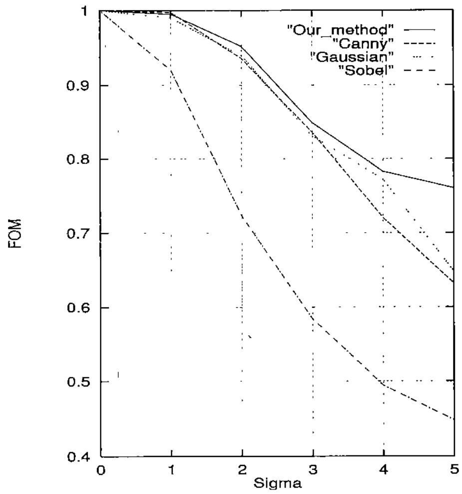


Fig. 8 Variation of FOM as a function of the diffuseness of edges.

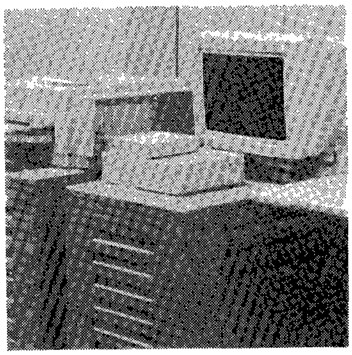


Fig. 9 Original image 432 × 432 pixels (F2).

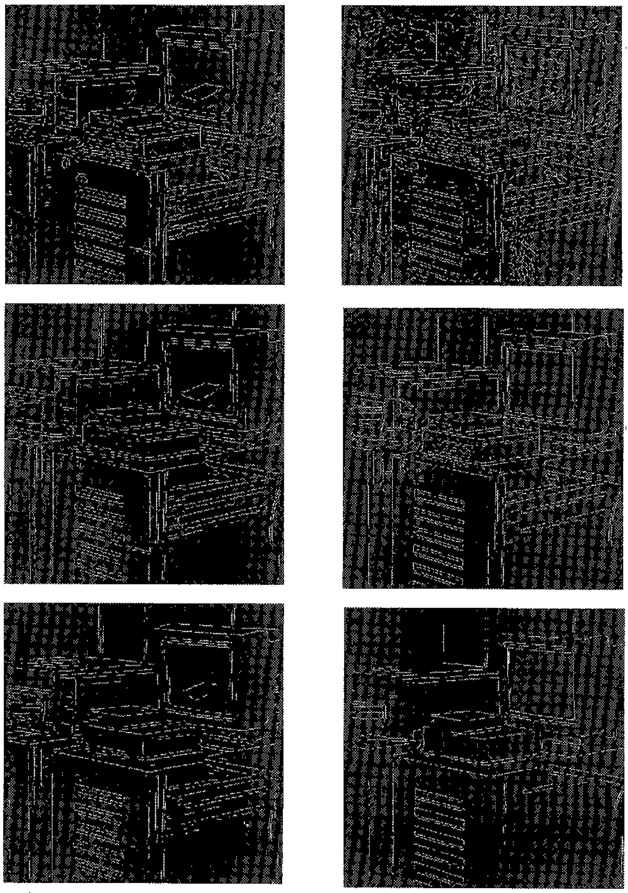
where I_I and I_E are the number of ideal and extracted edge points respectively; and $d(i)$ is the pixel miss distance of the ith edge detected. When the method detects all the edge points perfectly, FOM is equal to 1.0.

Figure 7 shows the variation of FOM as a function of SNR for our method (7×7 and 13×7, $\sigma_L{}^2 = 30$) and for various conventional methods, such as those of Sobel, Canny (Deriche's method [8] (7×7), $\alpha = 1.2$), and the Gaussian method using the first derivative of a Gaussian function (7×7) with $\sigma = 1.0$. SNR is defined as $(\frac{h}{\sigma_n})^2$ where σ_n is the standard deviation of noise and h is the height of the step edge. In this case, FOM is the highest value obtained from the edge points extracted by non-maximum suppression in a direction perpendicular to the extracted edge with thresholding using various threshold value. When SNR is higher than 10, there is little difference in FOM. When SNR is lower than 10, however, our method has a high FOM value compared with the other methods. This implies that our method is more robust to noise than the others. FOM for other edge extraction methods can be referred to in [9].

Figure 8 shows the variation of FOM as a function of the dullness of edges for our method (7×7, $\sigma_L{}^2 = 30$) and for the conventional methods. The test images with noise (SNR = 20) are dulled using a Gaussian filter with a standard deviation of sigma. When sigma is higher than 3, the proposed method maintains a higher FOM value and robustness relative to the others.

4.2 Robust Selection of the Threshold Value

The robustness of our method to selection of the threshold value for edge extraction is compared with that of the Gaussian method. Figure 9 shows a test image (432×432) with iris value 2.0. Figure 10 (a) show the edge images which our method (6×3, $\sigma_L{}^2 = 16$) outputs for Fig. 9 with three levels of threshold values: 10 percent, 50 percent and 70 percent of the largest edge intensity, and Fig. 10 (b) show the edge images which the Gaussian method (7×7, $\sigma = 1.0$) outputs for Fig. 9 with



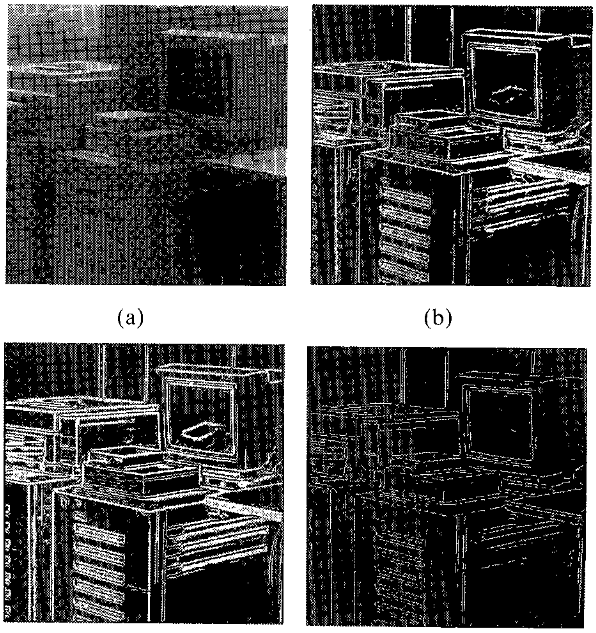
(a) Our method (b) The Gaussian method

Fig. 10 Variation of the edge image by the selection of the threshold value. (a) Top: $T_r = 0.1$, Middle: $T_r = 0.5$, Bottom: $T_r = 0.7$. (b) Top: $T_r = 10$, Middle: $T_r = 20$, Bottom: $T_r = 60$.

three levels of threshold values: 10 percent, 20 percent and 40 percent of the largest edge intensity.

In our method, there is little difference among the three edge images as shown in Fig. 10 (a). This result shows that the performance of edge extraction is not strongly influenced by the precision of the selection of threshold value. On the other hand, in the Gaussian method, the performance of edge extraction is sensitive to the selection of the threshold value as shown in Fig. 10 (b).

Figure 11 (a) shows the test image with the different iris value from Fig. 9. Figures 11 (b) and (c) show the edge intensity images ($\eta \times 255$) which our method outputs for Fig. 9 and Fig. 11 (a) using the same parameters. Although the gray level distributions differ widely between this two images, our method can output an almost uniform edge intensity and a final edge image is not strongly influenced by changes in gray level caused by changes in iris value as shown in Fig. 11 (d). Hence, if the threshold value is determined once, it does not need to be changed, when the iris value and the illumination condition change.



(a) (b)

(c) (d)

Fig. 11 (a) Original image (F4). (b) Edge intensity image for (a). (c) Edge intensity image for Fig. 9. (d) Final edge image for (a).

Fig. 12 Original image 512×512 pixels.

4.3 Threshold Selection for the Image with Texture Noise

When an image contains many texture noises, the selection of an adequate threshold value for extracting the contour edges distinctly with few texture noises is more difficult than that in Sect. 4.2. Figure 12 shows an example image containing an object with low contrast and many texture noises. Figures 13–15 show the edges extracted from the edge intensity image which the proposed method (14×7, $\sigma_L{}^2 = 30$, $Tr = 0.6$) and the Gaussian method (14×14, $\sigma = 2.0$, $Tr = 20$ and $Tr = 50$) outputs for Fig. 12. In this experiment, since the Gaussian method uses a large mask size (14×14) to reduce the effects of texture noises, our method also

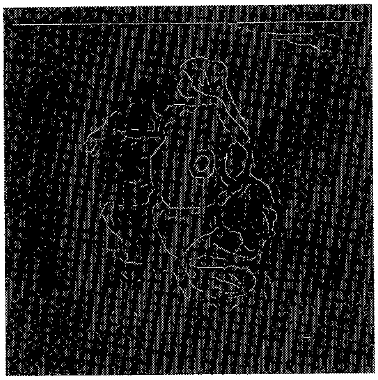


Fig. 13 Edge image by our method ($Tr = 0.6$).

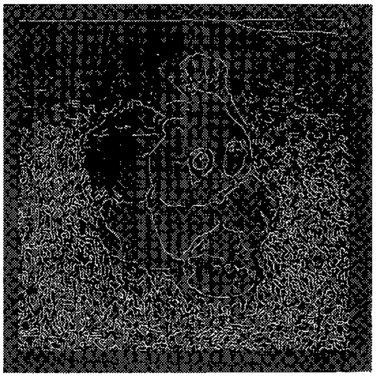


Fig. 14 Edge image by the Gaussian method ($Tr = 20$).

Fig. 15 Edge image by the Gaussian method ($Tr = 50$).

uses the same mask size for the purpose of comparision with the Gaussian method.

Our method obtains excellent contour edges distinctly with few texture noises using $Tr = 0.6$. This result is little changed, even if Tr is set in the range from 0.2 to 0.6. On the other hand, in the case of the Gaussian method, it is very difficlut to select an adequate threshold value for extracting contour edges, because there is little difference between the egde intensity of texture noise and that of contour edge. When Tr is low (20) in Fig. 14, the Gaussian method obtains many texture noises. When Tr is high (50) in Fig. 15, it removes the texture noises, but does not obtain the contour edges.

5. Conclusions

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 the *separability* of image features which can be calculated by linear discriminant analysis. Based on this definition, the edge intensity can be obtained from the *separability*, which depends only on the shape of an edge. The experiment results demonstrated that the proposed method is robust to noisy and blurred edges, especially at high noise, in comparison with the conventional gradient-based methods, in terms of FOM. In addition, our method allows easy selection of an adequate threshold value. The expansion of this method to obtain color edges, texture edges, and other features is possible and will be done in feature work.

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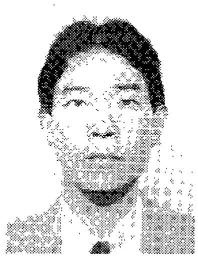

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