A Region-Based Edge Detection Technique for Noisy Images

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***Abstract*: Edge detection is a basic and important issue in computer vision and image processing. The traditional methods of image edge detection are sensitive to noise and often cannot locate the edge exactly. We propose a new method of edge detection which can eliminate the fake edges caused by the noise disturbance, and ensure the veracity of edge orientation to have a proper result for noisy images. A problem introduced as "cross effect" occurs in the derivative of Gaussian filter method, which will be eliminated in this paper. As will be shown, our method is robust in confrontation with noise.**

***Key-words*: Edge Detection, Gaussian Filter, Ridge, Steerable Filter**

I. INTRODUCTION

The most essential features of an image are its edges. Intuitively, an edge is a set of connected pixels that lay on the boundary between two regions whose gray level has outstanding change. The edge can be located between objects and background or two objects. The edge detection is widely applied in areas like image recognition, image classification, image enhancement, and in pattern recognition in general.

Applying gradient operators on images can result in image edges when the edge gradient values exceed some defined thresholds. The traditional methods of image edge detection such as Robert, Sobel, Prewitt or Laplacian filter can properly detect the edges when the gray level changes obviously, but these operators are weak in confrontation with noisy images and the edges whose gray levels change faintly.

However, a factual image includes noise and the above mentioned edge detection operators including Canny operator usually cannot differentiate the edge from noisy area, which results in detecting fake edges. Therefore, eliminating these edges and ensuring the veracity of edge orientation have been the most important issue in edge detection in recent years.

Many researches have focused on edge detection over noisy images. In reference [1] in order to confront noise disturbance a separate wavelet based noise reduction block is used as a pre-processing before edge detection. References [2] and [3] have used morphological operators in order to detect edges, and at the same time, to denoise the image. But these methods are difficult to detect complex edge features, because they are only sensitive to edges which have the same direction as their structure element [4]. Reference [4] has proposed an algorithm based on multi-structure elements morphology of eight different directions, which seems to be time-consuming for real time applications. Sun et al. [5] have an interesting method of edge estimation using wavelet approximation for noise reduction and then evaluating the edges using wavelet detail components.

In this paper, we propose a robust region-based edge detection filter that can adopt different noise distributions. Computer simulations show that our approach gives satisfactory results.

This paper is organized as follows: in section II we discuss the basic concepts of our approach that is based on steerable filters. Section III describes the proposed method of edge detection. Section IV focuses on simulation results, and finally, section V reports the conclusions.

II. FILTER DESIGN

Estimates of derivatives are generally important in edge detection. Sharp changes in an image can be associated with edges, and such changes are associated with large gradients. One diagnosis for large gradient magnitude is a zero of a second derivative at a point where the gradient is large, but gradient has the advantage of detecting the orientation of an edge where it can be positive or negative. Finite gradient filters used for edge detection often give strong responses to noise. This suggests that some noise reduction methods are required before differentiation.

A. Noise Reduction

One way to reduce the noise is to smooth the image before applying edge extractors. Although a Gaussian is not the only possible smoothing kernel but it is more convenient because of its useful properties [6]. The most important property comes from the central limit theorem (CLT) which states that the convolution of a large number of functions is approximately a Gaussian function. These functions either

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can be different kinds of noise distributions or here different kinds of smoothing filter. Furthermore, since discrete convolution can be an expensive operation when the kernel of the filter is large, separability of Gaussian 2D-filters into two 1D-filters or separating a Gaussian filter of large variance into small variance filters can also be important properties to simplify the calculations.

$$G_\sigma(x,y) = G_\sigma(x) \times G_\sigma(y) \quad (1)$$

$$G_{\sqrt{\sigma_1{}^2+\sigma_2{}^2}} = G_{\sigma_1} * G_{\sigma_2} \quad (2)$$

B. Derivative of Gaussian Filter

From the associative property of convolution, smoothing an image with a Gaussian filter and then differentiating it to find edges is the same as convolving the image with the derivative of a Gaussian smoothing filter. If we assume ∇ as the gradient operator and G as the Gaussian smoothing filters, we can apply it on image "I" to obtain:

$$\nabla * (G * I) \;\rightarrow\; (\nabla * G) * I \quad (3)$$

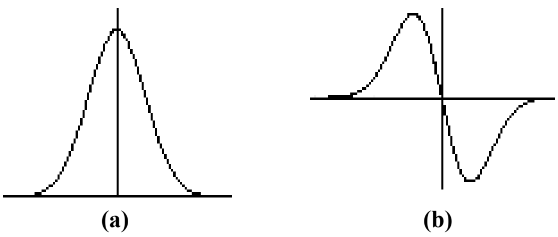

Fig.1. (a) Gaussian function, (b) Derivative of Gaussian $(\nabla * G)$

The one-dimensional plot of these functions is shown in Fig.1. The optimal two-dimensional functions for derivative of Gaussian filter have been before introduced in [7]. The filter used here is optimized for a 7×7 edge detection kernel. The definition of this filter is given in (2) and (3) and the absolute value of the filter is illustrated in Fig. 2(a).

Gaussian: $$G_y = \frac{-y}{4\pi\sigma^2} e^{\frac{-(x^2+y^2)}{2}} \quad (4)$$

Optimum Derivative Filter:

$$-0.966G_y - 0.256\sigma^2 G_{xxy} \quad (5)$$

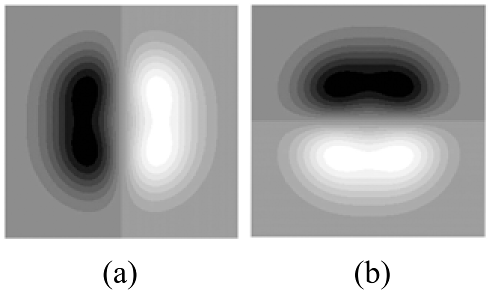

Fig.2. (a) Optimal Gaussian filter defined by (3).
(b) Rotated filter.

C. Region-Based Variance

One factor of the designed filter that is already unknown is its variance (σ^2) which can be an important variable. The variance of the filter defined in (4) and (5) can be related to the variance of noisy image which is affected by image structure and noise distribution. It will be shown that if the filter variance is selected as in (6), then this will cause the best response and as a result "cross effect", as described in the next section, will be minimized.

$$\sigma^2{}_{Filter} = \frac{\sigma^2{}_{Noisy\,\mathrm{Im}age}}{38.4} \quad (6)$$

III. Proposed Method

The block diagram of our edge detection system is shown in Fig. 3. First, the variance of input image is calculated and then the 7×7 filter kernel is constructed using equasions (4), (5) and (6). This kernel is the quantized form of two-dimensional Gaussian filter shown in Fig. 2(a). This filter mostly varies in horizontal direction which detects the vertical edges. By rotating the kernel, its variation will be in vertical direction to detect the horizontal edges [see Fig. 2(b)]. The resulting image is both smoothed and derived to reduce noise and to detect variations like edges. Therefore, the result can be between an interval of large negative and positive values.

A. Thresholding

In order to have a real image of convolution and then threshold the image, first, the convolution result is scaled into the range [0 1]. Here we define two upper and lower thresholds (τ_{up}, τ_{low}). If the magnitude of the resulting image falls out of the interval, then this is assumed as edge. The more relaxed the threshold, the more edges will be detected, which results in an increasingly susceptibility to noise, and the irrelevant feature detection. Conversely, a strict threshold may miss subtle edges, or result in

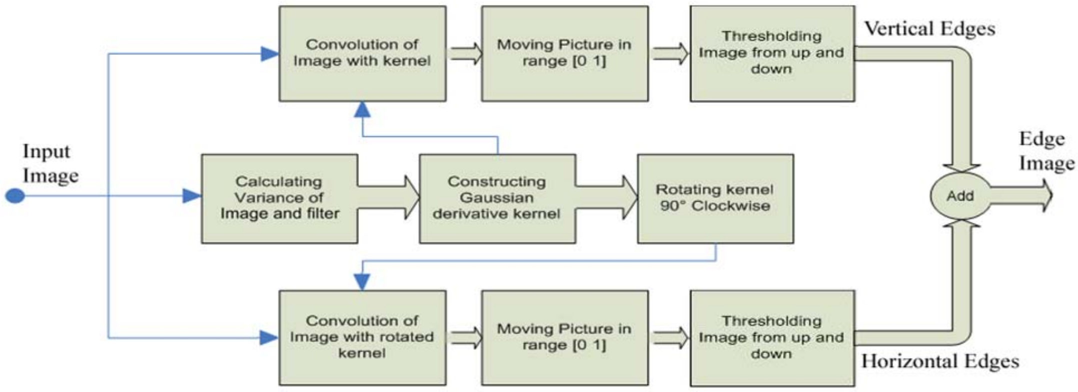

Fig.3. Block diagram of region-based edge detection system

fragmented edges. As a result, the problem is to choose appropriate thresholding parameters, and suitable thresholding values that may vary over the image. The algorithm used here is as follows.

Let $f_{i,j}$ be the normalized gray level at location (i,j) in the convolved image $(f_{\min} \leq f_{i,j} \leq f_{\max})$. Then, we have:

$$\tau_{\text{up}} \square f_{\max} - 0.35 f_{\max} \equiv 0.65 \tag{7}$$

$$\tau_{low} \square f_{\min} + 0.35(1 + f_{\min}) \equiv 0.35 \tag{8}$$

$$f_{i,j} = \begin{cases} 1 & if \quad f_{i,j} \geq \tau_{up} \ or \ f_{i,j} \leq \tau_{low} \\ 0, & if \quad \tau_{low} < f_{i,j} < \tau_{up} \end{cases} \tag{9}$$

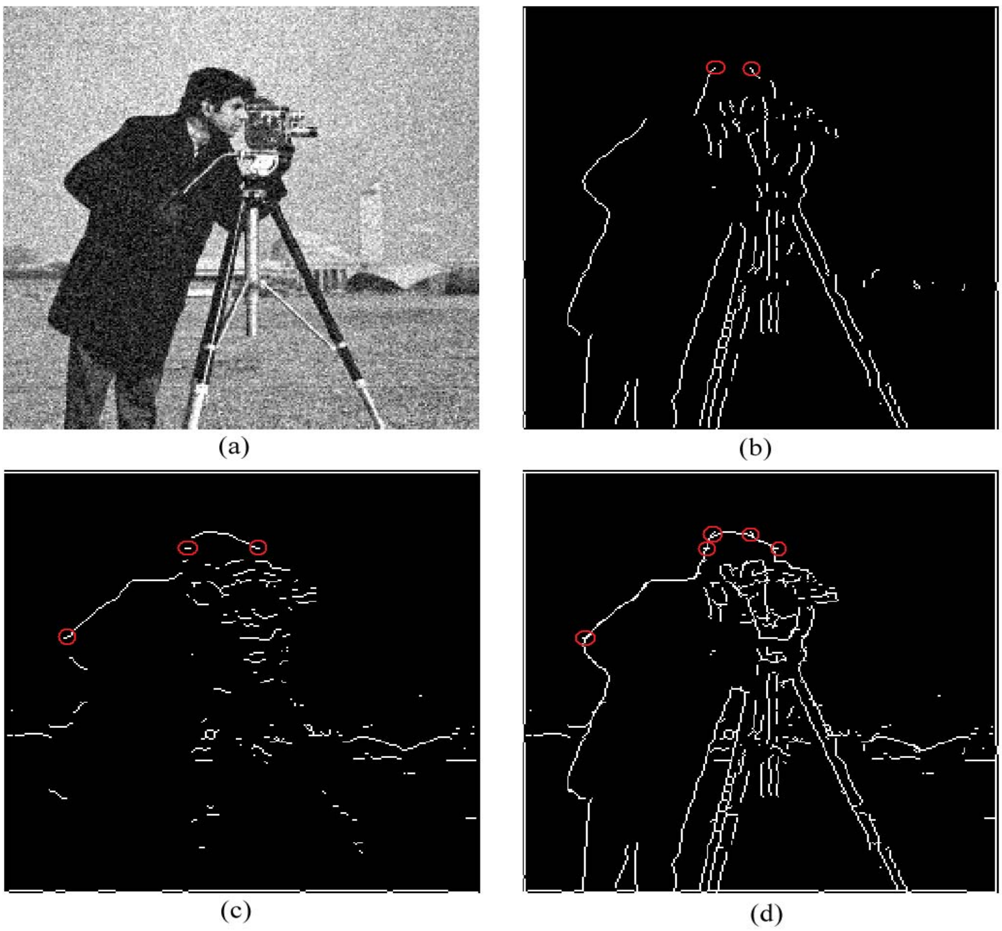

Fig.4. The Cross Effect: (a) Original noisy image. (b) Vertical edges and its fake endings. (c) Horizontal edges and its fake endings. (d) Result of adding (b) and (c) and the cross effect caused by fake edge pixels.

If the edge thresholding is just applied to the gradient magnitude image, the resulting edges will in general be thick and some type of edge thinning post-processing is necessary.

B. Cross Effect

In general all edge detectors behave badly at corners [6]. After thresholding, we will have two edge maps, one for vertical and the other one for horizontal edges. However, for diagonal edges or the corners, both of the images have estimations that are not exactly the same. Therefore, in the process of adding images, there might be two different estimations for one point of the edge. We introduce this as "Cross Effect" that can be clearly seen in Fig. 4. It usually occurs while computing derivative of Gaussian, when the horizontal edge is changing to vertical or vice versa. Simulation results on different images show that selecting variance according to the proposed formula in (6) can reduce the cross effect.

IV. Simulation Results

In order to assess the performance of the proposed edge detection system, we performed many computer simulations on different images. Some results are reported in Fig. 5. In this experiment, Gaussian noise with mean 0 and variance 0.1 is added to the standard image of the "cameraman" [see Fig. 5(a)]. The proposed region-based edge detection algorithm is performed on this image. Figures 5(b) and 5(c) show the vertical and horizontal edges obtained by using the proposed filter and its rotated version, respectively. As you see the final result in Fig. 5(d), the horizontal and vertical edges are continuous and the cross effect has been minimized by using the region-based variance of filter. Figure 5(e) is the edge map of the same noisy image using Canny edge detector. As observed, there are many fake edges caused by noise disturbance that Canny method has detected as true edges.

Figure 6 has the same order of operations on the noisy image of the "house" shown in Fig. 6(a). In comparison with Canny edge detector, the robust result of the proposed method is extremely good.

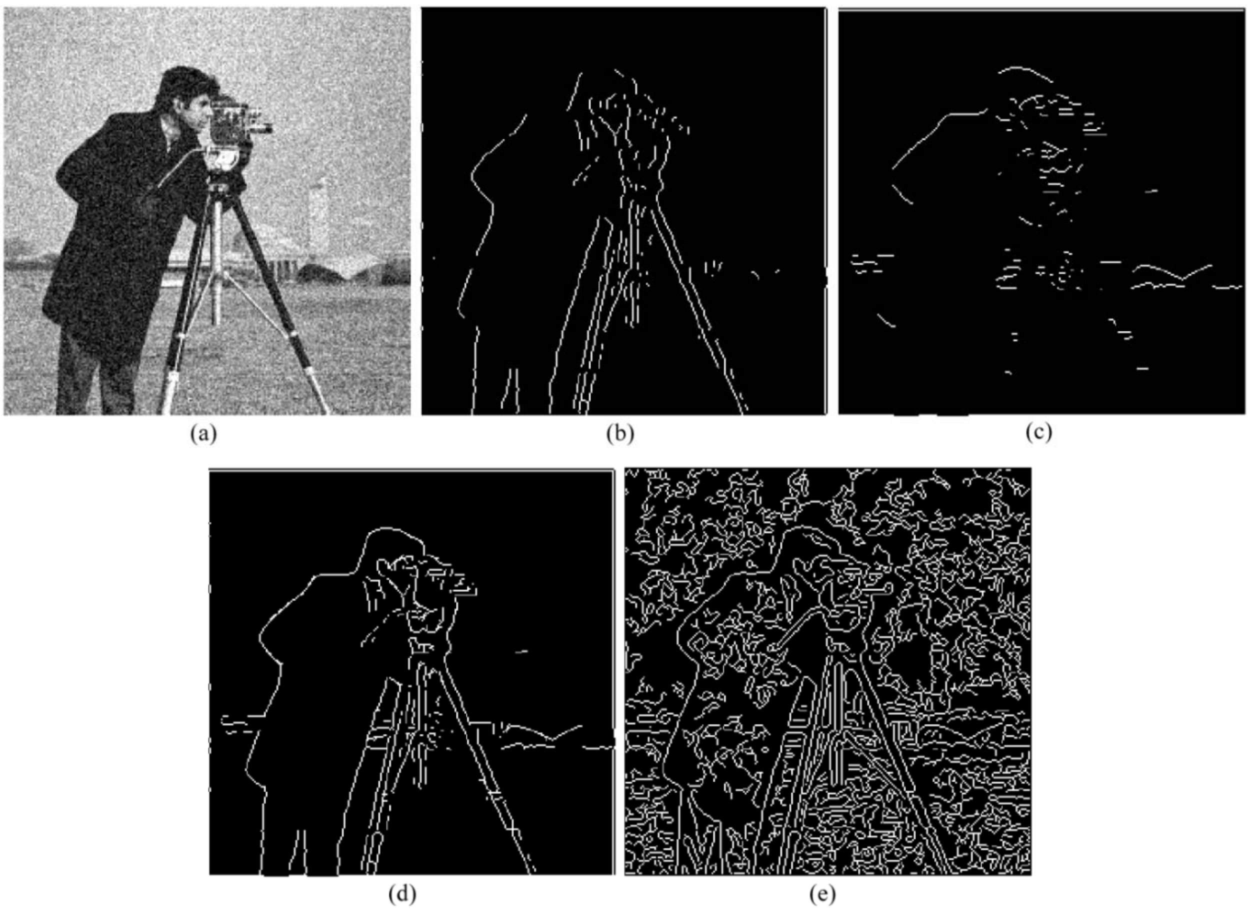

Fig.5. (a) Cameraman image with Gaussian noise of variance 0.1. (b) Result of edge detection for vertical edges. (c) Result of edge detection for horizontal edges. (d) Final result of adding (b) and (c). (e) Result of Canny edge detector on (a).

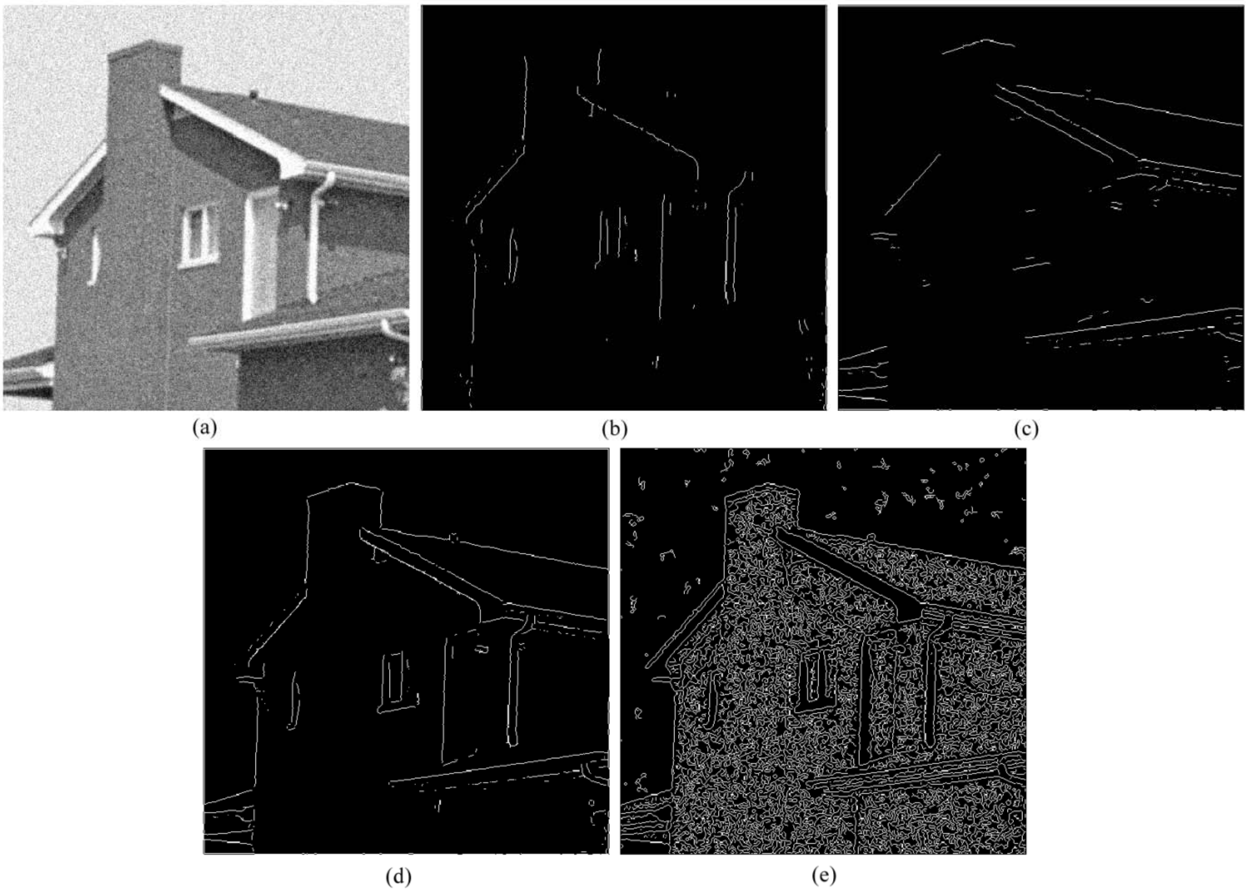

Fig.6. (a) House image with Gaussian noise of variance 0.01. (b) Result of edge detection for vertical edges. (c) Result of edge detection for horizontal edges. (d) Final result of adding (b) and (c). (e) Result of Canny edge detector on (a).

V. CONCLUSION

In this paper, a new region-based edge detecting system for noisy images has been presented. The method is composed of different modules. The proposed filter is related to the variance of selected areas. The kernel is applied on an image twice. One for detecting vertical edges, and the other for detecting horizontals. As shown, by adding the result of these two stages, the best result, i.e. the elimination of the cross effect, is obtained when the variance parameter of the designed filter is changed. The robustness of our method in confrontation with noisy images is approved, as we compare the results with those obtained by other operators like Canny.

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