

Performance Study of Different Medical Images Based on Morphology in Noisy Environment

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ABSTRACT

Identification of Medical images is done using their regional structures. Edge detection is a basic element in the area of image processing and computer vision particularly for feature extraction. Edge detection simplifies the amount of data to be processed with modifying the structural properties of the image. Edge is a boundary between the foreground and background. Medical image edge detection concentrates on object recognition of human organs but involves noise along with shadows and boundaries. Several diagnostic tools used to detect the disease are CT, MRI, PET, US and DICOM. In this paper performance of CT and DICOM images are evaluated in noisy environment using morphology and edge detection algorithms. A comparison of different edge detecting methods using different noises is performed and evaluated based on parameters like correlation coefficient and PSNR. The results judge the ability of operators in presence of noise.

Keywords: Edge detection, CT, DICOM, Noise, Edge detecting methods, Morphology, PSNR.

1. INTRODUCTION

An image is defined as a two dimensional light intensity function $f(x,y)$, where x and y are spatial coordinates, and the value f at any pair of coordinates (x,y) is called intensity or grey level value of the image at that point. Edge detection is one of the most commonly used operations in image analysis. An edge is defined by a discontinuity in grey level values. Edge can also be defined as the boundary between an object and the background. Edges are the sign of lack of continuity, and ending. As a result of this transformation, edge image is obtained without encountering any changes in physical qualities of the main image. Edge detection reduces the amount of data that is to be processed without disturbing the structural properties of the image. Edge detection filter mainly improves the appearances of the blurred images. Edge detection converts original image into edge

image by forming boundaries or outlines. The shape of the edges in images depends on many parameters: the geometrical and optical properties of the object, the illumination conditions, and the noise level in the image [1]. Medical image detection is a line through which the work of object recognition of the human organs such as lungs, brain and ribs, abdominal extremities and it is an essential pre-processing step done in medical image segmentation. In real world applications, medical images contain object boundaries and object shadows and noise [2]. This paper distinguishes the exact edge from noise and which operator better suits for the noise environment to extract the edges.

2. Review of Previous Work

In the past two decades several algorithms were developed to extract the contour of homogenous regions within a digital image. L.J.Spreuwens and F.vander Heijden [3] evaluated the performance of

edge detectors using average risk with arbitrary test images which estimates the probabilities on different types of errors. Mike Heath et al. [4] has made comparison of four edge detectors which allows to make quantitative comparisons using subjective ratings made by people using experimental procedure and statistical methods borrowed from psychology. Tuba Sirin et al. [5] made evaluation of competitive learning algorithms for edge detection enhancement (segmentation) followed by an edge detector and concluded that the performance of two stage algorithm is superior to one stage algorithm. Shin.M.C et al [6] presented an evaluation of edge detector performance using structure from motion task and concluded that canny detector had the best test performance. Mohesen Sharifi et al. [7] introduces a new classification of most important and commonly used edge detection methods namely ISEF, Canny, Marr-Hildreth, Sobel, Kirsch and Laplacian. Raman Maini and J.S.Sohal [8] evaluated the performance of Prewitt edge detector for noisy images and concluded that Prewitt operator works quite well for images corrupted with Poisson noise. M.Roushdy [9] made a classified and comparative study of edge detection algorithms using morphological filter.

3. Image Segmentation

Segmentation procedures partitioning an image into its constituent parts or objects. In general, the more accurate the segmentation, the more likely recognition succeeds. The concept of segmenting an image based on discontinuity and similarity. Segmentation refers to the process of partitioning a digital image into multiple segments (sets of pixels, also known as super pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is

typically used to locate objects and boundaries (lines, curves, etc.) in images. The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image.

3.1 Classification of Edge Detectors

The major edge detecting methods may be grouped into two categories, Gradient and Laplacian. The gradient method detects the edges by looking for the maximum and minimum in the first derivative of the image. The Laplacian method searches for zero crossings in the second derivative of the image to find edges[7].

Gradient edge detectors: It includes algorithms such as: Sobel (1970), Prewitt (1970), Kirsch (1971), Robinson (1977), Frei-Chen (1977), Deatsch and Fram (1978), Nevatia and Babu (1980), Ikononopoulos (1982), Davies (1986), Kitchen and Malin (1989), Hancock and Kittler (1990), Woodhall and Linquist (1998), and Young-won and Udpa (1999)[1,10,11].

- *Robert edge detection:*

It is a simple, quick to compute, 2-D spatial gradient measurement on an image. It highlights regions of high spatial frequency which often correspond to edges.

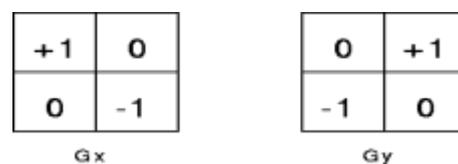


Figure 1: Roberts cross kernels

One kernel is simply the other rotated by 90°. This is very similar to the Sobel operator. The gradient magnitude is given by:

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

- *Sobel edge detection:*

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

Figure 2: Sobel operator masks

A way to avoid gradient calculation about an interpolated point between pixels is to use a 3 x 3 neighbourhood for the gradient calculations. The Sobel operator is the magnitude of the gradient computed by:

$$M = \sqrt{S_x^2 + S_y^2}$$

$$S_x = (a_2 + ca_3 + a_4) - (a_0 + ca_7 + a_6)$$

$$S_y = (a_0 + ca_1 + a_2) - (a_6 + ca_5 + a_4)$$

S_x and S_y can be implemented using the masks with constant $c=2$

- *Prewitt edge detection:*

The Prewitt operator uses the same equations as the Sobel operator, except that the constant $c=$

-1	-1	-1	-1	0	1
0	0	0	-1	0	1
1	1	1	-1	0	1

1. Therefore:

Figure 4: Prewitt operator masks

Unlike the Sobel operator, this operator does not place any emphasis on pixels that are closer to the centre of the masks.

- *Kirsch Compass Kernels:*

Another approach is to apply rotated versions of these around a neighbourhood and “search” for edges of different orientations; there are eight kirsch kernels which can run on the image to get edges in

different directions. By rotating the above mask by clock wise by eight times edges in different directions are obtained.

3	3	3
3	0	3
-5	-5	-5

Figure 5: Kirsch compass kernels

- *Canny edge detection:*

The aim of Canny edge detection was to develop an algorithm that is optimal which runs in 5 steps:

1. Smoothing: Blurring of the image to remove noise.
2. Finding gradients: The edges should be marked where the gradients of the image has large magnitudes.
3. Non-maximum suppression: Only local maxima should be marked as edges.
4. Double thresholding: Potential edges are determined by thresholding.
5. Edge tracking by hysteresis: Final edges are determined by suppressing all edges that are not connected to a very certain (strong) edge.

Zero crossing: This uses second derivative [12] and includes laplacian operator and second directional derivative.

Laplacian of Gaussian (LOG): This was invented by Marr and Hildreth (1980) who combined Gaussian filtering with the Laplacian. This algorithm is not used frequently in machine vision. Those who continued his way were Berzins (1984), Shoh, sood and Jain (1986), Huertas and Medioni(1986) [12, 11].

0	1	0	0	0	0
0	-4	0	0	1	2
0	1	0	1	2	-16
			2	1	0
			0	1	2
			0	0	1
			0	0	0

(a)

(b)

**Figure 6: (a) 3x3 Laplacian mask.
(b) 5x5 Laplacian mask.**

4. Advantages And Disadvantages Of Edge Detectors[1,8,12,14]

It is important to choose edge detectors that fit best to the application. In this respect some advantages and disadvantages of algorithms within the context of our classification are.

Advantages

The Sobel and Prewitt operators are very simple to detect their edges and orientations. LoG uses second derivative, finds exact location of edges and tests wider area around the pixel. Gaussian edge detector like Canny uses probability for finding error rate.

Disadvantages

First derivative operators have inaccurate detection sensitivity in the presence of noise. The LOG cannot find edge orientation as it uses Laplacian filter and cannot respond correctly at corners where the intensity function varies. Canny edge detectors include complex computations and are time consuming.

5. Medical Images

CT (computer tomography)

It is introduced in 1972. It is also called as Computer axial tomography (CAT) or X-Ray computer tomography. It is used for medical & industrial imaging and used to diagnose head, lung, pulmonary angiogram, cardiac, abdominal extremities. Image quality is a 8-bit pattern.

Advantages: CT data increases radiologist efficiency and provides more accurate diagnosis for lung cancer. Eliminates superimposition of images of structures. High contrast resolution.

Disadvantage: Uses high level of ionising radiation that alters DNA of each cell of the body. Inferior soft tissue contrast compared to DICOM.

DICOM

DICOM stands for Digital Imaging and Communications in Medicine and represents universal and fundamental standard in digital medical imaging. It is not just a image or file format. It provides all necessary tools for diagnostically accurate representation and processing of medical imaging data. It is an all-encompassing data transfer, storage, and display protocol & has high diagnostic standards and best performance. DICOM provides much of the ease and flexibility in work. DICOM-based workflow builds a robust and efficient radiology practice. DICOM is used to collect the original medical images. DICOM can send, distribute and store images irrespective of machine, manufacturer or modality. DICOM controls proper image display and image post processing

Advantages

A universal standard of digital medicine. Excellent Image quality - supports up to 65,536(16 bits) shades of gray for monochrome image display. Full support for numerous image. Complete encoding of medical data.

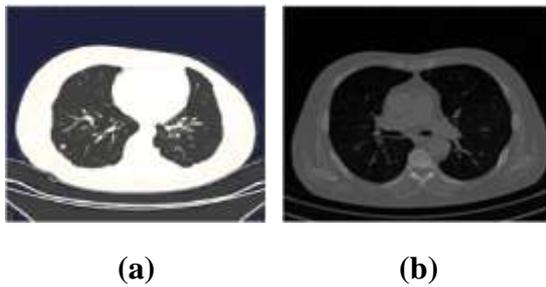


Figure 7: (a) CT image (b) DICOM image.

6. Morphology

Morphology refers to the study of shapes and structures. These operators transform the original image into another image through the iteration with other image of a certain shape and size which is known as structuring element. The basic morphological filters are opening and closing with structuring elements. The binary morphology can be easily extended to gray-scale morphology [18]. Morphological image analysis can be used to perform Object extraction Image filtering operations, such as removal of small objects or noise from an image segmentation operation. Morphological image analysis can be used to perform image filtering, image segmentation, and measurement operations. Mathematical morphology uses structuring element to measure the shape of image and then carry out image processing. Based on set theory, mathematical morphology is the operation which transforms from one set to another.

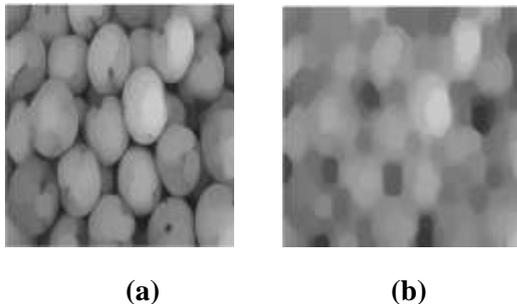


Figure 8: (a) open operation (b) open & close operation.

Morphological edge detection algorithm selects appropriate structuring element of

the processed image and makes use of the basic theory of morphology including erosion, dilation, opening and closing operation.

7. Noise

Noise is considered to be any measurement that is not a part of the phenomena of interest. Images are prone to different types of noises Such as Gaussian, speckle, salt & pepper and Poisson noise. The image data dependency arises because detection and recording processes involve random electron emission having a Poisson distribution with mean response value [14]. Gaussian noise that occurs in all recorded images to a certain extent is detector noise. This kind of noise is due to the discrete nature of radiation. The noise has zero-mean Gaussian distribution described by its standard deviation or variance [15]. Another noise is data drop out noise commonly referred as speckle noise. This noise is, in fact caused by errors in data transmissions [16]. The corrupted pixels are either set to the maximum value, which is something like a snow in image. The type of noise caused by errors in data transmission. single pixels are set alternatively to zero or to the maximum value giving the image a salt and pepper like appearance [17].

8. Results and Evaluation

The Performance of edge detecting operators is evaluated for CT & DICOM lung images with and without noise. The methods considered are Sobel, Prewitt, Roberts, Canny, LOG, Kirsch, and Morphological. The noise added is Gaussian, speckle, salt & pepper and Poisson noise.

8.1. Images without Noise

The edge images of the operators are computed in MATLAB applied to CT &

DICOM Lung image. These images are shown in fig.10 & 11(a, b, c, d, e, f & g) and are compared with the same operators applied to CT & DICOM Lung image after adding noise.

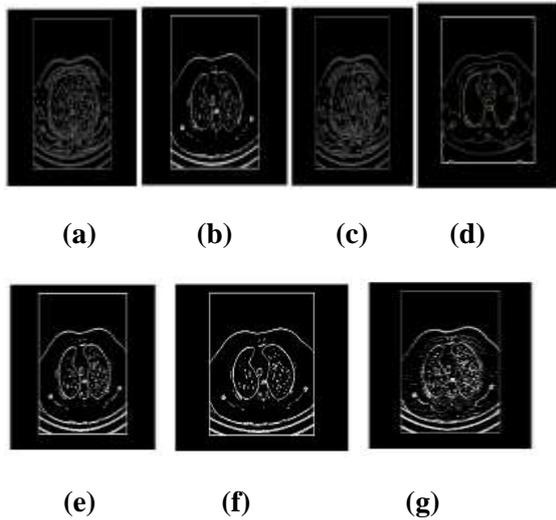


Figure 9: Edges on CT lung image without noise using (a) canny (b) kirsch (c) LoG (d) morphological (e) sobel (f) prewitt and (g) roberts edge operators.

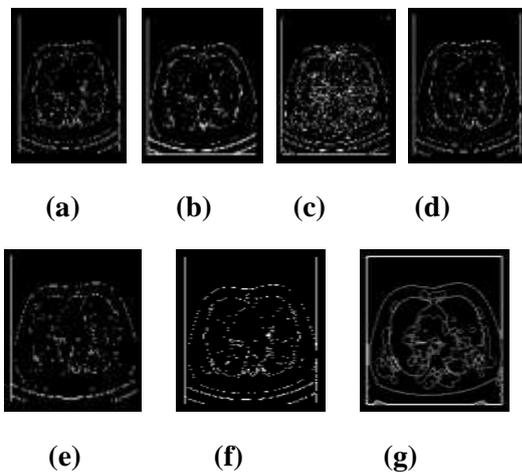


Figure 10: Edges on DICOM lung image without noise using (a) canny (b) kirsch (c) LoG (d) Prewitt (e) roberts (f) sobel (g) morphological.

8.2. Images with Noise

Noises are added to CT & DICOM Lung image with default value and Gaussian noise with zero mean and standard deviation values $\sigma_N = 5, 11, 25$.

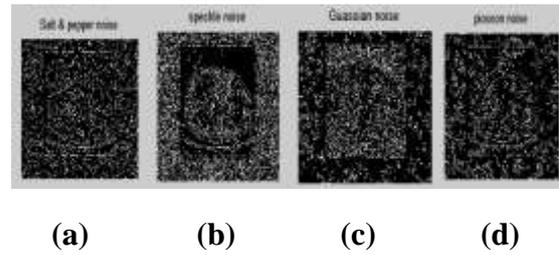


Figure 11: canny operator on CT image with noises (a) Salt & pepper (b) Speckle (c) Gaussian and (d) Poisson noise.

The results of various methods on noise added CT lung image are shown in fig. 12,13,14,15,16,17 & 18(a, b, c, d).

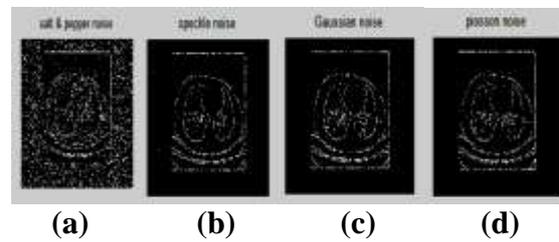


Figure 12: Sobel operator on CT image with noises (a) Salt & pepper (b) Speckle (c) Gaussian and (d) Poisson noise.

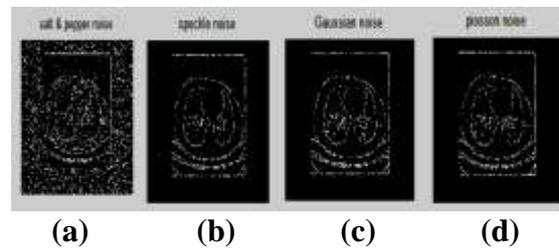


Figure 13: Prewitt operator on CT image with noises (a) Salt & pepper (b) Speckle (c) Gaussian and (d) Poisson noise.

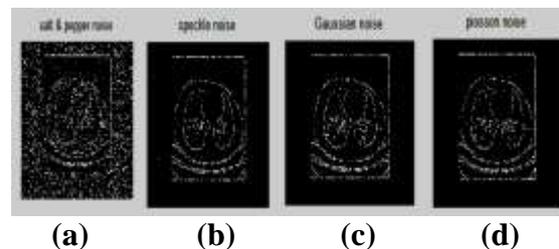


Figure 14: Roberts operator on CT image with noises (a) Salt & pepper (b) Speckle (c) Gaussian and (d) Poisson noise.

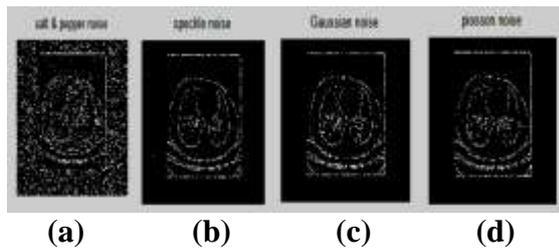


Figure 15: kirsch operator on CT image with noises (a) Salt & pepper (b) Speckle (c) Gaussian and (d) Poisson noise.

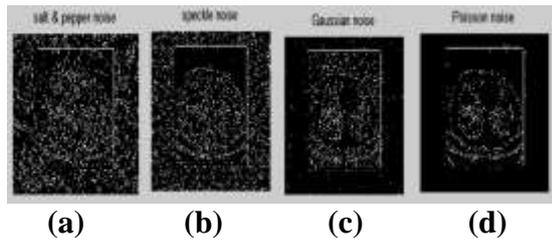


Figure 16: LoG operator on CT image with noises (a) Salt & pepper (b) Speckle (c) Gaussian and (d) Poisson noise.

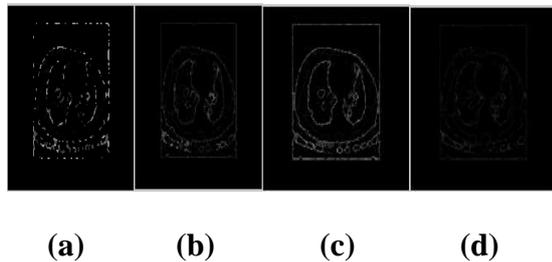


Figure 17: Morphological operator on CT image with noises (a) Salt & pepper (b) Speckle (c) Gaussian and (d) Poisson noise.

The results of various methods on noise added DICOM lung image are shown in the fig. 19,20,21,22,23,24& 25(a, b, c, d).

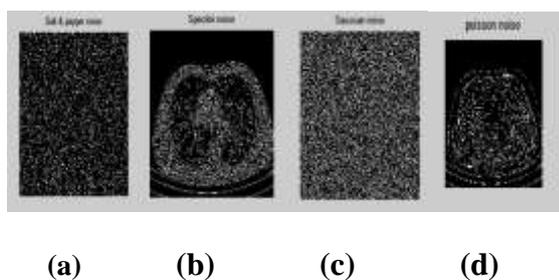


Figure 18: Canny operator on DICOM image with noises (a) Salt & pepper (b) Speckle (c) Gaussian and (d) Poisson noise.

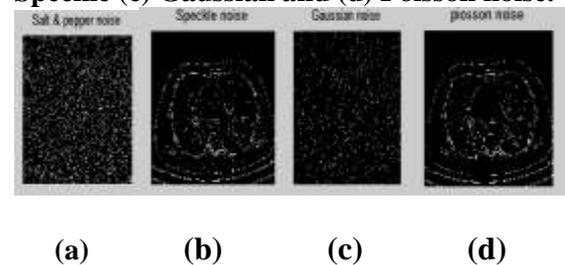


Figure 19: Sobel operator on DICOM image with noises (a) Salt & pepper (b) Speckle (c) Gaussian and (d) Poisson noise.

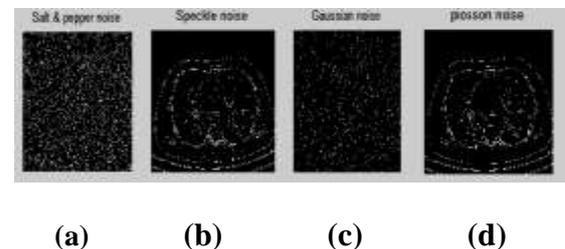


Figure 20: Roberts operator on DICOM image with noises (a) Salt & pepper (b) Speckle (c) Gaussian and (d) Poisson noise.

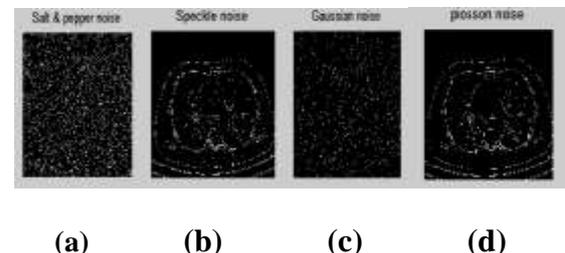


Figure 21: Prewitt operator on DICOM image with noises (a) Salt & pepper (b) Speckle (c) Gaussian and (d) Poisson noise.

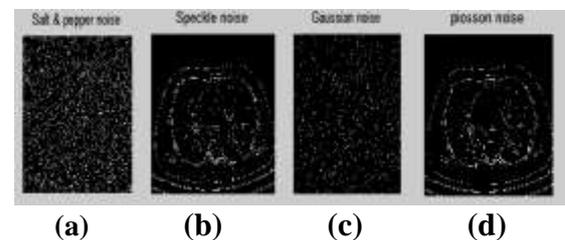
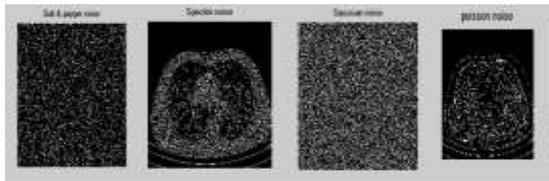
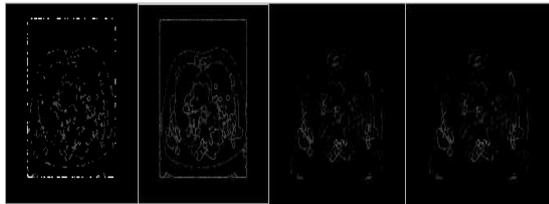


Figure 22: kirsch operator on DICOM image with noises (a) Salt & pepper (b) Speckle (c) Gaussian and (d) Poisson noise.



(a) (b) (c) (d)
Figure 23: LoG operator on DICOM image with noises (a) Salt & pepper (b) Speckle (c) Gaussian and (d) Poisson noise.



(a) (b) (c) (d)
Figure 24: Morphological operator on DICOM image with noises (a) Salt & pepper (b) Speckle (c) Gaussian and (d) Poisson noise.

Method	Gaussian			Poisson
	$\sigma_N = 5$	$\sigma_N = 11$	$\sigma_N = 25$	Default
Sobel	0.7235	0.7017	0.7070	0.8194
Prewitt	0.7187	0.7074	0.7086	0.8188
Roberts	0.7926	0.7887	0.7881	0.9145
Canny	0.5770	0.5625	0.5340	0.8251
LoG	0.7781	0.7711	0.7793	0.9180
Kirsch	0.8886	0.8914	0.8888	0.9593
Morphological	0.9510	0.9505	0.9556	0.9899

Table 1. Correlation coefficient for CT lung with Gaussian and Poisson noise.

The parameters used to evaluate the performance of different methods is correlation coefficient, which defines the closeness of the edge images of different methods in the noisy environment to the original edge images without noise and SNR, estimates degradation introduced

with noise addition. As the value of sigma increases the Gaussian filter also increases and this implies more blurring, required for noise images for detecting large edges. The larger the scale of Gaussian the localisation of the edge becomes less accurate. Smaller values of sigma implies smaller Gaussian filter which limits the

Method	CT		DICOM	
	Salt & Pepper	speckle	Salt & Pepper	speckle
Sobel	0.7500	0.6767	0.1722	0.4906
Prewitt	0.7564	0.6731	0.1984	0.4977
Roberts	0.3709	0.7605	0.1426	0.4819
Canny	0.5781	0.5457	0.3566	0.2874
LoG	0.6871	0.7679	0.3374	0.4332
Kirsch	0.8305	0.8635	0.6317	0.7676
Morphological	0.9507	0.9719	0.9608	0.9643

Table 2. Correlation coefficient for CT & DICOM lung with salt & pepper and speckle noise.

amount of blurring, maintaining finer edges in the image. The user can choose the algorithm by adjusting these parameters to adopt in different environments.

Method	Gaussian			Poisson
	$\sigma_N = 5$	$\sigma_N = 11$	$\sigma_N = 25$	Default
Sobel	1.0244	1.0256	1.0248	1.0162
Prewitt	1.0246	1.0252	1.0257	1.0157
Roberts	1.0038	1.0040	1.0038	1.0048
Canny	1.1217	1.1346	1.1583	1.0289
LoG	1.0264	1.0278	1.0251	1.0072
Kirsch	1.0069	1.0064	1.0071	1.0058
Morpho logical	1.3381	1.3328	1.3189	1.3049

Table 3. SNR for CT lung with Gaussian and Poisson noise.

The values for correlation coefficient and SNR are shown in Table. 1 & 3 for CT lung and in Table. 5 & 6 for DICOM lung with Gaussian & Poisson noises. Table 2 & 4 represent correlation coefficient and SNR for CT & DICOM with salt & pepper and speckle noise.

Method	CT		DICOM	
	Salt & Pepper	speckle	Salt & Pepper	speckle
Sobel	1.0241	1.0281	1.1589	1.0202
Prewitt	1.0288	1.0291	1.1595	1.0196
Roberts	1.0675	1.0072	1.0743	1.0019
Canny	1.1213	1.1421	1.2016	1.3799
LoG	1.0615	1.0373	1.2220	1.1545
Kirsch	0.2717	1.0118	0.5995	0.9960
Morpho logical	1.6966	1.8089	1.9559	1.9554

Table 4. SNR for CT & DICOM lung with salt & pepper and speckle noise.

Method	Gaussian			Poisson
	$\sigma_N = 5$	$\sigma_N = 11$	$\sigma_N = 25$	Default
Sobel	0.0073	0.0013	0.0086	0.9297
Prewitt	0.0049	0.0037	0.0102	0.9326
Roberts	0.0031	0.0018	0.0041	0.9142
Canny	0.0043	0.0036	0.0033	0.7456
LoG	0.0036	0.0046	0.0029	0.8893
Kirsch	0.0032	0.0038	0.0052	0.9736
Morpho logical	0.0178	0.0036	0.0106	0.9947

Table 5. correlation coefficient for DICOM lung with Gaussian and Poisson noise.

Among all the operators such as sobel, prewitt, Roberts, kirsch, LoG, Morphological, Canny edge detection algorithm is computationally more expensive while performing in the presence of noise environment.

Method	Gaussian			Poisson
	$\sigma_N = 5$	$\sigma_N = 11$	$\sigma_N = 25$	Default
Sobel	1.0544	1.0542	1.0534	1.0028
Prewitt	1.0544	1.0557	1.0538	1.0027
Roberts	1.0108	1.0113	1.0114	1.0039
Canny	1.9212	1.9604	1.9320	1.0452
LoG	1.5834	1.5775	1.5901	1.0092
Kirsch	1.0324	1.0317	1.0307	1.0022
Morpho logical	1.1350	1.1346	1.1302	1.3281

Table 6. SNR for DICOM lung with Gaussian and Poisson noise.

9. Conclusions and Future scope

Edge detection is the initial step in object recognition, it is essential to know the differences between edge detection methods.

In this paper the evaluation of different edge detecting methods is performed on CT &

DICOM medical images. Four types of noises are Gaussian, salt & pepper, speckle and Poisson. From visual examination of the results, it can be noticed that Morphological operator exhibits superior performance than all the edge operators and well resist to noise. LOG, Canny methods exhibit better performances in noisy conditions and partially resistant to noise. When the content in the image has simple structure it has a non uniform contrast. Sobel and Prewitt performances are almost similar for all noises. Kirsch operator exhibits better performance than Sobel and Prewitt. The detected edges in the noise conditions decreases when compared with the edge images of the methods without noise. Signal to Noise ratio decreases as noise increases. Canny operator shows better performance compared to all other methods but is inferior to Morphological.

This work can be further extended in future with all these noises by developing a new or improved method using the existing software tools and make the segmentation process easier and flexible for any type of modality.

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