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Medical image Edge detection using Gauss Gradient operator

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Abstract

Image segmentation is the process of extraction of desired region of interest and plays a vital role in medical images for the analysis of anatomical organs and anomalies like tumor, cyst. The edge represents the contour of an object and it is the boundary between object and background. In this paper, gauss gradient edge detector was proposed that produces superior results than conventional edge detectors like Sobel, Perwitt, Roberts, Canny and LOG algorithm. The boundary detection in noisy images is a crucial task and the proposed edge detector employs Gaussian filter that generates edges in the efficient manner. The algorithms weretested on abdomen CT images and for validation in terms of PSNR, MSE the benchmark images from Berkeley database were used. The Berkeley database provides gold standard images for evaluation and the algorithms were developed in Matlab2010a.

Key words: Edge detection, Gauss Gradient, Image Smoothing, Mask, Segmentation.

INTRODUCTION

The image comprises of pixel with varying gray level intensity and edges determine the discontinuity in image intensity from one pixel to another. Edge detection techniques are perhaps the traditional techniques to trace the contour of region of interest. Edge detection is the process of determining and locating sharp discontinuities in an image. The edge detection algorithms are designed to respond to sharp edges which can be caused by noisy pixels. In image analysis edge detection plays an important role and it is one of the traditional segmentation technique.The Gaussian filter plays a vital role in edge detectors to produce the refined result. The Gaussian filter was used for 1D signal smoothing and when moved from a fine-to-coarse scale, the zero crossings disappear in scale representation of their second order derivatives and new ones are not created. For 2D signals applications also, zero crossings are not created as the scale increases [1]. Jagadish H. Pujar et al proposed a medical image segmentation model comprising of edge detection by canny and normalized cut eigen vectors. Initially before edge detection, the pre-processing was done by Median, Gaussian or Frost filter based on the type of noise [2]. Gautam Appasaheb Kudale et al proposed that canny edge detector produces good boundary detection in X-ray images and Zero crossings operator, LOG operator also generates satisfactory results [3]. Krit Somkantha et al developed an edge detection technique for medical images to trace the boundaries of anatomical organs based on intensity gradient and texture gradient features; the proposed model produces efficient results when compared with conventional active contour models [4]. Nadeem Mahmood et al applied various edge detection techniques on knee joint articular cartilage MR images; the canny edge detector produces superior results [5].

Jamil A. M. Saif et al used various gradient-based edge detectors on MR and endoscopic images; the canny produces good result, however the tuning of parameters are required in some cases [6]. Zhao Yu-qian et al proved that morphology edge detector produces efficient result for lung CT images in the presence of noise when compared with the LOG and Sobel edge detector [7]. Emhimed Saffor et al proposed edge detection based on morphological operations on CT images of brain and chest. The edges were determined by taking the difference between the dilated and eroded images [8]. Ed-Edily Mohd. Azhari et al used canny edge detector for the tumor boundary detection on MR images of brain, the edge detectors are often used in hybrid segmentation approaches [9].Mohamed Abo-Zahhad et al performed an analysis of various edge detection operators on Berkeley data set images and pre-processing by Gaussian filter prior to edge detection produce superior results [10].

RELATED WORK

The most of the edge detection algorithms are based on the derivatives or gradient of the image. The medical images from the acquisition system are susceptible to noise. In general, CT images are corrupted by Gaussian noise, MR images are corrupted by rician noise and US images are affected by speckle noise. In medical images, an edge detection algorithm plays a vital role in the delineation of anatomical organs and pathological issues like tumor or cyst.

The objective of edge detector is to trace the boundary or contour of desired region of interest in the medical image.

The gradient of 2D function g (x, y) is as follows

$$\nabla g = \begin{pmatrix} f_x \\ f_y \end{pmatrix} = \begin{pmatrix} \partial g/\partial x \\ \partial g/\partial y \end{pmatrix}$$

The edge strength is given by the magnitude of the above vector which is represented as below

$$\nabla g = mag(\nabla g) = (fx^2 + fy^2)^{\frac{1}{2}}$$

$$\nabla g = \left(\left(\frac{\partial g}{\partial x}\right)^2 + \left(\frac{\partial g}{\partial y}\right)^2\right)^{\frac{1}{2}}$$

The gradient direction is determined as follows

$$\theta = tan^{-1}\left(\frac{fy}{fx}\right)$$

The edge detection algorithm should track the edges carefully and false edges due to noisy pixels have to be eliminated. The following are the assumptions made in the edge tracing of images.

- The gradient of edge pixels are stronger and greater than noisy pixels
- The edge magnitude and orientation varies slowly along the edges.

The Sobel operator comprises of a pair of 3×3 convolution kernels as shown in Figure 1. The kernels in the sobel operator produce maximum value to edges running vertically and horizontally. The kernels are applied individually in the input image to produce distinct measurements of the gradient component in each orientation (G_x and G_y). The kernel responseare then combined together to find the absolute magnitude of the gradient at each point and the orientation of that gradient [5].

The gradient magnitude is given by:

$$|G| = \sqrt{Gx^2 + Gy^2}$$

Typically, an approximate magnitude is computed using; $|G| = |Gx||Gy|$, which is much faster to compute.

The angle of orientation of the edge (relative to the pixel grid) giving rise to the spatial gradient is given by

$$\theta = \arctan\left(\frac{Gy}{Gx}\right)$$

The Sobeledge detection mask to determine the gradient in the x (vertical) and y (horizontal) directions is given below.

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

G_x

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

G_y

Figure 1. Masks for Sobel edge detector

The Roberts Cross gradient operator is simple and fast to compute, 2-D spatial gradient measurement on an image. The kernels in the Roberts operator produce maximum value to edges running at 45^0.

+1	0
0	-1

G_x

0	+1
-1	0

G_y

Figure 2. Masks for Robert operator

The Prewitt operator is analogous to the Sobel operator and is used for detecting vertical and horizontal edges in images. Unlike Sobel operator, it does not give importance to pixels closer to the center of the masks.

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

G_x

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

G_y

Figure 3. Masks for the Prewitt gradient edge detector

The Laplacian operator is based on second derivative of the image to find edges and searches for zero crossings. The Laplacian $L(x,y)$of an image with pixel intensity values $I(x,y)$is represented as follows.

$$L(x,y) = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2}$$

The Gaussian smoothing operation isperformed initially to make it insensitive to noise. The commonly used kernels in LOG operator are as follows.

1	1	1
1	-8	1
1	1	1

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

Figure 4. Masks for the Laplacian of Gaussian (LOG) operator

The canny edge detection comprises of two stages edge enhancement and tracking. The Gaussian filter is applied to smooth the image, the larger kernel size lowers the sensitivity to noise. The Sobel edge detection operator is applied to determine the magnitude and direction of the edges. After the edge orientation is determined, non-maximum suppression is applied to trace the path of edge and neglect those pixels that are not the part of the edge. Finally, hysteresis thresholding is applied to eliminate streaking. The two threshold values (t1 and t2) with t1> t2 are defined and applied to the gradient magnitude of the image. The pixels whose threshold value greater than t1 are considered as edge pixels and the pixels that are connected to edge pixels greater than t2 are presumed as edge pixels.

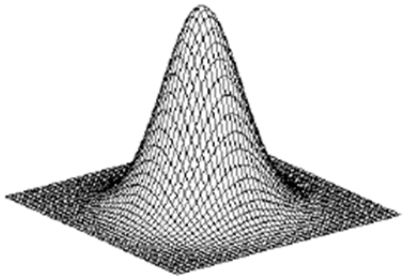
EDGE DETECTION USING GAUSS GRADIENT OPERATOR

The gauss gradient determines the gradient/derivative of the scalar 2D images and 3D volumes using derivatives of Gaussian approach.

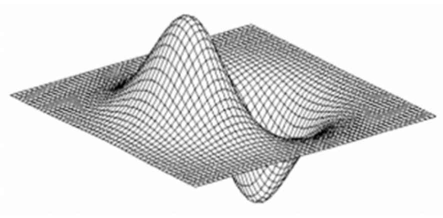
The Gaussian kernel in two dimensions is as follows

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

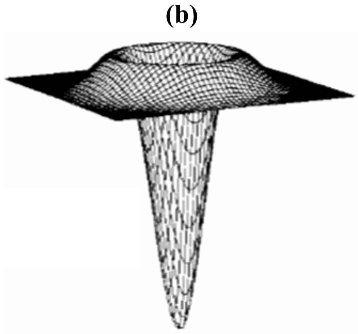
The term σ in the Gaussian filter is called scale of smoothing. The scale has substantial effect on the response of Gaussian filter. The larger the value of σ, the image will become blurred and sensitivity to noise decreases.



(a)



(b)



(c)

Figure 5. (a) Gaussian function (b) Derivative of Gaussian function (c) Laplacian of Gaussian function

In general, a function $f(x,y)$ in terms of the tensor product is written as follows

$$f(x,y) = g(x)h(y)$$

Here instead of applying the 2D kernel, a separable filtering approach is used to calculate the gradient along x and y direction by 1D kernel.

The Gaussian function is separable and can be decomposed into product of two 1 D Gaussian functions.

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

The important property of the Gaussian filter is the only filter that satisfies the uncertainty relation.

$$\Delta x \Delta w \geq 1/2$$

Where Δx and Δw are the variance in spatial and frequency domain respectively. The unique property gives the best tradeoff between the conflicting goals of the localization in spatial and frequency domain respectively. For a filter, the tensor products are called the separable kernel. The response of Gaussian kernel is non-zero over an infinite domain and for most of the domain; it is very small because of the exponential form.

The steps in gauss gradient edge detection are summarized as follows

Step 1: The input image can be gray scale or color image. The term sigma is used to determine the Gaussian kernel along both directions. The higher value of sigma will blur the resultant output. Choose appropriate value of sigma in gauss gradient edge detection approach.

Figure 6. Input Dicom medical image

Step 2: The Gaussian kernel is generated along the x and y direction. The Gaussian kernel generated involves the convolution of Gaussian function and first order derivative of Gaussian function.

$$g(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{x^2}{2\sigma^2}}$$

The first order derivative of gaussian function is expressed as follows

$$\frac{\partial}{\partial x}\big(g(x)\big) = \frac{1}{\sigma\sqrt{2\pi}} \frac{-2x}{2\sigma^2} e^{\frac{-x^2}{2\sigma^2}}$$

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

$$g'(x) = -x * g(x) * \sigma^2$$

The Gaussian kernels along x and y direction are represented as follows.

$$Hx = g(x) * g'(x) \; and \; Hy = Hx'.$$

0.0012	0.0041	0.0083	0.0081	0	-0.0081	-0.0083	-0.0041	-0.0012
0.0055	0.0195	0.0395	0.0384	0	-0.0384	-0.0395	-0.0195	-0.0055
0.0167	0.0592	0.1199	0.1168	0	-0.1168	-0.1199	-0.0592	-0.0167
0.0324	0.1153	0.2335	0.2274	0	-0.2274	-0.2335	-0.1153	-0.0324
0.0405	0.1440	0.2916	0.2840	0	-0.2840	-0.2916	-0.1440	-0.0405
0.0324	0.1153	0.2335	0.2274	0	-0.2274	-0.2335	-0.1153	-0.0324
0.0167	0.0592	0.1199	0.1168	0	-0.1168	-0.1199	-0.0592	-0.0167
0.0055	0.0195	0.0395	0.0384	0	-0.0384	-0.0395	-0.0195	-0.0055
0.0012	0.0041	0.0083	0.0081	0	-0.0081	-0.0083	-0.0041	-0.0012

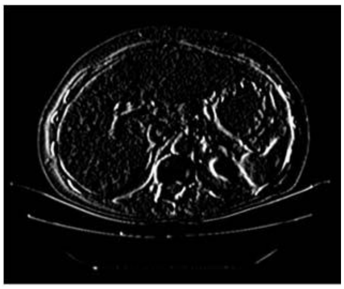
(a)

0.0012	0.0055	0.0167	0.0324	0.0405	0.0324	0.0167	0.0055	0.0012
0.0041	0.0195	0.0592	0.1153	0.1440	0.1153	0.0592	0.0195	0.0041
0.0083	0.0395	0.1199	0.2335	0.2916	0.2335	0.1199	0.0395	0.0083
0.0081	0.0384	0.1168	0.2274	0.2840	0.2274	0.1168	0.0384	0.0081
0	0	0	0	0	0	0	0	0
-0.0081	-0.0384	-0.1168	-0.2274	-0.2840	-0.2274	-0.1168	-0.0384	-0.0081
-0.0083	-0.0395	-0.1199	-0.2335	-0.2916	-0.2335	-0.1199	-0.0395	-0.0083
-0.0041	-0.0195	-0.0592	-0.1153	-0.1440	-0.1153	-0.0592	-0.0195	-0.0041
-0.0012	-0.0055	-0.0167	-0.0324	-0.0405	-0.0324	-0.0167	-0.0055	-0.0012

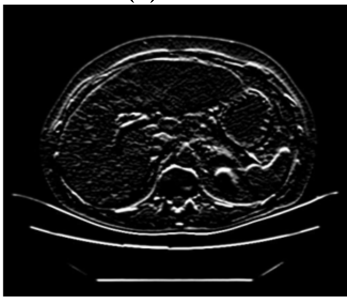
(b)

Figure 7. (a) Kernel generated along x direction (H_x), (b) Kernel generated along y direction (H_y)

Step 3: The Gaussian smoothing is performed on the image using the generated kernels and the results are depicted below



(a)



(b)

Figure 8. Gaussian kernel response of image along x and y direction

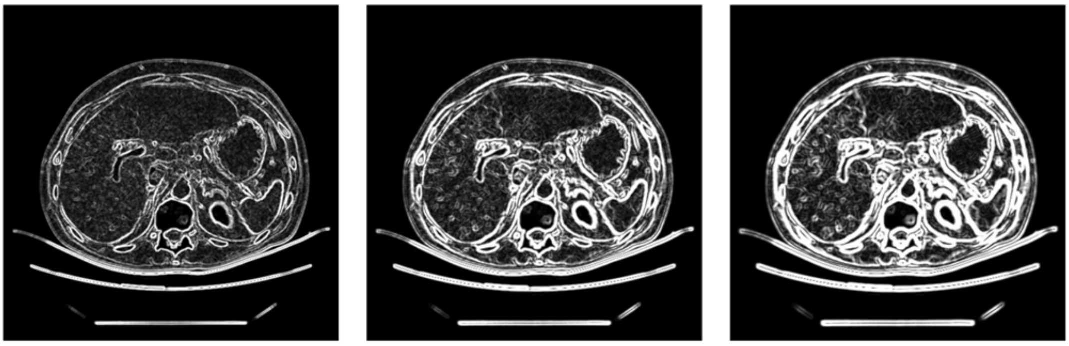
Step 4: The edge detected image is obtained as follows

$$Edge\ output\ =\ abs\ (Gx)\ +\ abs\ (Gy)$$

Where G_x and G_y are gaussian smoothed version of image. The gauss gradient output for σ =1, 1.5 and 2 are depicted above. From the results, the following inferences can be made. For σ=1, the resultant output has under segmentation effect, the over segmentation occurs for σ =2. An optimum value of σ=1.5 produces efficient result.

RESULTS AND DISCUSSION

In this section to determine the performance of the gauss gradient edge detector, the experiments was carried out on both The Berkeley segmentation dataset (BSD) and real medical images. The proposed gauss gradient edge detector in this paper was compared with the conventional edge detectors. The simulation was done by Matlab 2010a software on the system with the specifications: Intel core i3 @ 3.30 Ghz with 4 GB RAM, Windows 10 operating system running on 64 bit processor.



(a) **(b)** **(c)**

Figure 9. Gauss gradient output for σ= 1, 1.5, 2.

(a) **(b)** **(c)**

(d) **(e)** **(f)**

Figure 10. (a) Input image from BSD, (b) Sobel, (c) Prewitt, (d) Canny, (e) Log Operator, (f) Gauss Gradient

The figure 10 above depicts the proposed gauss gradient edge detector output along with the conventional edge detectors. The performance of the proposed algorithm was evaluated by metrics like PSNR and MSE.

$$PSNR = 10log_{10}\left(\frac{R^2}{MSE}\right)$$

$$MSE = \frac{\sum_{M,N}[I_I(M,N) - I_O(M,N)]^2}{M,N}$$

Where $I_I(M,N)$ represents the edge detector output and $I_0(M,N)$ represents the ground truth image.

The gauss gradient approach produce efficient result for all the images in the Berkeley segmentation dataset and the result of selective images are depicted in figure 11. The performance metrics plot in figure 12 reveals that the gauss gradient approach has high PSNR and low MSE. The computation time of the algorithms are depicted in figure 13. The computation time of the gauss gradient approach was slightly higher than the Log, Canny and Prewitt approaches, however in terms of the quality of edge tracing the gauss gradient outperforms the other conventional techniques. For the computation of PSNR and MSE, ground truth images are available in the Berkeley segmentation dataset.

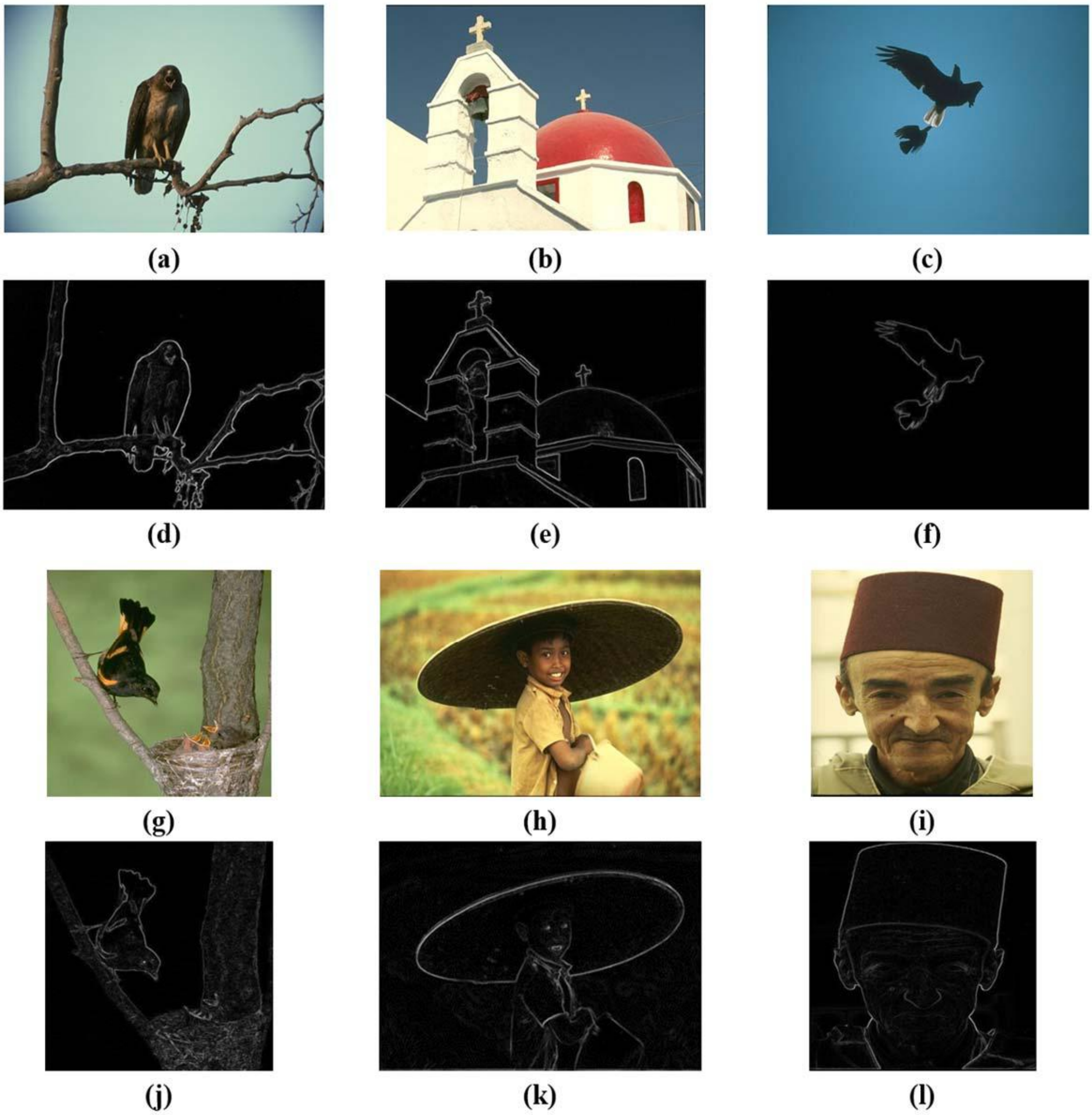
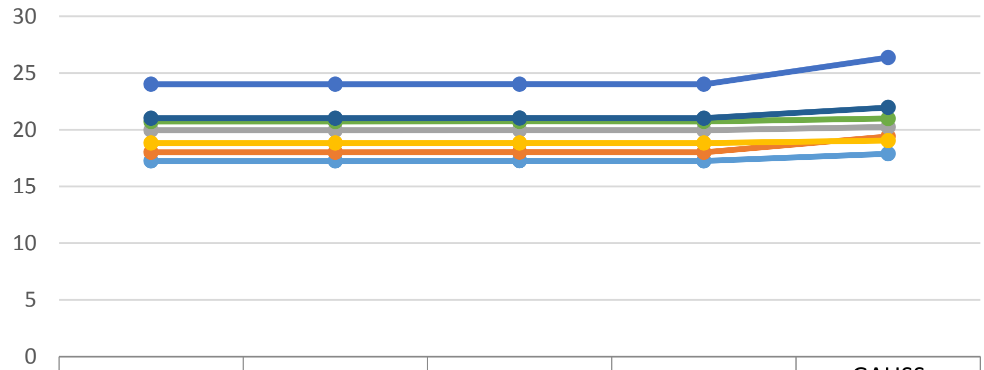
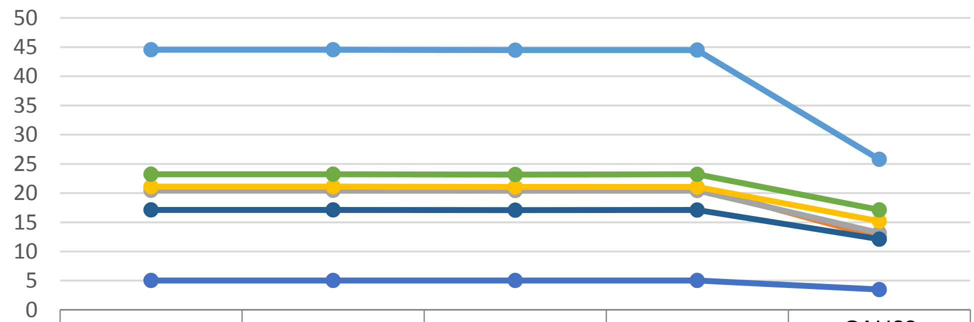


Figure 11. Input images from Berkeley Segmentation Dataset and their corresponding Gauss Gradient edge detected images ($\sigma = 1.5$)



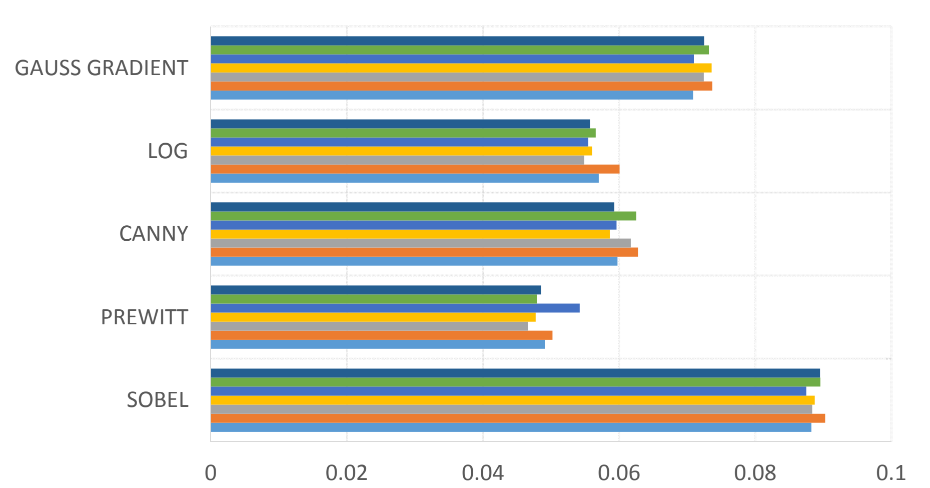
	SOBEL	PREWITT	CANNY	LOG	GAUSS GRADIENT
I1 (#35010)	17.2445	17.2444	17.2581	17.2458	17.8779
I2 (#42049)	18.008	18.008	18.0203	18.0066	19.4065
I3 (#118035)	19.9521	19.9519	19.9646	19.9508	20.2376
I4 (#163014)	18.8203	18.8205	18.833	18.8215	19.039
I5 (#135069)	24.0098	24.0101	24.0166	24.0086	26.3657
I6 (#189011)	20.7199	20.72	20.7343	20.7214	20.9857
I7 (#189080)	21.0137	21.0136	21.0272	21.0151	21.9658

Figure 12. PSNR plot of edge detector algorithms for input images from BSD



	SOBEL	PREWITT	CANNY	LOG	GAUSS GRADIENT
I1 (#35010)	44.5364	44.5357	44.4729	44.4798	25.7616
I2 (#42049)	20.9536	20.9531	20.9474	20.9332	12.4498
I3 (#118035)	20.4437	20.4422	20.4147	20.4368	13.1676
I4 (#163014)	21.0859	21.0868	21.0372	21.043	15.1819
I5 (#135069)	5.0235	5.0234	5.0248	5.0192	3.4645
I6 (#189011)	23.2151	23.2148	23.1539	23.1979	17.1165
I7 (#189080)	17.103	17.1037	17.068	17.0837	12.1031

Figure 13. MSE plot of edge detector algorithms for input images from BSD



	SOBEL	PREWITT	CANNY	LOG	GAUSS GRADIENT
I7 (#189080)	0.089505	0.048492	0.059276	0.055692	0.07248
I6 (#189011)	0.089542	0.04789	0.062491	0.056555	0.073169
I5 (#135069)	0.087469	0.054197	0.059609	0.055448	0.070968
I4 (#163014)	0.088722	0.047734	0.058614	0.056013	0.07358
I3 (#118035)	0.088358	0.046584	0.061699	0.054849	0.072424
I2 (#42049)	0.09026	0.050191	0.062764	0.060053	0.073669
I1 (#35010)	0.088224	0.049077	0.059745	0.056983	0.070848

Figure 14. Time plot of edge detector algorithms for input images from BSD

The gauss gradient approach also produces robust result for the real abdomen CT images. The figure 15 represents the edge detection for abdomen CT images of .png format. The computation time is depictedin figure 16.

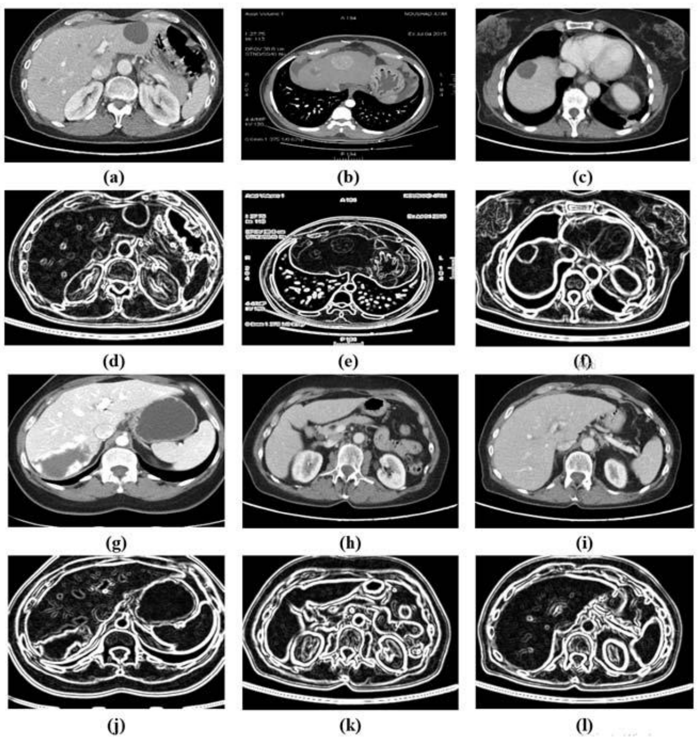
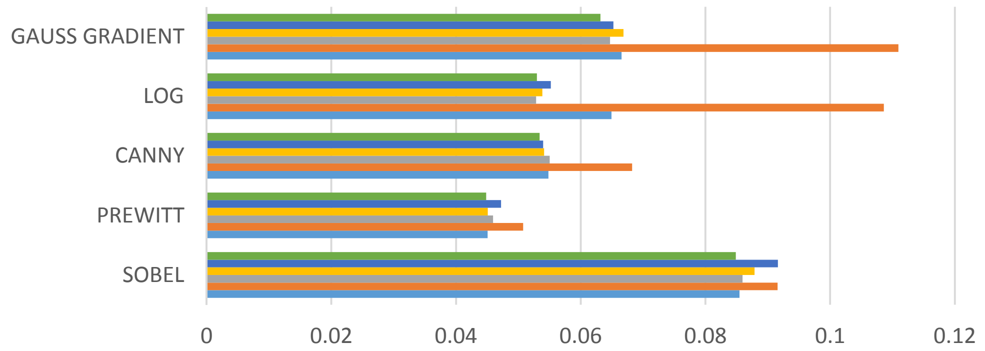


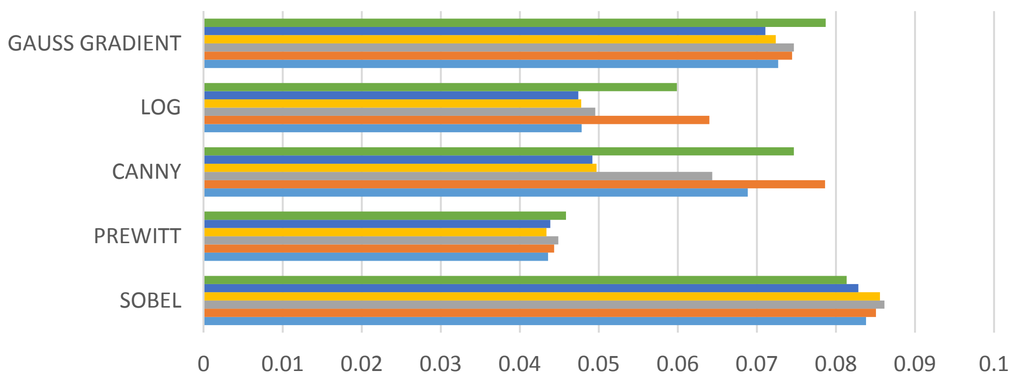
Figure 15. Input images I 8 – I 13 (a,b,c,g,h,i) and their corresponding Gauss Gradient output images (d,e,f,j,k,l)



	SOBEL	PREWITT	CANNY	LOG	GAUSS GRADIENT
I 13	0.084868	0.044827	0.053401	0.052965	0.063167
I 12	0.091611	0.04722	0.053979	0.055199	0.065238
I 11	0.087862	0.045091	0.054122	0.05384	0.066861
I 10	0.085947	0.045939	0.055016	0.052835	0.064707
I 9	0.091571	0.050759	0.068237	0.108618	0.110946
I 8	0.085449	0.045062	0.054815	0.064925	0.06654

Time (seconds)

Figure 16. Time Plot of edge detector algorithms for .png format medical images



	SOBEL	PREWITT	CANNY	LOG	GAUSS GRADIENT
ID 12	0.08135	0.04584	0.07468	0.05987	0.07871
I 18	0.082837	0.043855	0.049187	0.047402	0.071071
I 17	0.085573	0.043366	0.04971	0.047761	0.072383
I 16	0.086134	0.044859	0.06434	0.049547	0.074669
1 15	0.085066	0.044337	0.078614	0.063973	0.074457
I 14	0.08381	0.043577	0.068852	0.04783	0.072691

Time (seonds)

Figure 18. Time Plot of edge detector algorithms for Dicom medical images

The edge detection techniques were also tested on medical Dicom abdomen CT images and the results are depicted below. The computation time is depicted in figure 18.

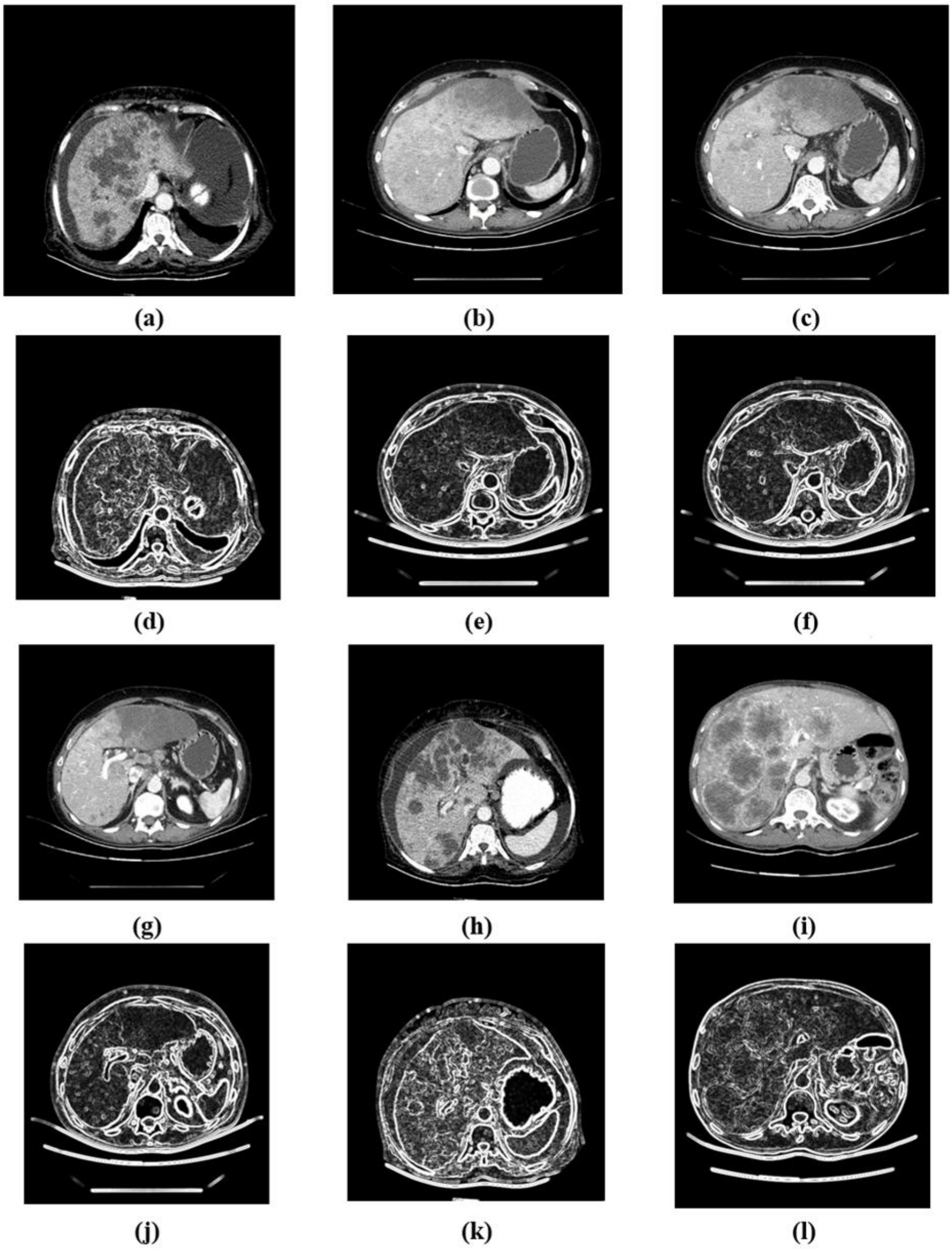


Figure 17. Dicom input images I 14 – I 19 (a,b,c, g, h, i) and their corresponding Gauss Gradient output images (d,e,f,j,k,l)

CONCLUSION

This paper proposes gauss gradient technique for edge detection and satisfactory results were produced when compared with the conventional edge detectors. The algorithm works well on images from Berkeley segmentation dataset and real abdomen CT Dicom images. The PSNR and MSE for Berkeley segmentation dataset images show the superiority of gauss gradient approach with the conventional edge tracer algorithms. The computation time is slightly higher than the conventional edge detectors, however the quality of edge detection is greatly improved. The segmentation plays a vital role in telemedicine applications for the analysis of region of interest. The significance of this work is that, the proposed algorithm can be an effective aid for telemedicine applications.

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