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Gauss Gradient Algorithm for Edge Detection in Retinal Optical Coherence Tomography Images

Ranjitha Rajan [a,b], S.N Kumar [b]

[a]*Lincoln University College,Kota Bharu, 15050*
[b]*Amal Jyothi College of Engineering, Kanjirappally, 686518*

Abstract

Medical imaging modalities play a vital role in the healthcare sector for disease diagnosis and prediction. Optical Coherence Tomography uses near-infrared rays for generating cross-sectional images of the retina. Edge detection is a traditionalROI extractionalgorithm thatextracts the boundary of objects in an image. This research work focuses on the gauss gradient-based edge detection model for boundary detection in Optical Coherence Tomography images of the retina. The separable feature of a 2D Gaussian kernel is used, and a 1D kernel for the x and y directions is created. The Gaussian kernel utilized in this research work is the convolution result of Gaussian function and first-order derivative of Gaussian function. For performance validation, the Berkeley segmentation data set was utilized, when compared to traditional edge detection models, and better results were obtained for the gauss gradient algorithm.

*Keywords:*OCT, edge detection, canny operator, sobel operator, prewitt opertaor

1. Introduction

Medical images are becoming increasingly vital in various applications in the medical field, and digital images play a significant part in this field. Medical image processing aims to address a variety of issues that arise in medical images, with noise being one of the most typical issues. Medical images are crucial in supporting healthcare professionals in diagnosing and treating patients. The radiologists' visual assessment of medical images is important while examining them. This, however, takes time and is usually subjective, based on the radiologist's experience. As a result, the usage of computer-assisted systems is becoming increasingly important to overcome these constraints[1]. In medicine, imaging technology allows doctors to see inside the body for a more accurate diagnosis. It also assisted doctors in performing keyhole surgeries, which allowed them to reach the interior sections of the body without having to open up the entire body [2].In medical imaging, noise can come from a variety of sources,

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and it's also defined as the random variations in brightness or color information in images, edges depict the boundary of objects. However, due to noise and the subjectivity of the edge detection limit, designing and implementing an edge detector with the ability to detect all valid edges in an image is a tedious process. Edge detection is a widely employed ROI extraction in medical images, and the conventional methods include Canny, Sobel, Prewitt, Roberts, Zero cross, and Gaussian Laplacian edge detectors. [3]

In image analysis, image segmentation is a crucial stage. The image segmentation objective is to group pixels into a sub-image, which corresponds to specific areas or structures, or natural components of objects [4]. The process of segmenting an image into its objects and backgrounds is referred to as "segmentation." The nature of the problem determines the extent to which the separation is carried out. When the desired region of interest are inaccessible, segmentation comes to halt [5]. Edges, also known as a shift of intensity in a digital image, are particularly significant in computer image analysis. It can also be defined as an abrupt change in discontinuities in an image. Edges in a digital image depict the boundaries that exist between objects[6]. Many image processing techniques rely on the accuracy with which they recognize meaningful edges. As a result, the goal is to compare and analyze the performance of various edge detection approaches using a variety of criteria [7].

Edge detection plays an inevitable role in computer vision and image processing [8], and gains prominence in the health care sector. The following are the important phases of the proposed gauss gradient edge detection model; the local edges of the images are initially highlighted with an edge enhancement operator, edge strength is estimated, and the edge points are obtained using threshold value. The performance of the edge detection technique has a direct impact on the precision of retrieved outlines of the image and the overall performance of the system. Section 2 describes the classical edge detection operators, section 3 describes the gauss gradient edge detection model for OCT images, and section 4 highlights the simulation results with the conclusion stated in section 4.

2. Materials and Methods

The majority of edge detection techniques depend on image or gradient derivatives. The noise present in the medical image relies on the imaging modality[9]. The identification of anatomical parts and pathological concerns such as tumors and cysts requires ROI extraction. The edge detection model traces the boundary of objects in an image[10].

The following shows the gradient of the 2D function T (x, y).

$$\nabla \mathrm{T} = \begin{pmatrix} \partial T/\partial x \\ \partial T/\partial y \end{pmatrix} \quad (1)$$

The magnitude of the above vector determines the edge strength which is expressed below.

$$\nabla T = mag(\nabla T) = \left(T_x + T_y\right) \quad (2)$$

$$\nabla \mathrm{T} = \left(\left(\frac{\partial T}{\partial x}\right)^2 + \left(\frac{\partial T}{\partial y}\right)^2\right)^{1/2} \quad (3)$$

The direction of the gradient is determined as follows:

$$\theta = \tan^{-1}\left(\frac{T_x}{T_y}\right) \quad (4)$$

First order and second derivative of the Gaussian function are utilized to trace the edges in an image [13]. The different types of operators for edge detection are depicted below in figure 1.

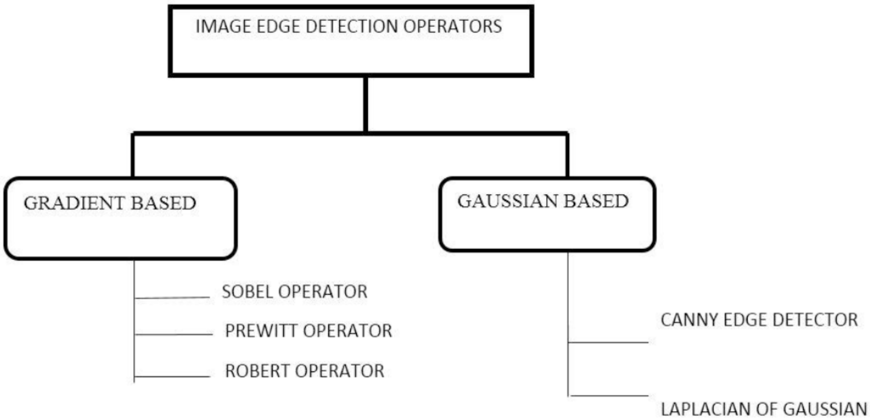


Figure 1: Classification of edge tracing algorithms

Sobel Operator: It estimates the gradient of the image along the x and y direction. The higher weight values are assigned to the pixels closer to the candidate pixels[11].To digitally calculate the first derivative Gx and Gy, it uses 3 × 3 two masks or kernels as illustrated in figure 2.

-1	-2	-1
0	0	0
1	2	1

G_x

-1	0	1
-2	0	2
-1	0	1

G_y

Figure 2: Sobel edge detection mask

Prewitt Operator: The gradient is estimated along x and y direction similar to sobel edge detector. Similar weight values are assigned to the neighborhood of the candidate pixels.It is proficient to sense the orientation and magnitude of an image [12]. It makes use of the masks depicted in figure 3

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

G_x

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

G_y

Figure 3: Prewitt edge detection mask

Robert operator: Using discrete differentiation, this operator sums the squares of the differences between adjacent pixels on the diagonal of an image [13]. The gradient approximation is then calculated. As shown in Figure 4, it employs 2 x 2 kernels.

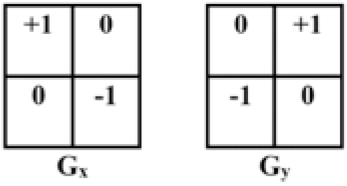


Figure 4: Robert operator mask

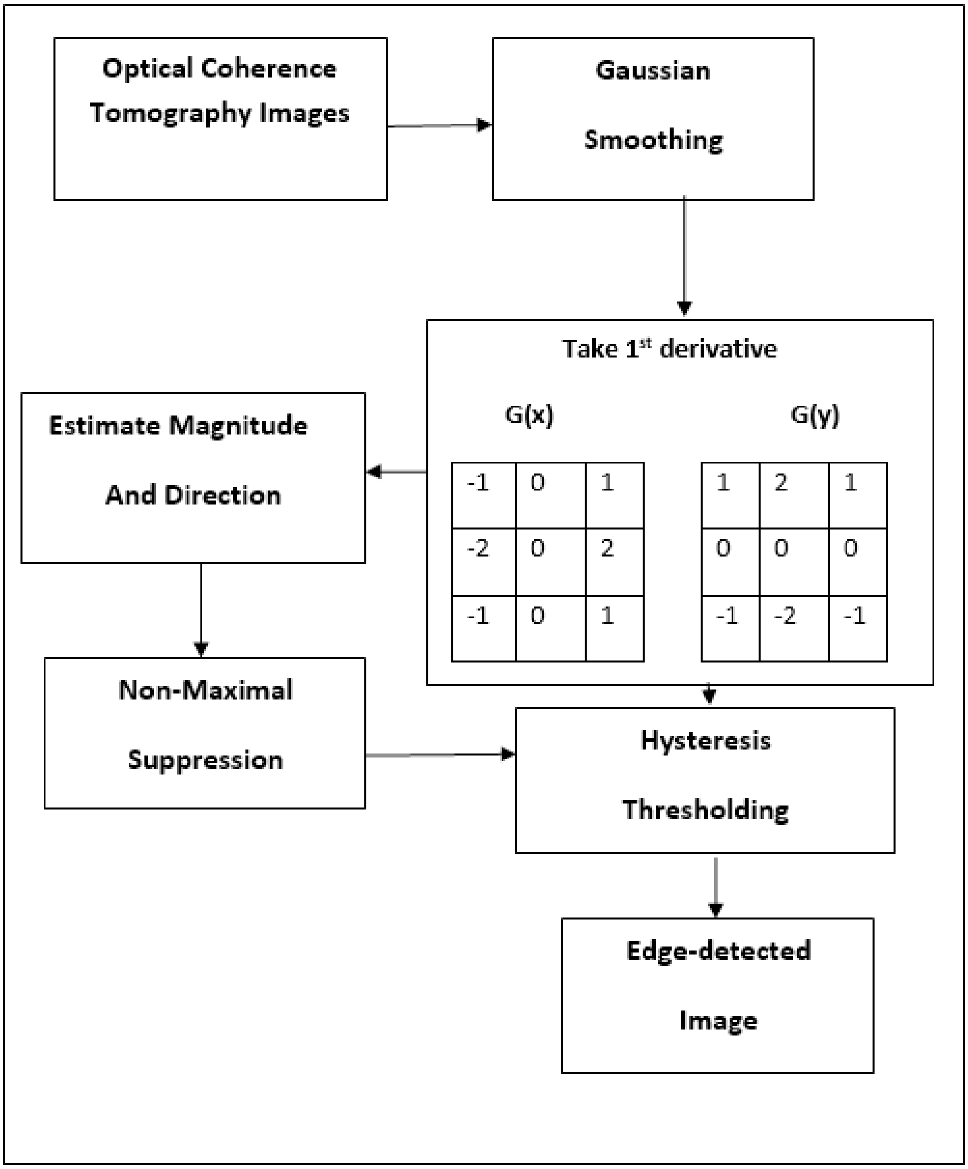


Figure 5: Canny operator flow diagram

Canny operator: Unlike the Sobel and Robert operators, which are susceptible to noise, the Canny operator is an efficient tool for detecting edges and can be applied to a number of different situations without changing or modifying them [14]. The canny edge detection flow diagram is depicted in figure 5.

Laplacian of Gaussian: This is particularly useful when the grey level transition appears to be abrupt. Calculating the second-order derivative is required to assure a smoother transition. It's important to remember that when the second order derivative passes zero, the location corresponds to the highest possible level, known as an edge identification [15]. Figure 6 below depicts the Laplacian of the Gaussian edge detector mask.

1	1	1
1	-8	1
1	1	1

-1	2	-1
2	-4	2
-1	2	-1

Figure 6: Laplacian of Gaussian edge detection mask

3. OCT Image Boundary Detection Using Gauss Gradient Approach

The gradient operator is widely used in edge detection and gains prominence in signal and image processing applications. The Gaussian derivatives are utilized in this research work for tracing the edges and are applicable to 2-dimensional and 3-dimensional data.

In two dimensions, the Gaussian kernel is expressed as follows

$$h(x,y) = \frac{1}{2\pi\sigma^2} e^{-\left(\frac{x^2+y^2}{\sigma^2}\right)} \tag{5}$$

The term σ representsthe scale of the smoothing. The Gaussian filter's response is strongly influenced by the scale. The higher the value, the blurrier the image becomes and the less sensitive to noise it is.

In general, a function $z(x,y)$ can be written as follows in terms of the tensor product:

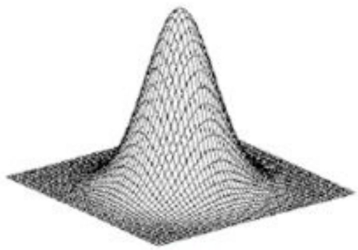
$$z(x,y) = a(x)b(y) \tag{6}$$

A separable filtering method is used instead of a 2D kernel to compute the gradient in the x and y directions using a 1D kernel.

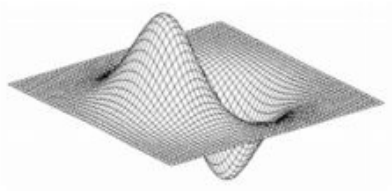
The separable property of the Gaussian function favors the decomposition of a two-dimensional function into two single-dimensional functions.

$$z(x,y)=\left(\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\left(\frac{x^2}{\sigma 2}\right)}\right)\left(\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\left(\frac{y^2}{\sigma 2}\right)}\right) \tag{7}$$

The Gaussian filter has a unique featurein that it satisfies the uncertainty relation,$\Delta x \Delta w \geq 1$



(a)



(b)

Figure 7: Gaussian kernel and its derivative (a,b)[9]

In the spatial and frequency domains,Δx and Δw are the variances. The unique characteristic provides the best compromise between the spatial and frequency domain goals of localization. The separable kernel of a filter is made up of tensor products.

The following are the steps in gauss gradient edge detection:

Step 1: Grayscale or color images are used as input. The Gaussian kernel is determined in both directions; the sigma is a user-defined parameter. The higher the sigma value, the more blurred the output will be.

Step 2: The Gaussian kernel is expressedin X and Y directions. The Gaussian kernel is formulated by the convolution of the Gaussian function and I[st]order derivative of the Gaussian function.

$$a(x) = \left(\frac{1}{\sigma\sqrt{2\pi}} e^{-\left(\frac{x^2}{\sigma^2}\right)} \right) \tag{8}$$

TheI[st] order derivative of the Gaussian function is expressedas follows

$$\frac{\partial}{\partial x}(a(x)) = \frac{1}{\sqrt{2\pi\sigma}} \frac{-2x}{2\sigma^2} e^{-\left(\frac{x^2}{2\sigma^2}\right)} \tag{9}$$

$$a(x) = -x \left(\frac{1}{\sqrt{2\pi\sigma}}\right) \frac{e^{-x^2}}{2\sigma^2} * \frac{1}{\sigma^2} \tag{10}$$

$$a(x) = -x * a(x) * \sigma^2 \tag{11}$$

Step 3: The generated kernels are used to perform Gaussian smoothing on the image, with the results shown below.

Step 4: The ROI extracted image is represented as follows

$$Edge\ output = abs\ (Gx + Gy) \tag{12}$$

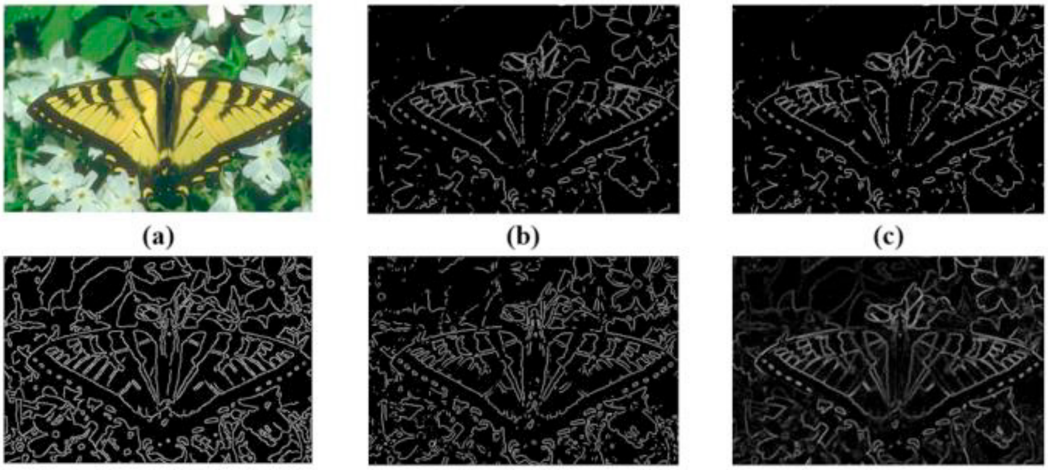
Where Gx and Gy are a Gaussian-filtered version of the image [16].

The gauss gradient-based edge detection generates proficient results when compared with the classical edge detection models.

4. Results and Discussion

This research work proposes a gauss gradient edge detection model for the OCT images of the retina. MATLAB 2020 software was utilized for the simulation and the system specifications are as follows; Intel i5 processor, 8 GB

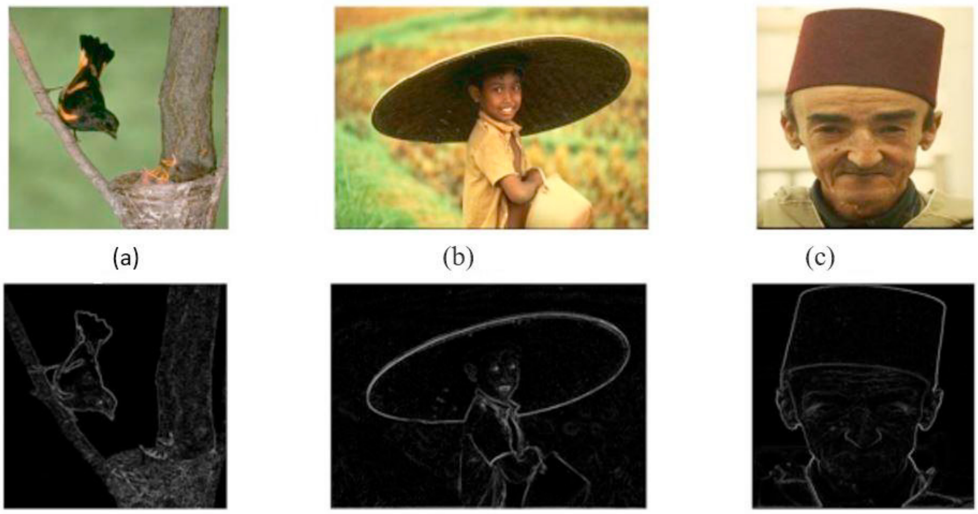
RAM. The algorithms are initially validated on Berkeley segmentation dataset images(https://www2.eecs.berkeley.edu/Research/Projects/CS/vision/bsds). The gold standard images are present in the data base and the results are validated by performance measures. Figure 8 below depicts the input images from the Berkely database and gauss gradient edge detection output.



(d) (e) (f)

Figure 8 : (a) Input image from Berkeley database (I1), (b) Sobel edge detector output, (c) Prewitt edge detector output, (d) canny edge detector output, (e) gauss edge detector output[9]

Figure 9 below depicts the input images from the Berkeley database and the gauss gradient edge detector output. Figure 10 and 11 below represents the PSNR and MSE plot of edge detection models with respect to the gold standard image from the database. Gauss gradient approach was found to have high PSNR and low MSE, when compared with the other approaches.



(d) (e) (f)

Figure 9: (a,b,c) Input images from Berkely segmentation data set (I2,I3,I4), (d,e,f) Gauss Gradient Edge Detector output[9]

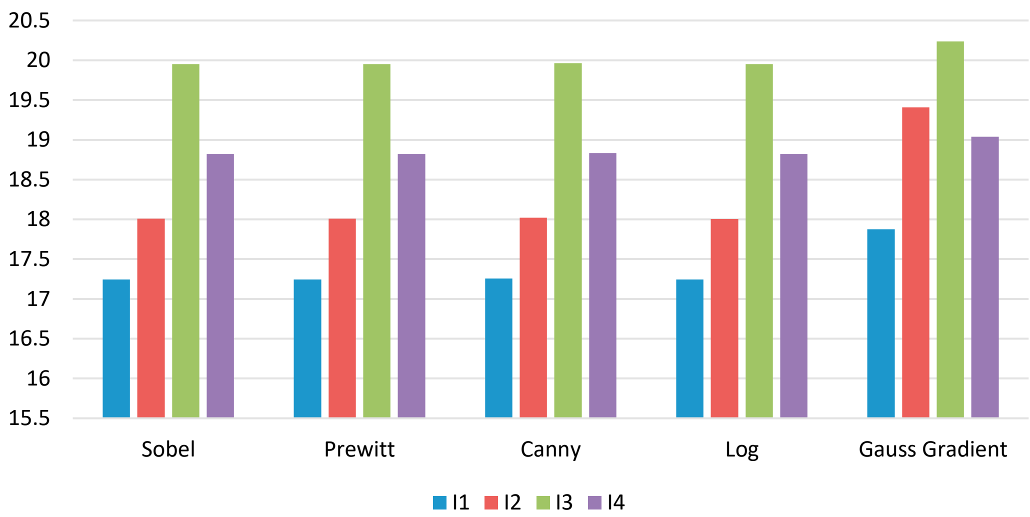


Figure 10: PSNR plot of edge detection algorithms[9]

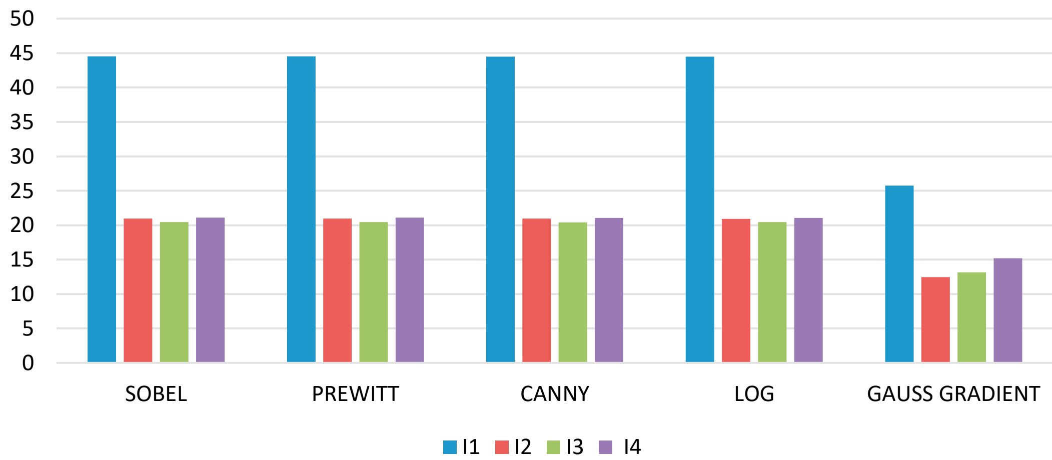


Figure 11: MSE values of the edge detection algorithms [9]

The figure 12 below depicts the input OCT images (IM1 to IM9) from the database (https://www.kaggle.com/paultimothymooney/kermany2018). Figure 13 depicts the preprocessing results by applying fast bilateral filter.

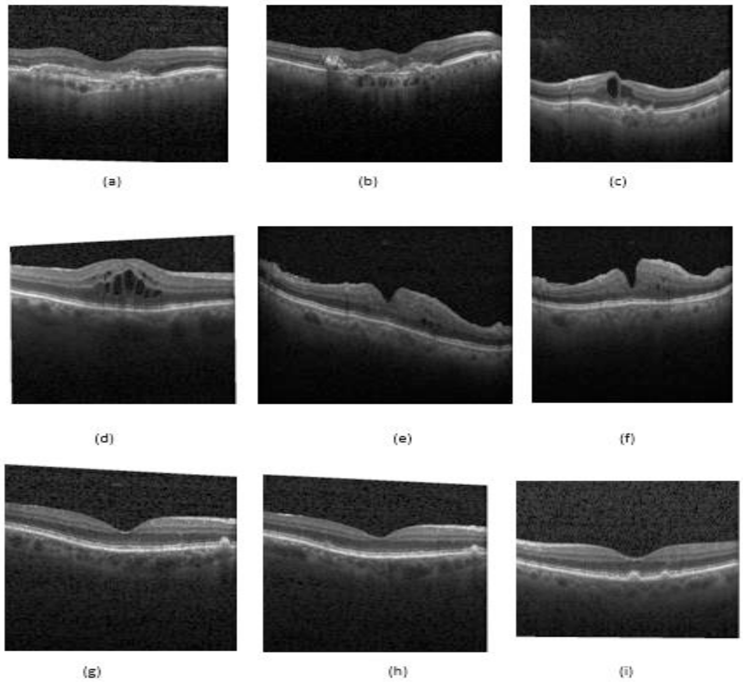


Figure 12: Input OCT images (IM1 to IM9)

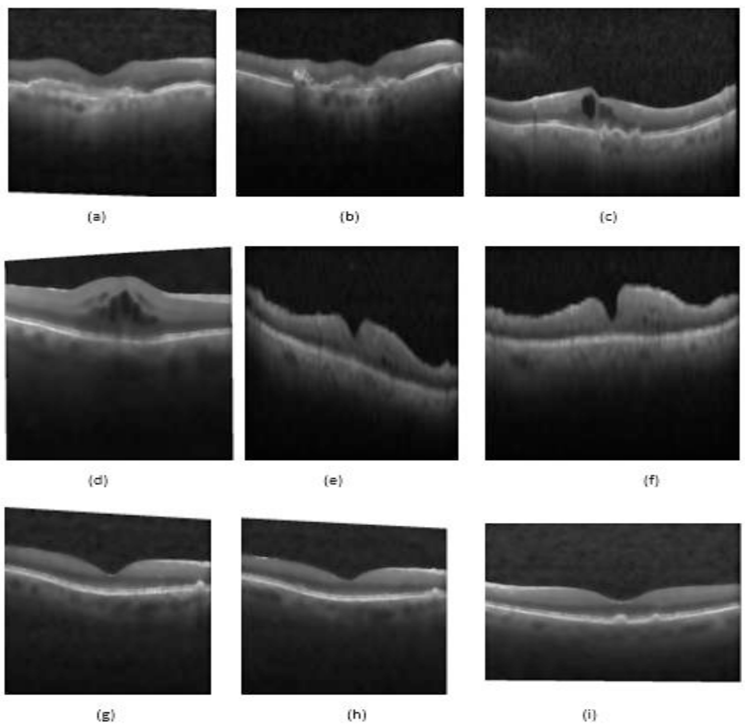


Figure 13: Preprocessing of input images by the fast bilateral filter with respect to the input images (IM1-IM9)

The benchmark images were initially validated by classical edge detection operators and the proposed gauss gradient approach. The performance evaluation was done by metrics PSNR and MSE. The proposed gauss gradient method was found to produce good results in terms of PSNR and MSE. Prewitt operator results are depicted in figure 14 and Robert operator results are depicted in figure 15. Figure 16 depicts the edge detection by the canny edge detection operator.

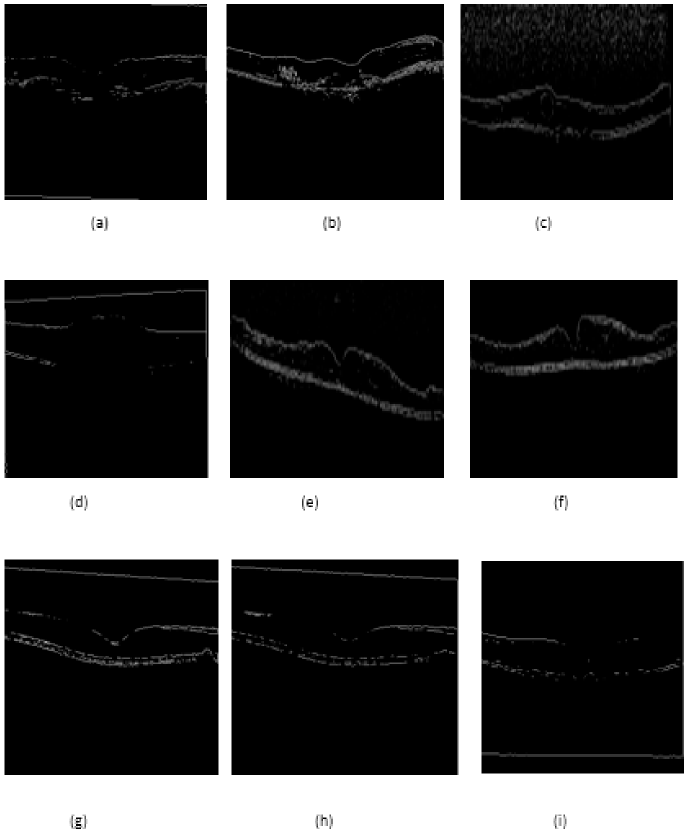


Figure 14: OCT image edge detection by Prewitt edge detection operator (IM1-IM9)

The gauss gradient edge detector results are depicted in figure 17, corresponding to various values of sigma with respect to the IM1 as input. The results reveals that, for the sigma value of 1.5, output is proficient. The outputs corresponding to the value of sigma=1.5 for the images IM2-IM9 are depicted in figure 18.

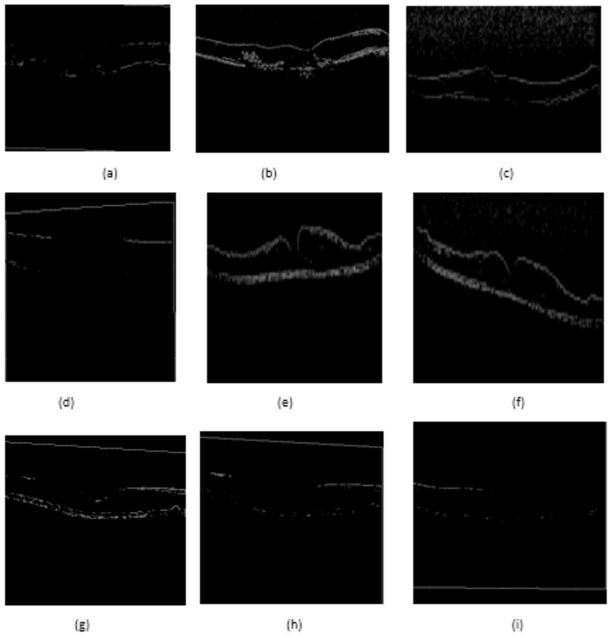


Figure 15: OCT image edge detection by Roberts's edge detection operator (IM1-IM9)

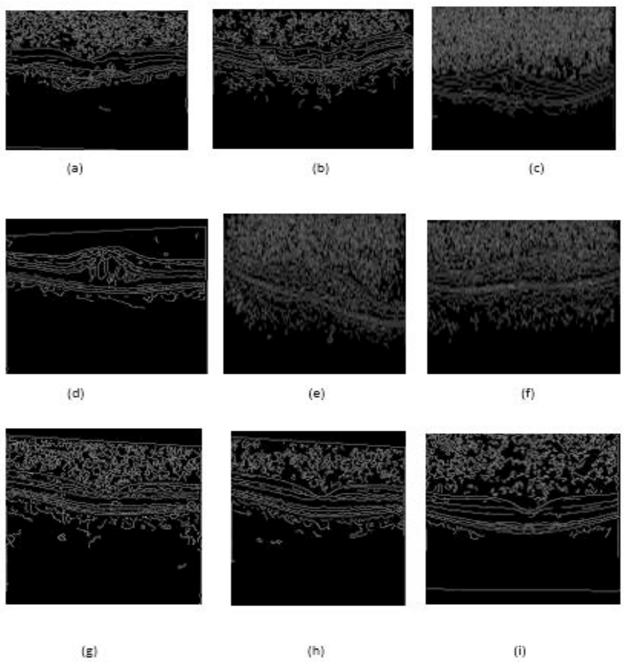


Figure 16: OCT image edge detection by the canny edge detector (IM1-IM9)

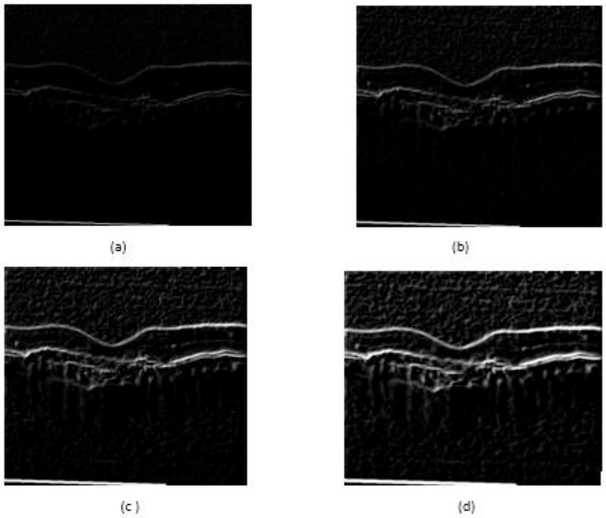


Figure 17: Gauss gradient edge detector output (a) input OCT image (IM1), (b) edge detector output for sigma=0.5, (c) edge detector output for sigma=1, (d) edge detector output for sigma=1.5

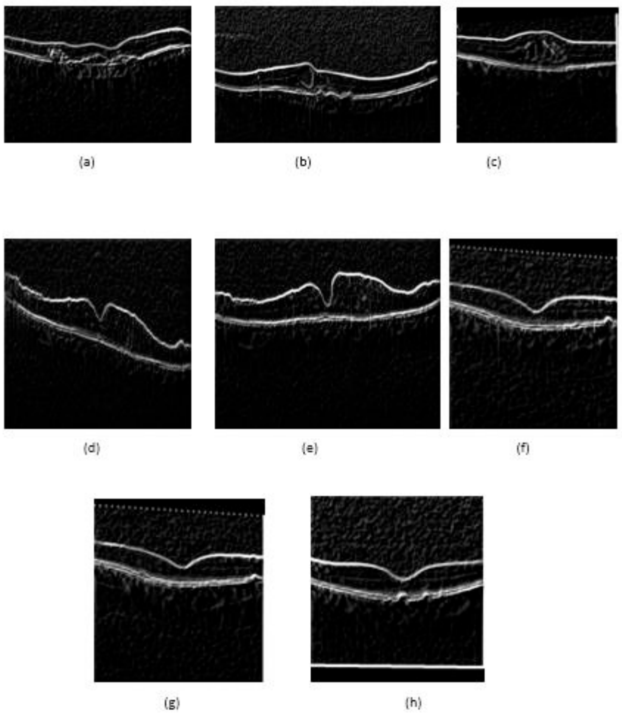


Figure 18: OCT images edge detection using Gauss Gradient operator with respect to the input images (IM2-IM9) for sigma=1.5

4. Conclusion

Segmentation role is vital in health care sector for the analysis of anomalies and edge detection is a simple classical ROI extraction model that trace the boundary of objects. The classical edge detection operators are initially utilized in this research work for tracing the boundary of medical images. The gauss gradient edge detection model results were compared with the classical edge detection models and for analysis, initially the Berkley database images are used. The validation was done using the metrics PSNR and MSE. The gauss gradient edge detector output was found to be satisfactory for a sigma value of 1.5 with less computation time. The outcome of this research work enables the researchers working in medical image processing to utilize this edge detection approach for boundary detection in medical images. The future work will focus on the hardware implementation of the edge detection model on FPGA for teleradiology applications.

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