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A Fast and New Approach to Gradient Edge Detection

[1]M.A. Rabbani and [2]C. Chellappan
[1]BSA Crescent Engineering College, Chennai-600 025, India
[2]Anna University, Chennai-600 025, India

Abstract: Edge detection is an important task in Computer Vision for extracting meaningful information from digital images. The main goal of our proposed method is to obtain thin edges so that the result is more suitable for further application such as boundary detection, image segmentation, motion detection/estimation, texture analysis, object identification and so on. In this study, we propose a new approach based on gradient edge detection method (using canny edge detector) capable of operation on smooth edges. In this study we introduce convolution masks to obtain better edges. We have tested our results with Bonferroni test for mean performance and edge detector performance with Pratt measure and good acceptable results were obtained.

Key words: Edge detection, image processing, canny edge detector, gaussian function, gradient

INTRODUCTION

Edge detection is the process of finding edges in images. Edge detecting an image significantly reduces the amount of data and filters out useless information, while preserving the important structural properties in an image. Several algorithms have been designed to detect edges and range in complexity. These approaches can be grouped into two main categories: gradient and zero-crossing based methods. While the gradient approach uses the first-order directional derivatives of the image to compute a quantity related to edge contrast for edge detection, the zero-crossing approach requires computation of the second order directional derivatives to identity locations with zero crossings.

Some of the early gradient operators include the Roberts (1965), Sobel (1975), Prewitt (1970), Canny (1986) edge operators. They will involve using small kernels to convolve with an image to estimate the first-order directional derivatives of the image brightness function. While simple to use, these filters give very little control over image noise and edge location. Canny described a gradient-based edge-finding algorithm that has become one of the most widely used edge detectors. This algorithm uses an optimal filter kernel for computing the first-order directional derivatives of an image in two orthogonal directions. The optimal filter is obtained by maximizing a criterion function consisting of signal-to-noise ratio of the image, the edge location accuracy and the false positive probability. In practice, the optimal filter can be closely approximated by the first-order derivative of a Gaussian function which allows noise suppression and an efficient implementation. A widely used method for noise elimination is the Gaussian filter, in which signals, in one and two dimensions, are smoothed out by the convolution of the image with a Gaussian kernel. The Gaussian operator is isotropic and therefore smoothes the image in all directions blurring sharp boundaries. All these approaches deal with the first derivatives of the image, thus slightly, but not totally, doing away with noise in the image (Marry and Hilderth, 1980). To overcome these problems we introduced a new method called an enhanced approach to gradient edge detection method based on canny edge detector in a simple and efficient manner.

EDGE DETECTION BACKGROUND

Edge detection is a fundamental tool used in most image processing applications to obtain information from the frames as a precursor steps to feature extraction and object segmentation. This process detects outlines of an object and boundaries between objects and the background in the image. An edge detection filter can also be used to improve the appearance of blurred or anti-aliased video streams.

The basic edge-detection operator is a matrix-area gradient operation that determines the level of variances between different pixels. The edge detection operator is

Corresponding Author: M.A. Rabbani, BSA Crescent Engineering College, Chennai-600 025, India

calculated by forming a matrix centered on a pixel chosen as the center of the matrix area. If the value of this matrix area is above a given threshold, then the middle pixel is classified as an edge. Examples of gradient-based edge detectors are Roberts, Prewitt, Sobel and Canny operators. All the gradient-based algorithms have kernel operators that calculate the strength of the slope in directions which are orthogonal to each other, commonly vertical and horizontal. Later, the contributions of the different components of the slopes are combined to give the total value of the edge strength.

The canny algorithm uses an optimal edge detector based on set of criteria which include finding the most edges by minimizing the error rate, marking edges as closely as possible to the actual edges to maximize localization and marking edges only once when a single edge exists for minimal response (Canny, 1986). According to Canny, the optimal filter meets all three criteria above can be efficiently approximated using the first derivative of a Gaussian function

$$G(x,y)=(i/2\pi\sigma^2)e^{x^2+y^2/2\sigma} \quad (1)$$

$$\partial G(x,y)/\partial x\, \alpha e^{x^2+y^2/2\sigma^2}$$

and

$$\partial G(x,y)/\partial y \alpha e^{x^2+y^2/2\sigma^2} \quad (2)$$

The first stage involves smoothing the image by convolving with a Gaussian filter. This is followed by finding the gradient of the image by feeding the smoothed image through a convolution operation with the derivative of the Gaussian in both the vertical and horizontal directions. The 2-D convolution operation is described in the following Eq.

I'(x, y) = g (k, l) oI (x,y)

$$=\sum_{k=-N}^{N} \sum_{l=-N}^{N} g(k.l) I(x-k, Y-l) \quad (3)$$

$$K=-N \; l=-N$$

Where

g (k,l) = Convolution kernel
I (x, y) = Original image
I' (x, y) = Filtered image
2N + 1 = size of the convolution kernel

-1	-1	-1
0	0	0
+1	+1	+1

(a)

-1	0	+1
-1	0	+1
-1	0	+1

(b)

Fig. 1: Convolution masks for canny edge detector (a) Horizontal direction (b) Vertical direction

The non-maximal suppression stage finds the local maxima in the direction of the gradient and suppresses all others, minimizing false edges. The local maximum is found by comparing the pixel with its neighbors along the direction of the gradient. This helps to maintain the single pixel thin edges before the final threshold stage. Instead of using a single static threshold value for the entire image, the canny algorithm introduced hysteresis threshold, which has some adaptivity to the local content of the image. Canny edge detector uses two convolution masks one for horizontal direction and one for vertical direction they are shown in Fig. 1.

MATERIALS AND METHODS

In our proposed method we introduce four more convolution masks in addition to two convolution masks which is used in Canny edge detector. First one for horizontal, second one for vertical, third one for positive left diagonal, the fourth one for positive right diagonal, fifth one for negative left diagonal and sixth one for negative right diagonal. They are shown in Fig. 2.

The proposed method first smoothes the image to eliminate the noise using Gaussian filter (Zuniga and Haralic, 1987). It then finds the image gradient to highlight the regions with high spatial derivatives. The proposed method then traces along these regions and suppresses any pixel that is not at the maximum. The gradient array is now further reduced by hysteresis (Canny, 1986). Hysteresis is used to track along the remaining pixels that have not been suppressed. Hysteresis uses two thresholds and if the magnitude is below the first threshold, it is set to zero. (made a non-edge). If the magnitude is above the high threshold, it is made an edge. And if the magnitude is between the two thresholds, then

-1	-1	-1
0	0	0
+1	+1	+1

(a)

-1	0	+1
-1	0	+1
-1	0	+1

(b)

0	+1	+1
-1	0	+1
-1	-1	0

(c) Positive left diagonal

-1	-1	0
-1	0	+1
0	+1	+1

(d) Positive right diagonal

0	-1	-1
+1	0	-1
+1	+1	0

(e) Negative left diagonal

+1	+1	0
+1	0	-1
0	-1	-1

(f) Negative right diagonal

Fig. 2: Convolution Masks for the proposed method

it is set to zero, unless there is a path from this pixel with a gradient above the high threshold. The detailed algorithm is given below:

Step1: Apply Gaussian filter to reduce the noise and then looking for maxima in the first derivatives of the resulting signal. Then we can convolve the image with six masks, looking for horizontal, vertical, positive left diagonal, positive right diagonal, negative left diagonal and negative right diagonal edges. The direction producing the largest result at each pixel point is marked. Record the convolution result and the direction of edge at each pixel. Norm of the gradient (NVI) is calculated as

$$\mathrm{SQRT}\ (Ix^2 + Iy^2 + Pld^2 + Prd^2 + Nld^2 + Nrd^2)$$

Step 2: Obtain non-maximal suppression. Any gradient value that is not a local peak is set to Zero. The edge direction is used in this process.

Step 3: Find the connected set of edge points and form into lists.

Step 4: Apply Hysteresis threshold on the gradient magnitude values. This involves having two different threshold values.

Step 5: Finally, compute thinning using interpolation to detect the pixels where the norms of gradient are local maximum.

RESULTS

A performance analysis: The performance of the canny and our proposed method depends heavily on the adjustable parameter, σ, which is the standard deviation for the Gaussian filter and the threshold parameter alpha (α). The standard deviation σ also controls the size of the Gaussian filter (Heath *et al*., 1998). The bigger the value for σ, the larger the size of the Gaussian filter becomes. This implies more blurring, necessary for noisy images, as well as detecting larger edges. Smaller values of σ imply a smaller Gaussian filter which limits the amount of blurring maintaining finer edges in the image and better results are obtained by performing six convolution masks on the image.

Both the canny and our proposed method allow the user to specify three parameters. The first is sigma (σ), the standard deviation of the Gaussian filter specified in pixels, the second parameter, low and the third parameter, high, are respectively, the low and high hysteresis thresholds. All together 10 images were selected for edge detection.

The best adapted parameters listed for each image in given in Table 1.

The best fixed parameters for canny edge detector (0.6 0.3 0.9) and our proposed method (1.0 0.5 0.8). The mean performance is calculated using Bonferroni test (Keppel, 1991). Relative edge detector performance using adapted parameters are listed in Table 2.

From Table 2 it is evident that our proposed method performed significantly better than the canny edge detector on average.

The above Table 3 clearly indicates that our proposed method performed significantly better than canny edge detector on average.

Table 1: Best adapted parameters

	Edge detection kethod	
Image	Canny(c)	Proposed(P)
Golf cart	0.6 0.3 0.9	0.7 0.3 0.6
Stapler	0.6 0.3 0.8	0.7 0.3 0.8
Tire	0.6 0.3 0.9	0.8 0.4 0.8
Orange	1.2 0.4 0.6	1.0 0.5 0.9
Egg	1.2 0.4 0.6	1.2 0.4 0.9
Gangaroo	1.5 0.5 0.7	1.2 0.4 0.8
Tiger	1.3 0.4 0.8	1.2 0.4 0.9
Mailbox	1.4 0.5 0.9	1.0 0.6 0.8
Lenna	1.5 0.4 0.8	1.2 0.5 0.8
Compass	1.5 0.5 0.7	1.2 0.4 0.8

Table 2: Relative edge detector performance

Edge detector	Mean	Significant difference
Canny(c)	4.20	C<P
Proposed(P)	5.60	

Table 3: Relative edge detector performance using fixed parameters

Edge detector	Mean	Significant difference
Canny(c)	3.95	C<P
Proposed(P)	5.21	

Table 4: Edge detector performance

	Edge detector performance	
Pratt measure	Canny (c)	Proposed (P)
FM	0.83	0.91

Pratt (Gonzalez and Woods, 2002) introduces a function FM for Edge detector performance. His measure is:

$$FM = 1/\max(I_A, I_I) \sum_{i=1} 1/1+d_i\alpha^2$$

where I_A, I_I, d and α are, respectively the detected edges, ideal edges, the distance between the actual and ideal edges and a design constant used to penalize displaced edges.

From Table 4 it is evident that our proposed method gives better results than Canny edge detector. The feasibility of the proposed model was reached by testing a large group of images principally synthetic and real life images which have different levels of noise and a zero mean Gaussian distribution (Marry and Hildreth, 1980). The time complexity for the proposed method is the size of the input image N x N (i.e., height x width).

The computational code was written in MATLAB. The results were obtained by using a Pentium IV PC (120 Mb RAM, 1.90 GHz). The running time for an image of 256× 256 pixels size was about 30s for each set of 100 iterations.

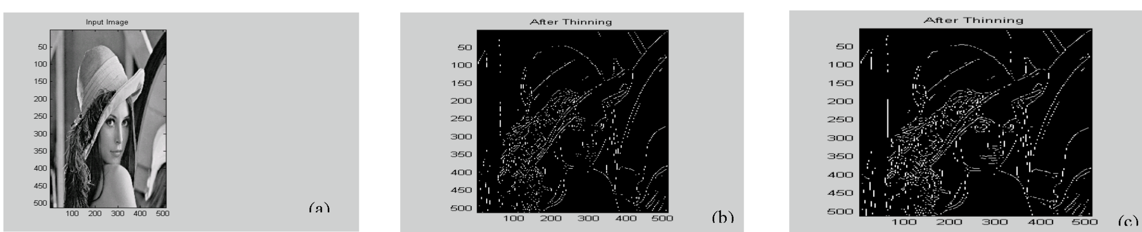

Fig.3: (a) Input image, (b) After edge detection using our proposed method (c) After edge detection using canny

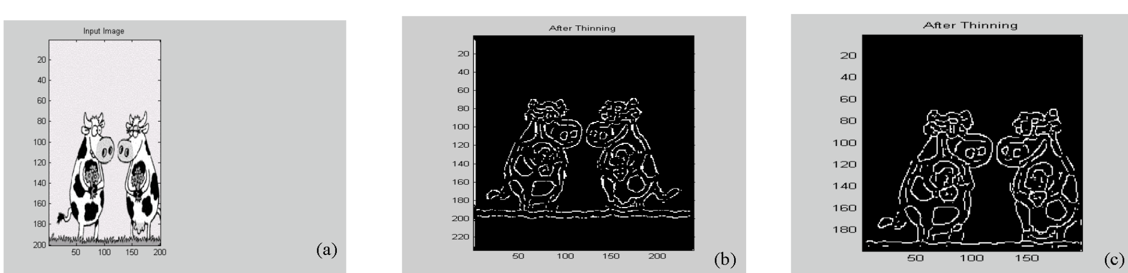

Fig. 4: (a) Input image (b) After edge detection using our proposed method and (c) After edge detection using canny

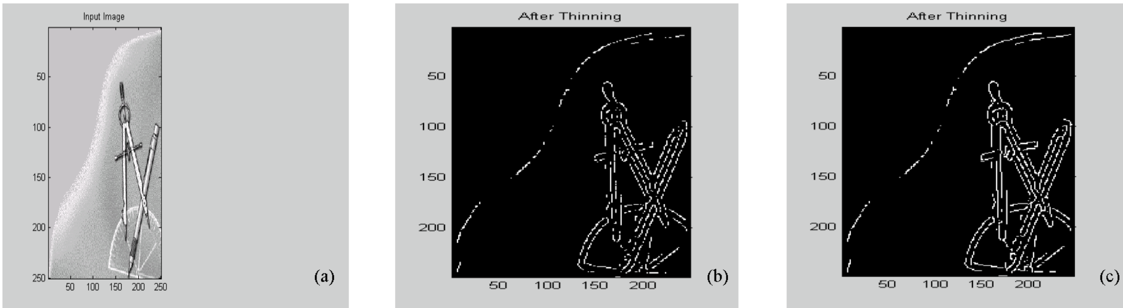

Fig. 5: (a) Input image (b) After edge detection using our proposed method (c) After edge detection using canny

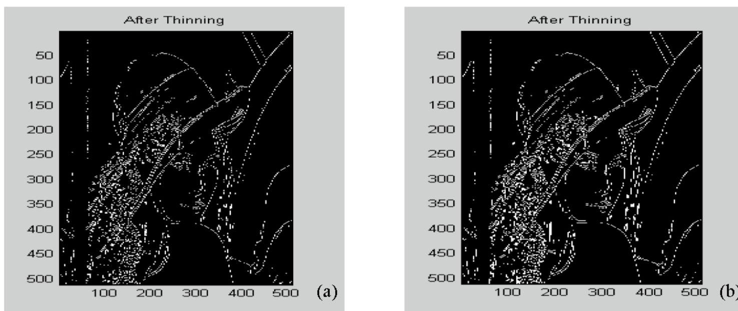

Fig. 6: (a) After edge detection using our proposed method and (b) After edge detection using canny

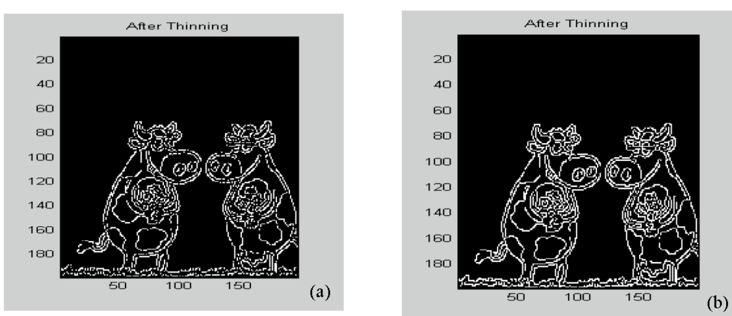

Fig. 7: (a) After edge detection using our proposed method and (b) after edge detection using canny

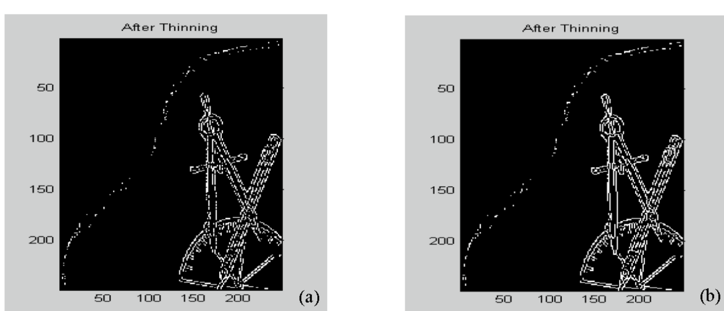

Fig. 8: (a) After edge detection using our proposed method and (b) After edge detection using canny

Experimental results: The objective of our experiments was to evaluate the performance of the algorithm and also compare the efficiency of canny edge detector with our proposed method.

Experimental results shows that our proposed method detects better edges when compared to Canny edge detector with size of Gaussian filter is 10×10 and $\sigma = 1.5$ (Fig. 3-5). And also our proposed method gives better edges when compared to Canny edge detector method with size of Gaussian filter is 5×5 and $\sigma = 1$ (Fig. 6-8).

CONCLUSION

The contributions of the paper are the following: First, we presented a new approach called an enhanced approach to gradient edge detection method. Second, we provided explanations for detecting more better (smooth), thin and finer edges. Finally, our proposed method accurately detects simple shapes like straight lines, elliptic and circular edges. Experimental results reveal this method to be more effective when compared with canny edge detector and less sensitivity to noise. However, this method takes longer time to compute results due to its higher degree of complexity. Our next step is to emulate this work by investigating how the detected edges can be effectively used for shape matching and object recognition.

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