

## A Better First- Derivative Approach For Edge Detection

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### Abstract

This paper shows a better approach (first derivative) for edge detection than the other commonly used first-derivative methods (like Robert's operator, Prewitt operator, Sobel operator etc.).

### 1. Introduction

In gray scale image, the edge is a local feature that, within a neighbourhood, separates two regions in each of which the gray level is more or less uniform with different values on the two sides of the edge. So, an ideal edge has a step like cross-section as shown in Fig. 1(a).

Fig. 1(b) exemplifies the cross section of a more realistic edge which has a shape of ramp function corrupted with noise.

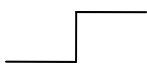


Fig. 1(a)



Fig. 1(b)

In derivative approach, edge pixels are detected by taking derivative (e.g. Robert's operator, 4-neighbor operator) followed by Thresholding. They occasionally incorporate noise-cleaning scheme (e.g. Prewitt operator, Sobel operator). The backbone of derivative approach is the discrete approximation of derivative operation.

### 2. Theory and Methods

Consider the following gray level values around the centre candidate pixel at (r, c) with gray level value g:

|    |    |    |    |    |
|----|----|----|----|----|
|    | A1 | A2 | A2 |    |
| C1 | A4 | A5 | A6 | D1 |
| C2 | F  | G  | H  | D2 |
| C3 | B1 | B2 | B3 | D3 |
|    | B4 | B5 | B6 |    |

The 4-Neighbor operator [1] approximates the actual edge strength at (r, c) as,

$$d_r = b_2 - a_5, d_c = h - f;$$

The magnitude of gradient at (r, c) is then given by  $g' = \sqrt{[(d_r^2 + d_c^2)/2]}$ .

However this method is very sensitive to noise & hence other operators like Prewitt operator, Sobel operator etc. are used more frequently which have averaging nature.

To minimize the noise effect on the edge-image & to get a proper Threshold for final edge image, the edge strengths at (r, c) can be defined as [method-1],

$d_r = [\text{average gray level over the } (3 \times 3) \text{ neighbourhood at } (r+1, c)] - [\text{average gray level over the } (3 \times 3) \text{ neighbourhood at } (r-1, c)],$

$$\Rightarrow d_r = (1/9)[\sum b_i - \sum a_i];$$

Where, ' $\sum$ ' defines summation over 'i'.

Similarly,  $d_c = [\text{average gray level over the } (3 \times 3) \text{ neighbourhood at } (r, c+1)] - [\text{average gray level over the } (3 \times 3) \text{ neighbourhood at } (r, c-1)],$

$$\Rightarrow d_c = (1/9)[a_6 + h + b_3 + \sum d_i - (a_4 + f + b_1 + \sum c_i)];$$

The corresponding masks are given by,

|   |    |    |    |    |    |   |
|---|----|----|----|----|----|---|
| 0 | -1 | -1 | -1 | -1 | -1 | 0 |
| 0 | -1 | -1 | -1 | -1 | -1 | 0 |
| 0 | 0  | 0  | 0  | 0  | 0  | 0 |
| 0 | 0  | 0  | -  | 0  | 0  | 0 |
| 0 | 0  | 0  | 0  | 0  | 0  | 0 |
| 0 | 1  | 1  | 1  | 1  | 1  | 0 |
| 0 | 1  | 1  | 1  | 1  | 1  | 0 |

|   |    |    |    |   |
|---|----|----|----|---|
| 0 | -1 | -1 | -1 | 0 |
| 0 | -1 | -1 | -1 | 0 |
| 0 | 0  | -  | 0  | 0 |
| 0 | 1  | 1  | 1  | 0 |
| 0 | 1  | 1  | 1  | 0 |

It can be seen from the above equivalent mask that the candidate pixel at (r, c) gets no edge information (horizontal) from its immediate neighbours, which is not desired, as maximum edge information is stored in immediate neighbours. Hence the method-1 mask is optimum for the proposed approach.

Average can also be computed on 4-neighbor basis [method-2]; the corresponding masks are given by,

|    |    |   |   |   |
|----|----|---|---|---|
| 0  | 0  | 0 | 0 | 0 |
| -1 | -1 | 0 | 1 | 1 |
| -1 | -1 | - | 1 | 1 |
| -1 | -1 | 0 | 1 | 1 |
| 0  | 0  | 0 | 0 | 0 |

|   |    |    |    |   |
|---|----|----|----|---|
| 0 | 0  | -1 | 0  | 0 |
| 0 | -1 | -1 | -1 | 0 |
| 0 | 0  | -  | 0  | 0 |
| 0 | 1  | 1  | 1  | 0 |
| 0 | 0  | 1  | 0  | 0 |

Among all the methods discussed in this paper, the above one is least sensitive to noise because of its robust averaging nature.

Now it will be shown that this mask size is optimum. If it is tried to find  $d_r$  by taking averages over (5x5) neighbourhood at (r+1, c) & (r-1, c) respectively, then the equivalent horizontal mask will be as follow:

|    |    |   |   |   |
|----|----|---|---|---|
| 0  | 0  | 0 | 0 | 0 |
| 0  | -1 | 0 | 1 | 0 |
| -1 | -1 | - | 1 | 1 |
| 0  | -1 | 0 | 1 | 0 |
| 0  | 0  | 0 | 0 | 0 |

### 3. Experiments and Results

A synthetic test image is taken & 'salt & pepper' noise is added. Original gradient image (X) & noisy gradient images (Y) are found for all the operators. From these the gradient images for noise (X-Y) are found & corresponding standard deviations & mean square measures are calculated (following table is to be referred for different types of operators & different measures of noise).

Table 1(a): Mean Square Noise measure

| Operator    | Mean Square Noise Estimation (1% noise) | Mean Square Noise Estimation (10% noise) |
|-------------|---|--|
| Roberts     | 617.43                                  | 6001                                     |
| 4-neighbour | 613.75                                  | 5907                                     |
| Prewitt     | 200.26                                  | 1960                                     |
| Sobel       | 226.61                                  | 2208                                     |
| Method-1    | 97.21                                   | 962                                      |
| Method-2    | 147.18                                  | 1442                                     |

Table 1(b): Standard Deviations of noise

| Operator    | Standard Deviation of Gradient noise image (1% noise) | Standard Deviation of Gradient noise image (10% noise) |
|-------------|---|--|
| Roberts     | 11.08   | 6.56   |
| 4-neighbour | 9.01  | 5.73   |
| Prewitt     | 5.04  | 3.29   |
| Sobel       | 5.18  | 3.11   |
| Method-1    | 2.46  | 2.08   |
| Method-2    | 3.43  | 2.23   |

The mean square measure is calculated as:  $[\sum g(r, c)^2]/(R*C)$ , where  $g(r, c)$  is the pixel value at location  $(r, c)$ ,  $R$  is the number of rows in the image &  $C$  is the number of columns in the image.

The following pictures show the results by the proposed methods:



Fig. 2(a): Original synthetic test image

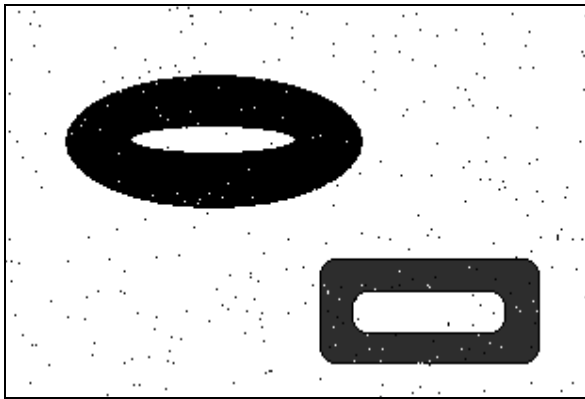


Fig. 2(b): Noisy gray level image (1% salt & pepper noise is added)

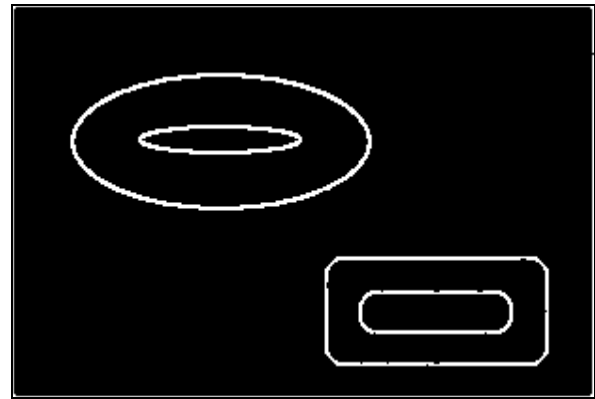


Fig. 2(e): Edge image (after Thresholding of noisy gradient image) by method-1

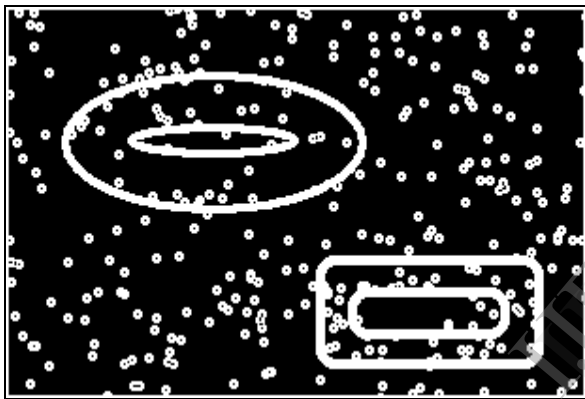


Fig. 2(c): Result (gradient image) by method-1

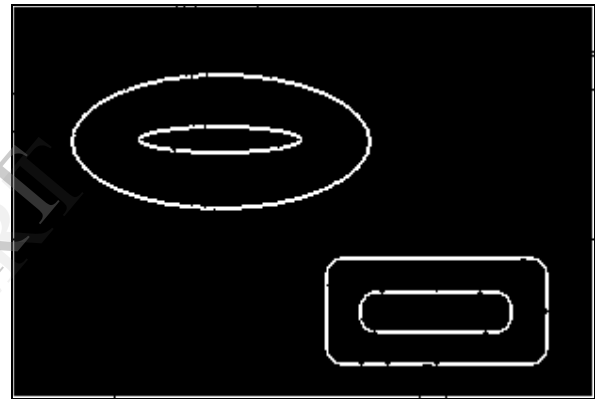


Fig. 2(f): Edge image (after Thresholding of noisy gradient image) by method-2

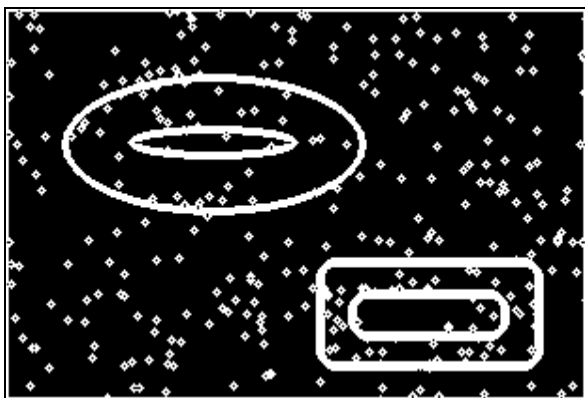


Fig. 2(d): Result (gradient image) by method-2

#### 4. Discussion

Even if here only 'salt & pepper' noise is taken, but the above methods give good results for other types of noises also because of its robust averaging nature. The above two approaches are the most general first derivative edge detection approaches.

#### 5. Conclusions

From Table 1(a) it is clear that Mean Square Noise is least for method-1 followed by method-2. Hence these are more effective in reducing noise effects.

From Table 1(b) it is clear that Standard Deviation of noises is least for method-1 followed by method-2. Hence noises are more around their means in these

methods; which helps to choose a better Threshold for final noise free edge image.

## 6. References

- [1] Bhabatosh Chanda & Dwijesh Dutta Majumder, Digital Image Processing and Analysis, Prentice-Hall of India Private Ltd, New Delhi, India,2007, pp. 239- 246.
- [2] Rafael C. Gonzalez & Richard E. Woods, Digital Image Processing, Pearson Education Asia Private Ltd, Delhi, India, 2002.

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