

## Comparison of Some Classical Edge Detection Techniques with their Suitability Analysis for Medical Images Processing

**Subhro Sarkar\***

M.Sc. (CS)

Siliguri, India

suvro.nbu@gmail.com

**Ardhendu Mandal**

Dept. of Computer Science and Application

University of North Bengal

Dist-Darjeeling, India

am.csa.nbu@gmail.com

**Abstract**—In digital image processing, understanding the scene is one of the most important and challenging tasks. Along with many features of an image like texture, color, line, point etc. edges are most vital feature that carries the information about the structure and overall geometry of objects the image is composed of. Edge detection is based on finding meaningful discontinuities in gray levels. This brief study is aimed towards exploring different edge detection techniques, the theories behind them and distinguishing their efficiency in finding suitable, meaningful edges in digital medical images.

**Keywords**-roberts; prewitt; sobel; LoG;canny; MRI

### I. INTRODUCTION

Edges play a crucial role in human visual perception for understanding world by providing boundaries among different objects, structural changes in single object and perceivable differentiation between background and other objects. Fundamentally, an edge is a “local” concept. A reasonable definition of “edge” requires the ability to measure gray-level transition in a meaningful way [2]. An abrupt change in the gray level is defined as an edge in a digital image.

Edge detection is by far the most common approach for detecting meaningful discontinuity in gray levels present in a digital image. Edge detection operation includes emphasizing changes in gray levels and suppressing areas with constant gray level or with gray level changes below certain level. The pixel location  $(x, y)$  is declared as an edge location if the magnitude of gradient, say  $g(x, y)$ , exceeds certain value  $t$ , called threshold [6]. Thus the locations of edge points constitute an edge map  $\mathcal{E}(x, y)$  which is defined as-

$$\mathcal{E}(x, y) = \begin{cases} 1, & (x, y) \in I_g \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

Where

$$I_g = \{(x, y) : g(x, y) > t\}$$

For computer vision and automatic computer analysis of images, comparison demands extraction of edges from an image in order to perform above mentioned operations with minimum but evident image data. Edges are detected to filter out other relatively less important finer details in order to enhance the processing, lowering the complexity without negotiating with the loss of required data. The performance measure for the edge detection is how well edge detector markings match with the visual perception of object boundaries [1].

## II. CLASSIFICATION OF DIFFERENT EDGE DETECTION TECHNIQUES

The edge map gives the necessary data for tracing the object boundaries in an image. Edge detection techniques can be categorized into three main classes as-

- Gradient Based or First order of derivation based.
- Laplacian Method or Second order of derivation based.
- Gaussian edge detection technique.

### III. FIRST ORDER DERIVATIVE OF EDGE DETECTION

Gradient is a measure of the changes in function. The gradient vector is used to define an edge in a digital image, by its magnitude value which is proportional to the degree of intensity changes in areas whose values are variable, along with the angle at which this maximum change is occurred [3]. First-order derivations are based on various approximations of 2-D gradients of a digital image. The gradient of an image  $f(x, y)$  at location  $(x, y)$  is defined as the vector:

$$\nabla f = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \partial f / \partial x \\ \partial f / \partial y \end{bmatrix} \quad (2)$$

The gradient vector points towards the direction where the maximum rate of change for  $f(x, y)$  at the coordinate  $(x, y)$  is seen.

There are two important quantities in edge detection in First-order:

The magnitude of the vector  $\nabla f$ , and is denoted by  $|\nabla f|$ , where

$$|\nabla f| = \text{mag}(\nabla f) = [G_x^2 + G_y^2]^{1/2} \quad (3)$$

However, for the computational burden required by squares and square root, this implementation is not always desirable. In practice, sometimes the magnitude is approximated by [4].

$$|\nabla f| = \text{mag}(\nabla f) = \left| \frac{\partial f}{\partial x} \right| + \left| \frac{\partial f}{\partial y} \right| \quad (4)$$

Or

$$|\nabla f| = \text{mag}(\nabla f) = \max \left( \frac{\partial f}{\partial x}, \frac{\partial f}{\partial y} \right) \quad (5)$$

This quantity gives the maximum rate of increase of the gradient function  $f(x, y)$ .

The direction of the gradient vector determines the direction of maximum  $\nabla f$  (3). Let  $\alpha(x, y)$  denotes the direction angle of the vector at  $(x, y)$ . Then from vector analysis,

$$\alpha(x, y) = \tan^{-1} \left( \frac{G_x}{G_y} \right) \quad (6)$$

The angle is measured with respect to the x-axis. The direction of an edge at  $(x, y)$  is perpendicular to the direction of the gradient vector  $\nabla f$ .

We require that any definition we use for a first order derivation-

- Must be zero in flat segments.
- Must be nonzero at onset of a gray level step or ramp.
- Must be nonzero along the ramp

### III. SECOND ORDER DERIVATIVE OF EDGE DETECTION

As the transition region gets wider, it is more advantageous to apply the second order derivatives. In second order derivatives the frequently used operator is the Laplacian operator defined as-

$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2} \quad (7)$$

This gradient operator is more sensitive to noise than that of first order. The thresholded magnitude of  $\nabla^2 f$  produces double edges. A better utilization of the Laplacian is to use its zero-crossing to detect edge location. The Laplacian of Gaussian (LoG) function is a powerful zero-crossing edge detector, defined as:

$$\nabla^2 h(r) = - \left[ \frac{r^2 - \sigma^2}{\sigma^2} \right] e^{-\frac{r^2}{2\sigma^2}} \quad (8)$$

Where,

$$h(r) = - e^{-\frac{r^2}{2\sigma^2}} \quad (9)$$

Is the Gaussian smoothing function and  $r^2 = x^2 + y^2$ ,  $\sigma$  is the standard deviation. Convolving the image with (8) results blurring of degree determined by the value of  $\sigma$ .

Any definition of second order requires–

- Must be zero in flat areas.
- Must be nonzero at the onset and of a gray level step or ramp.
- Must be zero along the ramp.

#### IV. EDGE DETECTION WITH DERIVATIVES OF GAUSSIAN

A well-known class of regularized derivative filters is the class of derivative of a Gaussian smoothing filter. Such a filter was used by Canny [8] for optimal edge detection and is also known as Canny edge detector. Smaller filters cause less blurring, and allow detection of small, sharp lines. A larger filter causes more blurring, smearing out the value of a given pixel over a larger area of the image. Larger blurring radii are more useful for detecting larger, smoother edges. This method aims to satisfy three main criteria-

- Low error rate: Good detection of existing edges only.
- Localization: The difference between detected edges and real edges must minimize.
- Minimal response: Response to a single edge must single.

#### V. EDGE DETECTION WITH GRADIENT BASED OPERATORS IN FIRST-ORDER DERIVATIVE

Computation of gradient for each pixel location of an image is based on the calculation of the partial derivatives  $G_x$  and  $G_y$  (or  $\partial f/\partial x$  and  $\partial f/\partial y$  respectively) components. These two components then are required to be combined in the manner shown in (3). An approach used frequently is shown in (4), or (5) sometimes.

The basic definition (discrete) of first-order derivative of a two dimensional function  $f(x, y)$  is

$$G_x = \frac{\partial f}{\partial x} \approx f(x+1, y) - f(x, y) \quad (10)$$

$$G_y = \frac{\partial f}{\partial y} \approx f(x, y+1) - f(x, y) \quad (11)$$

Some common Gradient Operators for finding edges in a digital image are:

### A. Roberts Operator

Roberts Operator is a differential operator. It is used to approximate the gradient of a digital image through discrete differentiation by computing the sum of squares of the two gradient vectors  $G_x$  and  $G_y$  and through diagonally adjacent pixels (as shown in (3)). The direction of the edge is defined by the (6). Edge detection with Roberts operator is performed by convolving the input image with the convolution kernels as follows (Figure 1):

$$G_x = \begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix} \quad \text{and} \quad G_y = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}$$

Figure 1: Roberts Operator

The resulting image after convolution will highlight the changes in intensity diagonally. One of the most appealing aspects of Roberts operator is its simplicity. The kernel is small and contains only integers. However with the speed of computers today this advantage is negligible and the Roberts cross suffers greatly from sensitivity to noise [4].

### B. Prewitt Operator

Prewitt operator is a discrete differentiation operator that computes an approximation of the gradient at each point of a digital image. At any point of digital image which is in a region of constant intensity, the Prewitt operator results a zero vector but at a points across the edge it results a gradient vector pointing across that edge, from darker to brighter values. The Prewitt operator uses two 3x3 kernel to be convolved with an image in order to calculate the approximation of gradient vectors –one for vertical and other for horizontal, as shown below (Figure 2):

$$G_x = \begin{bmatrix} -1 & 0 & +1 \\ -1 & 0 & +1 \\ -1 & 0 & +1 \end{bmatrix} \quad G_y = \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ +1 & +1 & +1 \end{bmatrix}$$

Figure 2: Prewitt Operator

### C. Sobel Operator

The Sobel operator is functionally same as the Prewitt operator with a slight variation which uses a weight of 2 in the center coefficient, thus changing the convolution kernel as(Figure 3):

$$G_x = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & -1 \end{bmatrix} \quad G_y = \begin{bmatrix} -1 & -2 & +1 \\ 0 & 0 & 0 \\ -1 & +2 & +1 \end{bmatrix}$$

Figure 3: Sobel Operator

The weight value 2 is used to achieve some smoothing by giving more importance to the center point [5].

## VI. EDGE DETECTION WITH GRADIENT BASED OPERATORS IN SECOND-ORDER DERIVATION

### A. Laplacian of Gaussian

LoG is an isotropic edge measurement technique based on the second-order of derivation of a digital image. Since second-order derivation is more sensitive to the noise, a low-pass filter is used which is chosen to be Gaussian smoothing function (8). The discrete 3x3 kernel approximating the second-order derivation is as follows (Figure 2):

$$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix} \quad \text{or} \quad \begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

Figure 4: LoG Operator

## VII. CANNY EDGE DETECTION TECHNIQUE

For Canny edge detection, there are important adjustable parameters, which can affect the computation time and effectiveness of the algorithm, the size of the Gaussian filter and thresholds. Smaller filters cause less blurring, and

allow detection of small, sharp lines. A larger filter causes more blurring, smearing out the value of a given pixel over a larger area of the image. Larger blurring radii are more useful for detecting larger, smoother edges.

Canny edge detection is based on finding the local maxima and suppressing the non-maxima of the gradient magnitude. The method can be summarized as:

- Reducing noise by applying Gaussian smoothing filter (8) with standard deviation  $\sigma$  (sigma).
- The magnitude of gradient  $|\nabla f|$  along with its direction is calculated as defined by (3) and (6)

respectively for each point using any above mentioned gradient based operator. An edge point is defined as local maximum towards the direction of magnitude.

- Next a process called non-maximal suppression is applied to track along the top of the ridge setting all other pixels in that ridge to zero. The ridge pixels are then thresholded by using two threshold values T1 and T2 with  $T1 > T2$ . Ridge pixels having value greater than T1 are said to be “strong” edge pixels and with values between T1 and T2 are called “weak” pixels.

- Finally, the algorithm performs edge linking by incorporating the “weak” pixels that are 8-connected to the “strong” edge pixels

### VIII. COMPUTATIONAL ANALYSIS OF DIFFERENT EDGE DETECTION OPERATORS

Edge detection operators can be compared in number of different ways. In this paper the operators are compared on the basis of human perception and ability to identify fine edges in an image. The parameter (threshold, sigma) values are not chosen explicitly, different values are tried using MATLAB and values for which most suitable edges are produced are chosen. Here the performance measure is judged according to the following parameters:

- Visibility of maximum number of edges present in an image.
- Minimum visibility of isolated points or noise.
- Produced edges are connected or disconnected by as few pixels as possible.
- Position of edge is true and edges are thinner.
- Response to the weaker edge should be prominent.

Based on the above mentioned parameters, different edge detection techniques are applied in order to find most suitable one among all the techniques described so far in this paper. The study is intentionally restricted to medical image processing. The suitability is testified and remarks are given using the following images (Figure 5: (a) and (b)) of human brain obtained through MRI (Magnetic Resonance Image) scan.

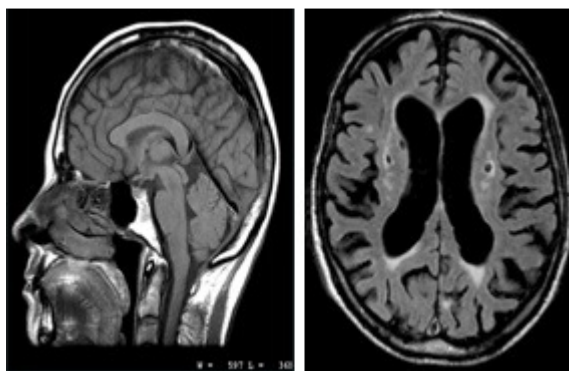


Figure 5:

(a)

(b)

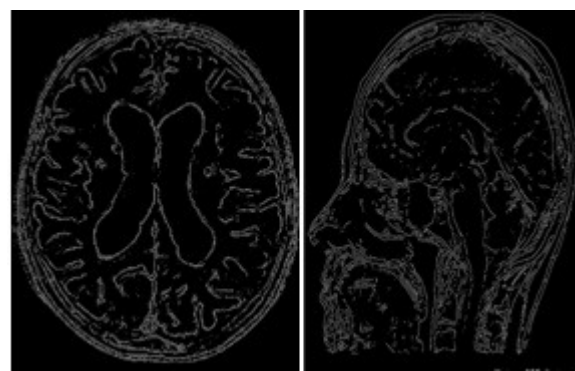


Figure 6:

(a) Threshold=0.0251787

(b)  
Threshold=0.026589

#### A. Using Roberts Operator

- Output images(Figure 6: (a) and (b)):

- Advantages: Simple, easy to compute, faster.
- Disadvantages: Many edges missing, noise suppression is low, suppressing noise cause more breaks in edges, edges are thick.
- Remarks: Simple, faster but not optimal for this purpose.

#### B. Using Prewitt Operator:

- Output images(Figure 7: (a) and (b)):

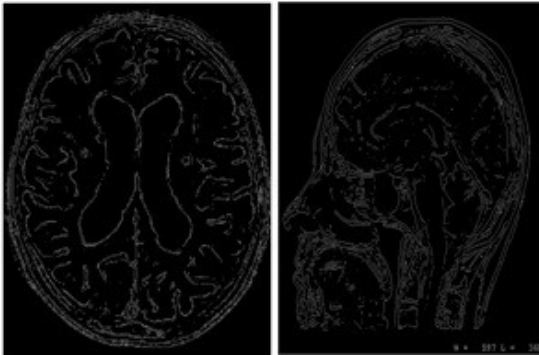


Figure 7:

(a)Threshold=0.0360987 (b)Threshold=0.0362536

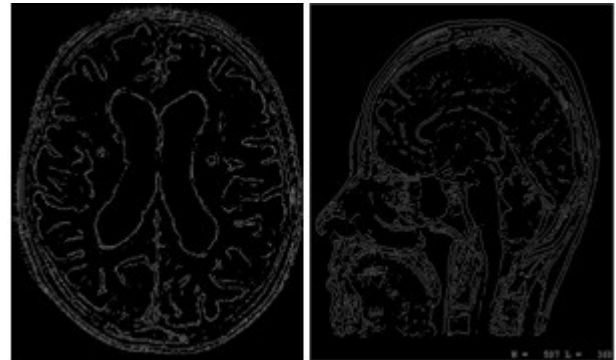


Figure 8:

(a)Threshold=0.0350331 (b)Threshold=0.0323941

- Advantages: Simple, fast. Edges are thinner, lesser noise.
- Disadvantages: Edges are fragmented response to weaker edges are not prominent.
- Remarks: Better than Roberts but still not optimal.

#### C. Using Sobel Operator

- Output images(Figure 8: (a) and (b)):
- Advantages: Simple, fast. Edges are thinner, lesser noise.
- Disadvantages: Edges are fragmented response to weaker edges are not prominent.
- Remarks: Almost same as Prewitt.

#### D. Using LoG Operator

- Output images(Figure 9: (a) and (b)):

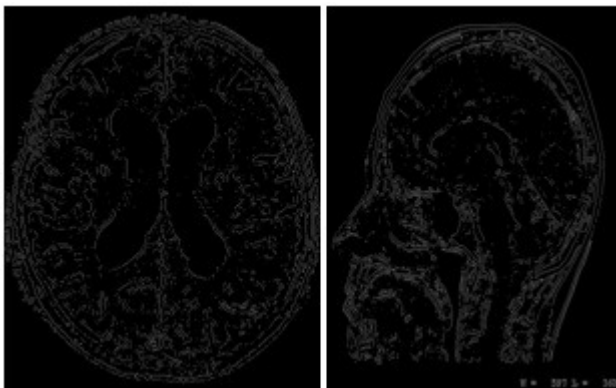


Figure 9:

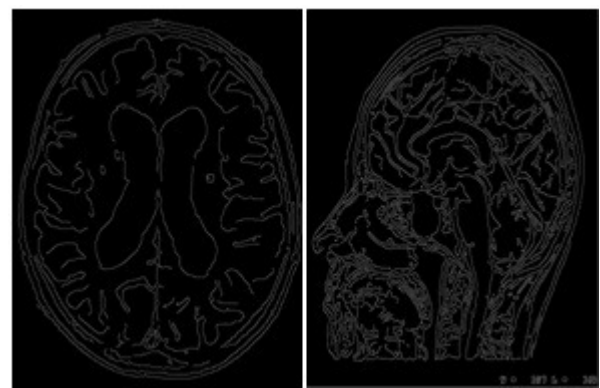
(a)  
Threshold=0.00222644  
Sigma=2(b)  
Threshold=0.00393,  
Sigma=2

Figure 10:

(a) Threshold=  
[0.359851, 0.143941]  
Sigma=2.28958(b) Threshold=  
[0.130112, 0.0520446]  
Sigma=2.27043

- Advantages: More edges are visible, edges are thinner.
- Disadvantages: Very sensitive to noise. Increasing sigma cause false edges. Edges are not much connected.
- Remarks: Not good for this kind of images.

#### E. Using Canny Operator:

- Output images(Figure 10: (a) and (b)):
- Advantages: Most of the edges are visible, most of the noises are suppressed, edges are thin and connected, and responses to weaker edges are prominent.
- Disadvantages: Complex and time consuming
- Remarks: Most suitable when compared to the other techniques mentioned previously.
- 

### IX. COMPARISON OF DIFFERENT EDGE-DETECTION TECHNIQUES

Depending on the analysis discussed so far are further assessed by assigning values based on the parameters defined in section IX for each of the edge detection techniques. The following is a tabular representation where points (out of 10) are given (Table 1).

Table 1

PARAMETERS	TECHNIQUES				
	Roberts	Prewitt	Sobel	LoG	Canny
Visibility of maximum number of edges	6	5	5	6	5
Minimum visibility of isolated points or noise.	4	5	5	3	8
Connectivity of edges.	4	4	4	3	6
Position of edge is true and edges are thinner.	5	6	6	5	6
Response to the weaker edges.	4	4	4	5	5

### X. CONCLUSION

In this paper, different edge detection operators are applied for medical images (MRI scanned) and its quality is compared. The edge detectors chosen for the study are Roberts, Prewitt, Sobel, LoG and Canny. Out of five operators, Canny detection method is found as the best in detecting the edges. From the above discussion, it is evident that the canny technique is more suitable in edge detection for medical MRI images with appropriate threshold values and sigma. Further we might need to categorize particular value or range of values of the thresholds and sigma for which the canny method will produce most suitable result for different types of medical images.

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