ED6001

MEDICAL IMAGE ANALYSIS

ASSIGNMENT 2

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INTRODUCTION

The objective of this analysis is to perform feature extraction (extract the sternum) from a set of CT images. The two images are visualized in Fig. 1 and Fig. 2 respectively.

We start by preprocessing the image to remove any inherent noise, and then enhance the contrast of the image for easier feature extraction. Edge detection is then done using multiple filters and their performances are compared. We then use hough transform on to extract the required feature (the sternum).

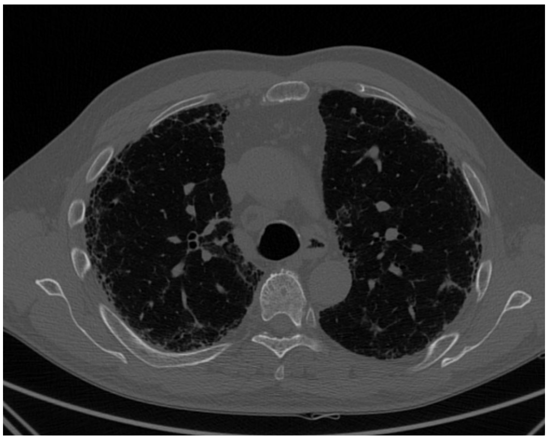


Figure 1: CT Scan 1, with size (914, 1150)

Figure 2: CT Scan 2, with size (917, 941)

Note: The .ipynb notebook has been added to the submissions, and can be run using google colaboratory. The function cv2_imshow() has been used instead of cv2.imshow() to display images on google colaboratory. This can be changed if any other software is being used to run the file.

QUESTION 1: DENOISING

Generally, CT images inherently have **Gaussian noise** due to the electrical signals which may interfere with the scanning process. For gaussian noise, mean and gaussian filters generally work well. Hence, we try denoising using mean and gaussian filters of various window sizes. The filtered images, along with the residuals and the PSNR values are shown in Fig. 3 to Fig. 11 for Scan 1.

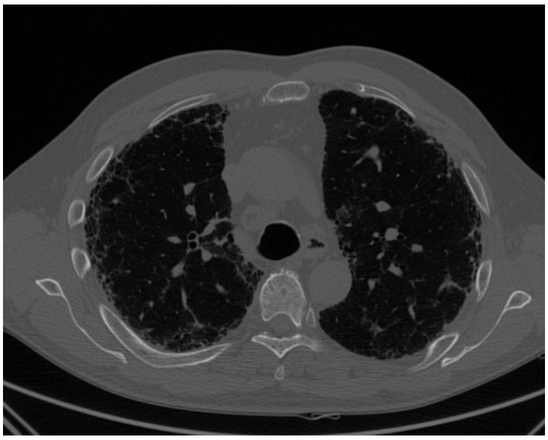


Figure 3: CT Scan 1, mean filtered with window size 3 (PSNR = 45.42 dB)

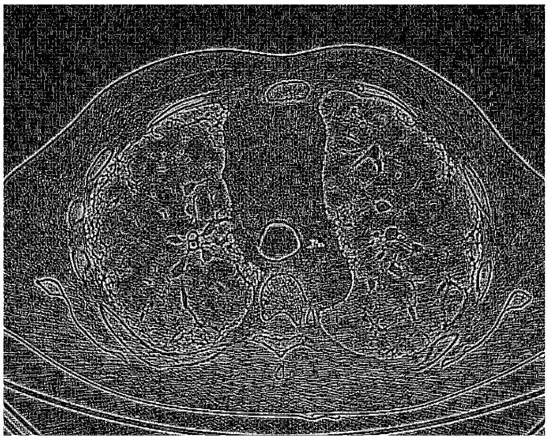


Figure 4: Residual for mean filter of window 3 (CT Scan 1)

Figure 5: CT Scan 1, mean filtered with window size 5 (PSNR = 39.37 dB)

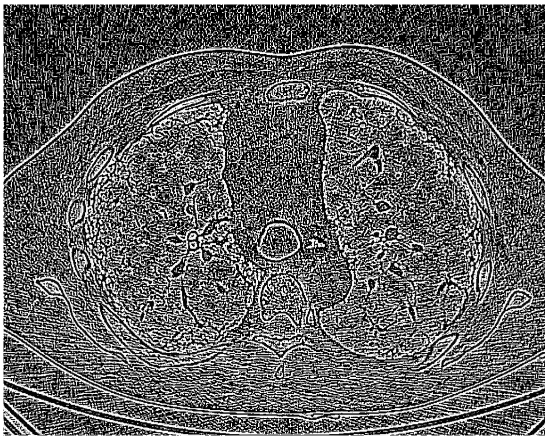


Figure 6: Residual for mean filter of window 5 (CT Scan 1)

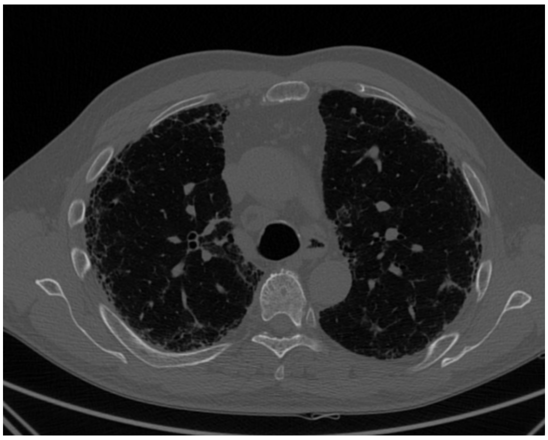


Figure 7: CT Scan 1, gaussian filtered with window size 3 (PSNR = 47.59 dB)

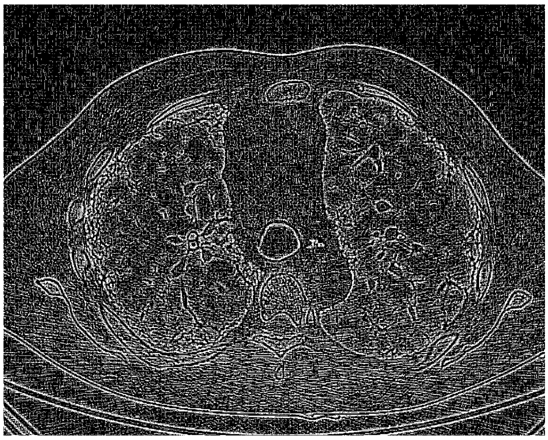


Figure 8: Residual for gaussian filter of window 3 (CT Scan 1)

Figure 9: CT Scan 1, gaussian filtered with window size 5 (PSNR = 43.76 dB)

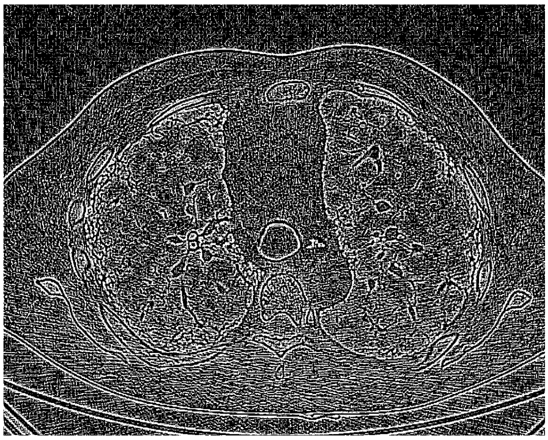


Figure 10: Residual for gaussian filter of window 5 (CT Scan 1)

```
mean_3.png , PSNR = 45.42835858751404
mean_5.png , PSNR = 39.373667067577024
gaussian_3.png , PSNR = 47.595231839728704
gaussian_5.png , PSNR = 43.761206885943494
```

Figure 11: PSNR values for various filters applied on CT Scan 1

We want to pick the filter which shows the least traces of the image in the residual, especially in the area surrounding the sternum. In general, a PSNR value of 30-40 dB is considered a good reconstruction of the image.

Observing the residuals shows that both mean filtering and gaussian filtering with window size 5 leads to excessive blurring. This is also evident with the low PSNR values for the same. The residuals and PSNR of the other two filters are also compared, and it is observed that best filter for CT Scan 1 is a gaussian filter with a window size 3. This also supports our assumption that CT images inherently have gaussian noise. Thus, this image will be considered for Questions 2 and 3.

A similar analysis was done for Scan 2 as well, and the gaussian filter with window size 3 was again selected. The PSNR values for the same is shown in Fig. 12, and the filtered and residual images are shown in Fig. 13 and Fig. 14.

```
mean_3.png , PSNR = 45.149568015652946
mean_5.png , PSNR = 39.532001629680714
gaussian_3.png , PSNR = 47.30592649899735
gaussian_5.png , PSNR = 43.65023901577043
```

Figure 12: PSNR values for various filters applied on CT Scan 2

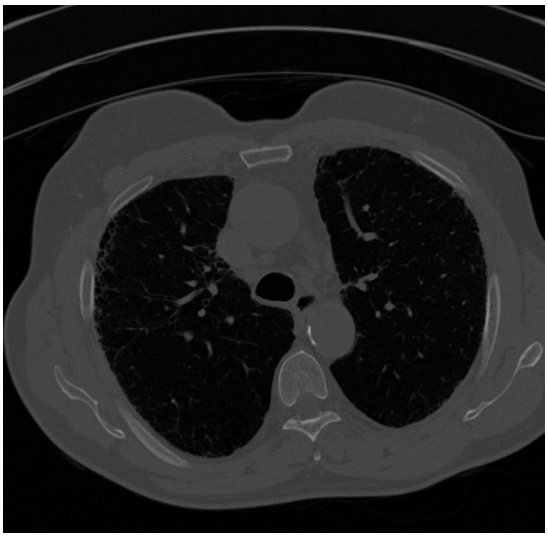


Figure 13: CT Scan 2, gaussian filtered with window size 3 (PSNR = 47.30 dB)

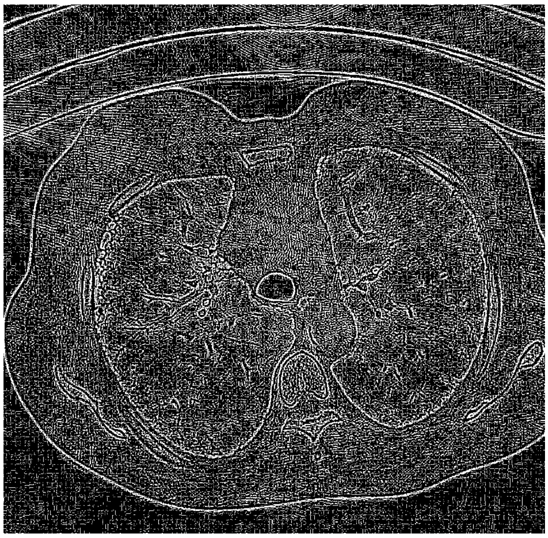


Figure 14: Residual for gaussian filter of window 3 (CT Scan 2)

Summary and Observations

- The major noise present in CT images is a gaussian noise, which is caused due to the interruptions in sensor signals by electric signals.
- To denoise images with gaussian noise, gaussian and mean filters are popularly used.
- A PSNR value of 30-40 dB is generally considered to be a good reconstruction of the image.
- While selecting the best filter, we prefer the one which shows least traces of the original image in the residual, especially surrounding the area of interest (the sternum in this case).
- For the given images, filters with a window size of 5 leads to excessive blurring.
- **Gaussian filters with window size 3** performed best on both the given images.

QUESTION 2: CONTRAST ENHANCEMENT AND EDGE DETECTION

Part 1: Contrast Enhancement

To understand whether histogram equalization or adaptive histogram equalization would be required to enhance the contrast of the image, the probability distribution function (PDF) and cumulative distributive function for the denoised image is first plotted. This is shown in Fig.15.

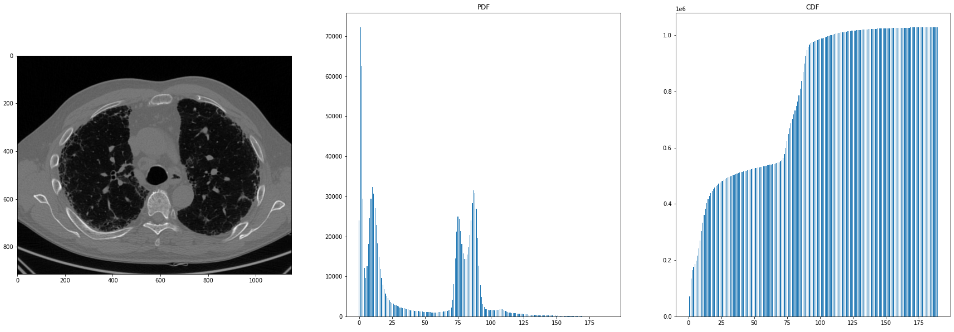


Figure 15: PDF and CDF of the denoised image (Scan 1)

Since the image has a very skewed distribution, and certain regions of the image contain more dark pixels than the others, adaptive histogram equalization is expected to give better results. To test this assumption, both histogram equalized and CLAHE equalized images are plotted, along with their PDF and CDF in Fig. 16 and Fig. 17.

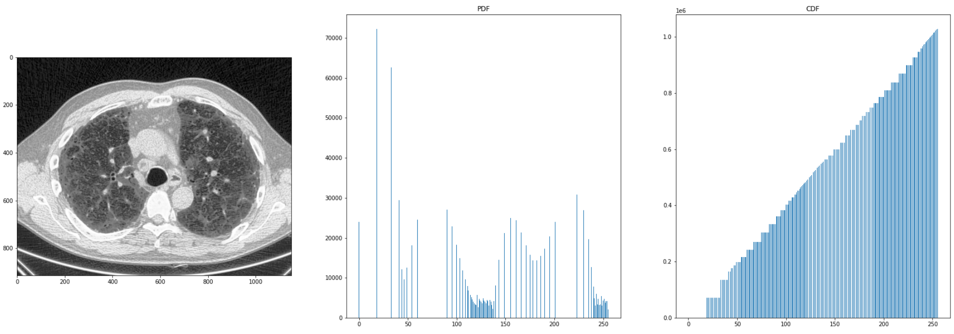


Figure 16: PDF and CDF of the histogram equalized image (Scan 1)

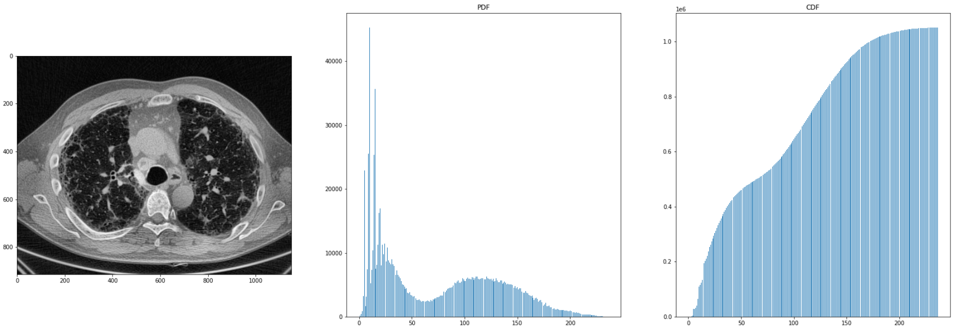


Figure 17: PDF and CDF of the CLAHE equalized image (Scan 1)

As expected, the results obtained by CLAHE are better, even though the PSNR value obtained for the histogram equalized and CLAHE equalized images were 27.83 dB and 27.79 dB respectively (slightly lower for CLAHE). However, the CLAHE equalized image will be used for edge detection since the sternum is clearly distinguishable in the same.

Similarly, the contrast enhanced image for Scan 2 is also obtained using CLAHE, which is shown in Fig. 18 and Fig. 19. The PSNR value obtained for the same was 27.61 dB.

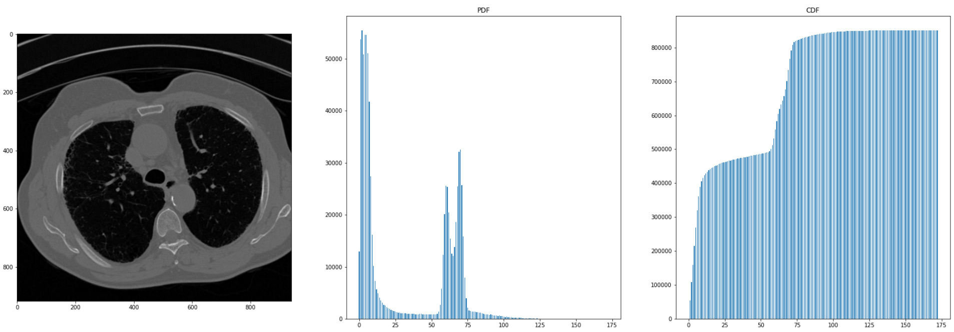


Figure 18: PDF and CDF of the denoised image (Scan 2)

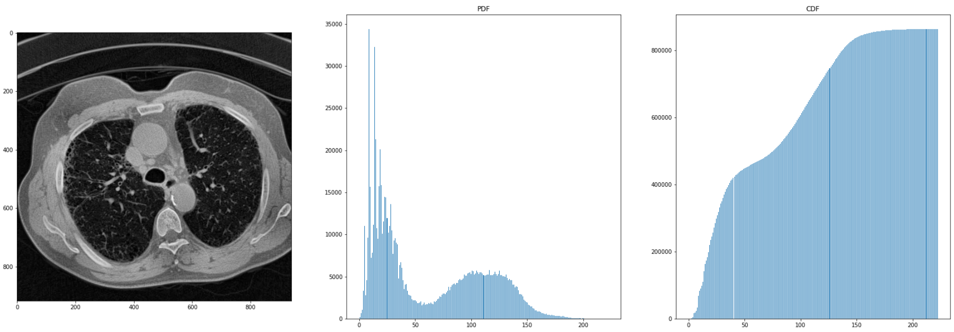


Figure 19: PDF and CDF of the CLAHE equalized image (Scan 2)

Part 2: Edge Detection

Various edge detection methods were applied on the CLAHE equalized image. The observations are shown in the following sections.

Robert's Cross Gradient Edge Detector

Robert's cross gradient detector implements the gradient operator using a 2×2 filter given by

$$\begin{bmatrix} -1 & 0 \\ 0 & -1 \end{bmatrix} \text{or} \begin{bmatrix} 0 & -1 \\ -1 & 0 \end{bmatrix} \tag{1}$$

Since the gradient is found, only the edges (or pixels which have a steep discontinuity) are reflected in the final edge-detected image.

The result of applying Robert's cross gradient on the contrast enhanced image of Scan 1 and Scan 2 are shown in Fig. 20 and Fig. 21 respectively.

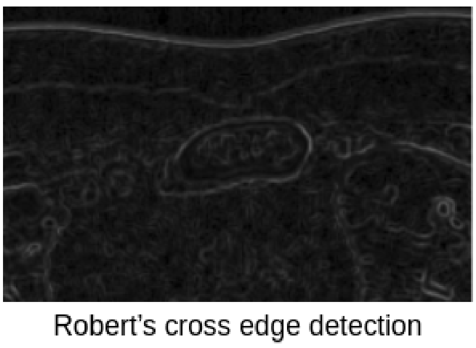


Figure 20: Robert's cross gradient operator applied for Scan 1

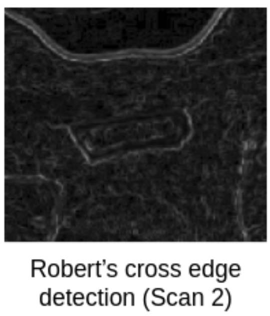


Figure 21: Robert's cross gradient operator applied for Scan 2

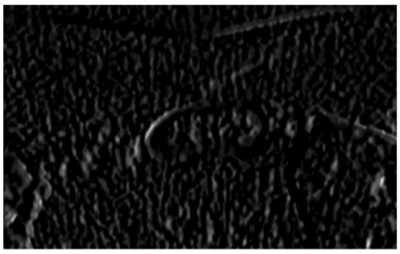
We observe that the gradients are not of high magnitude, hence Robert's edge detection gives images of weak intensity. This signifies that the edge is not a sharp discontinuity, instead, it is blurred.

Sobel Edge Detector

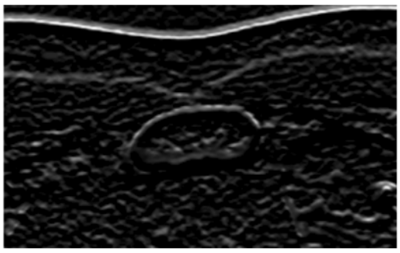
The sobel edge detector uses a filter to approximate the derivative at a given point, in either x or y direction. The 3×3 filters are given by

$$\begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \text{and} \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \tag{2}$$

The results of applying Sobel edge detector of various windown sizes on Scan 1 and Scan 2 are shown in Fig. 22 and Fig. 23 respectively.



Sobel's edge detector (x-direction) with ksize = 3



Sobel's edge detector (y-direction) with ksize = 3

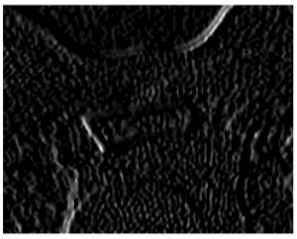
Sobel's edge detector (x and y-direction), with ksize = 3

Sobel's edge detector (x-direction) with ksize = 5

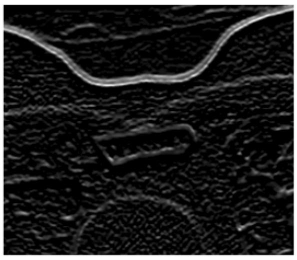
Sobel's edge detector (y-direction) with ksize = 5

Sobel's edge detector (x and y-direction), with ksize = 5

Figure 22: Sobel edge detector applied on Scan 1



Sobel's edge detector (x-direction) with ksize = 3



Sobel's edge detector (y-direction) with ksize = 3

Sobel's edge detector (x and y-direction), with ksize = 3

Sobel's edge detector (x-direction) with ksize = 5

Sobel's edge detector (y-direction) with ksize = 5

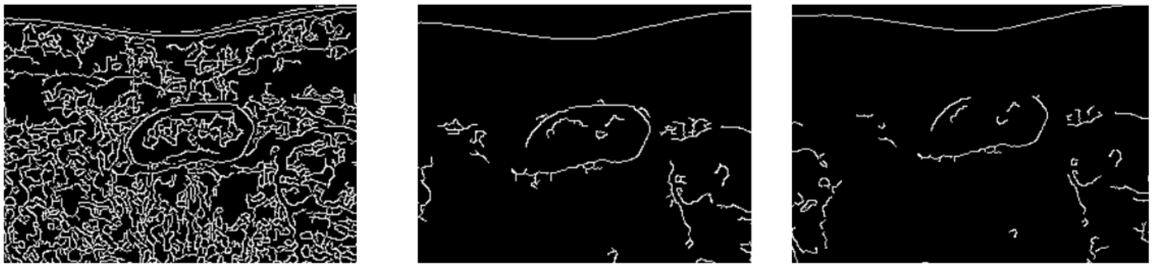
Sobel's edge detector (x and y-direction), with ksize = 5

Figure 23: Sobel edge detector applied on Scan 2

We observe that the in both the images, using a sobel filter of higher window size leads to detection of more edges. In both images, the sobel filter applied in x and y directions detect edges with a higher intensity than the combined sobel filter.

Canny Edge Detector

Canny edge detection is a popularly used five-step algorithm which performs the following operations:
1. **Noise reduction** - Gaussian filtering
2. **Gradient calculation**
3. **Non-max supression** - Leads to detection of thinner edges
4. **Double thresholding** - Creates 2 gradient images, one (T2) with lesser false edges than the other (T1)
5. **Edge tracking by hysteresis** - Uses T2 to bridge gaps in the edges of T2
The results of applying Canny edge detection with various thresholds is shown in Fig. 24 and Fig. 25.



Canny edge detector with lower threshold 30 and upper threshold 100

Canny edge detector with lower threshold 70 and upper threshold 200

Canny edge detector with lower threshold 100 and upper threshold 200

Figure 24: Canny edge detector applied on Scan 1

Canny edge detector with lower threshold 30 and upper threshold 100 (Scan 2)

Canny edge detector with lower threshold 70 and upper threshold 200 (Scan 2)

Canny edge detector with lower threshold 100 and upper threshold 200 (Scan 2)

Figure 25: Canny edge detector applied on Scan 2

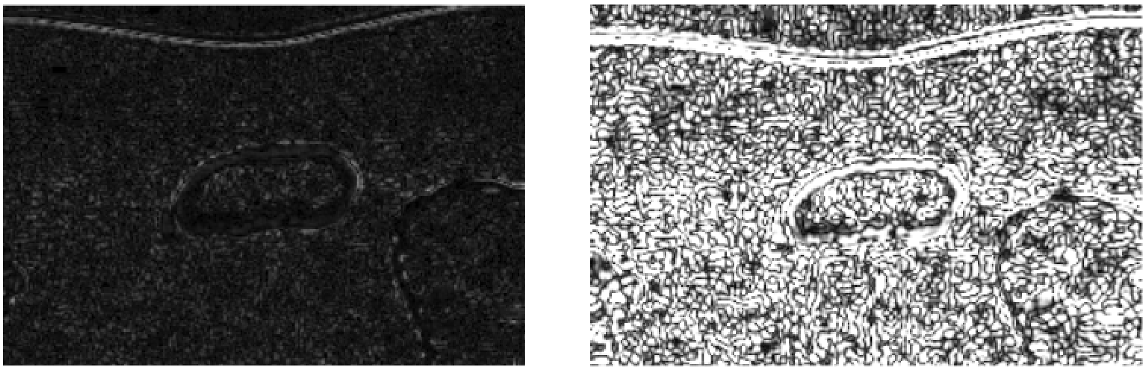
We observe that Canny edge detector gives much better results than the previously seen detectors. It does not give many double edges. It is also clear that increasing either of the two thresholds leads to a sparser edge detection.

Laplacian Edge Detector

Laplacian edge detector uses the laplacian of an image, the filters of which are given by

$$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix} \text{or} \begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix} \tag{3}$$

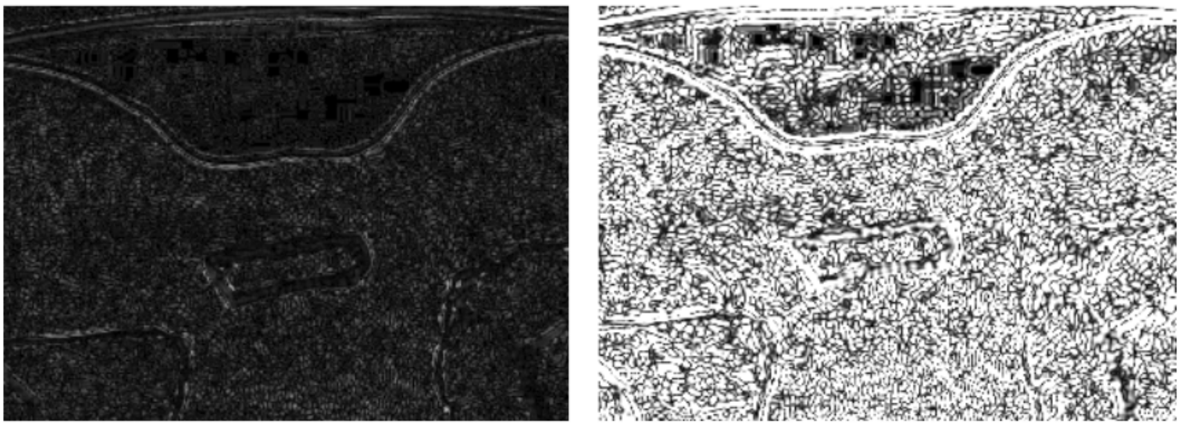
However, laplacian filters are not used in practice because they produce double edges. The results of applying laplacian filters to Scan 1 and Scan 2 are shown in Fig. 26 and Fig. 27 respectively.



Laplacian edge detector with ksize=3

Laplacian edge detector with ksize=5

Figure 26: Laplacian edge detector applied on Scan 1



Laplacian edge detector with window size 3 (Scan 2)

Laplacian edge detector with window size 5 (Scan 2)

Figure 27: Laplacian edge detector applied on Scan 2

As expected, there are many double edges visible in the above images. In this particular case, using a window size of 3 gives edges of very low intensity difference, and using a window size of 5 gives images where the edges are hardly visible.

Difference of Gaussian

This filter is a close approximation to Laplacian of Gaussian, which is computational much more expensive. The difference of gaussian works by applying gaussian filters of two different standard deviations on the image, and then subtracting one from another.

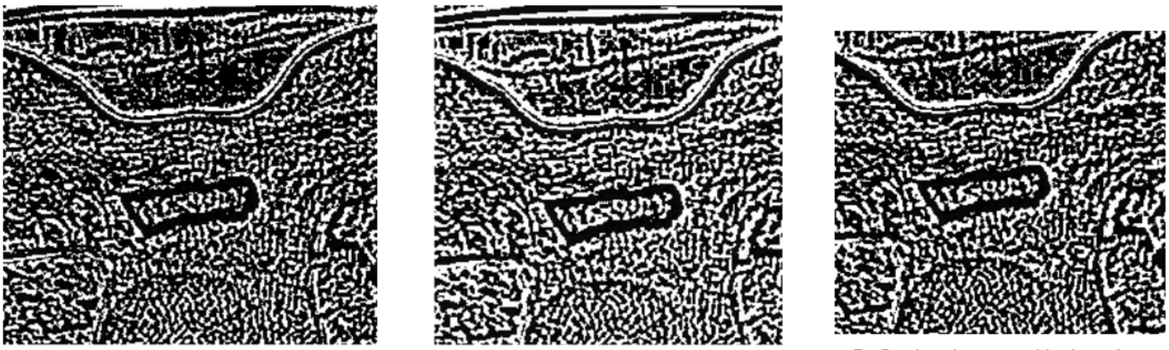
The results obtained are shown in Fig. 28 and Fig. 29.

Difference of Gaussian edge detector with sigma1 = 3, sigma2 = 5

Difference of Gaussian edge detector with sigma1 = 3, sigma2 = 7

Difference of Gaussian edge detector with sigma1 = 5, sigma2 = 7

Figure 28: DoG edge detector applied on Scan 1



DoG edge detector with sigma1 = 3 and sigma2=5

DoG edge detector with sigma1 = 3 and sigma2=7

DoG edge detector with sigma1 = 5 and sigma2=7

Figure 29: DoG edge detector applied on Scan 2

The general rule of thumb is that DoG operator works well for σ_1/σ_2 in the ratio 1.6. As expected, there is a slightly higher contrast between the edges of the sternum and the other parts using sigma1 = 3 and sigma2 = 5.

Summary and Observations

Contrast Enhancement:

- From the histogram equalized and CLAHE equalized images of both scans, it is clear that the contrast is better in case of CLAHE, even though the PDF is much more uniform in case of histogram equalization.
- This is because the original image contains a very skewed spatial distribution of intensities, with some regions having more lighter pixels than others.
- Upon performing histogram equalization (adaptive or otherwise), the PDF becomes more uniform (the intensities are spread out more evenly), and the CDF increases more steadily.

Edge Detection:

- **Robert's Cross Gradient Operator:**
  - Robert's cross gradient operator does not return gradients of high magnitude, which gives edges of very weak intensity.
  - This shows that the edges are blurred.
- **Sobel Edge Detector:**
  - Increasing the window size of the detector leads to many more edges being detected.
  - Sobel edge detector applied to x and y directions separately returns much more edges than the combined model.
- **Canny Edge Detector:**
  - Canny edge detector does not given many double edges.
  - Increasing any one of the thresholds leads to detection of much fewer images.
- **Laplacian Edge Detector:**
  - Laplacian detector leads to a lot of double edges.
  - Increasing the window size of the detector leads to detection of more and more false edges, which reduces the visibility of the actual edges.
- **Difference of Gaussian:**
  - Difference of Gaussian operator works well for standard deviations in the ratio 1.6.
  - The values sigma1=3 and sigma2=5 worked well for the given CT images.
  - Since the DoG takes the difference between two images, the edges are darker than the surrounding regions.

In general, edge detectors can be compared by visualizing the difference between the edge detected images, to see which detector performs better. In this case, for the subsequent parts, the canny edge detected image will be used, using which Edge linking using Hough's Transform will be analysed.

QUESTION 3: HOUGH'S TRANSFORM

Hough's transform is used to extract features of a particular shape that is present in an image. This is done by mapping each point in the image space to a line in the parameter space, and creating a registry to keep track of the same.

In this case, we will look at superellipses of the form $a^m x^m + b^m y^m = a^m b^m$. We take the image obtained from the canny edge detector. In general, a superellipse of any given dimension has five parameters, but in this case, we can reduce it to two by assuming that the sternum is located in the middle of the frame, and that it is oriented along the x and y axes. Another way to reduce the parameters would be to use lines instead of superellipses.

To select the parameter m, we look at various superellipses and choose m that is closest to the shape of the sternum. From Fig. 30 to Fig. 32, we can see that a superellipse with $m = 2$ would fit the shape of the sternum well in Scan 1, and $m = 3$ would fit the shape of the sternum well in Scan 2.

Figure 30: Cropped image of sternum (Scan 1)

Figure 31: Cropped image of sternum (Scan 2)

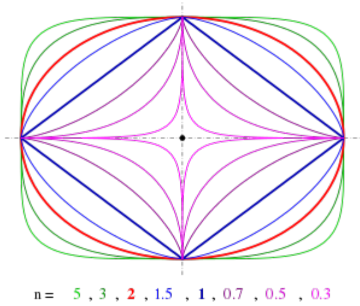


Figure 32: Superellipses for various values of m

The result of applying Hough's transform with the above said parameters is shown in Fig. 33 and Fig. 40 respectively.

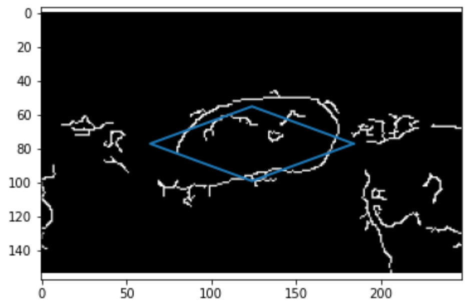


Figure 33: Detecting the sternum in Scan 1 using Hough Transform, with Lame parameter 1

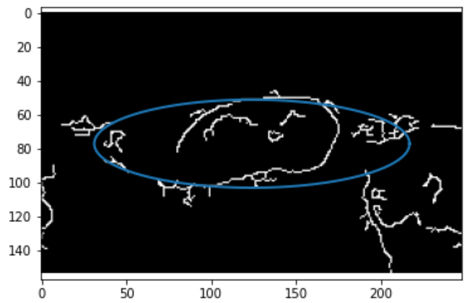


Figure 34: Detecting the sternum in Scan 1 using Hough Transform, with Lame parameter 2

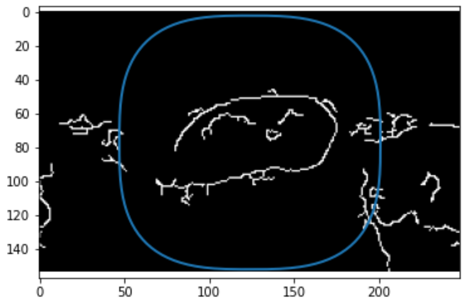


Figure 35: Detecting the sternum in Scan 1 using Hough Transform, with Lame parameter 3

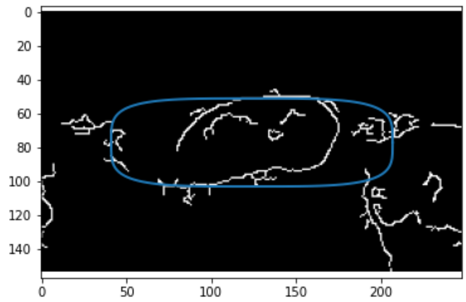


Figure 36: Detecting the sternum in Scan 1 using Hough Transform, with Lame parameter 4

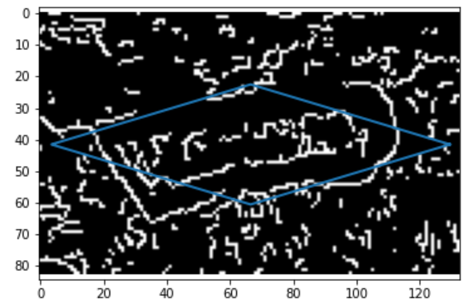


Figure 37: Detecting the sternum in Scan 2 using Hough Transform, with Lame parameter 1

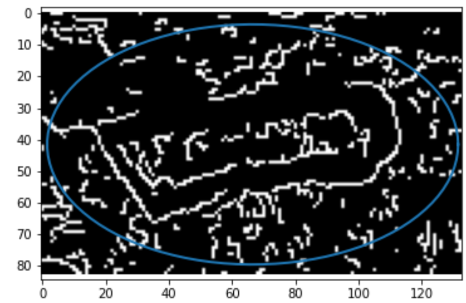


Figure 38: Detecting the sternum in Scan 2 using Hough Transform, with Lame parameter 2

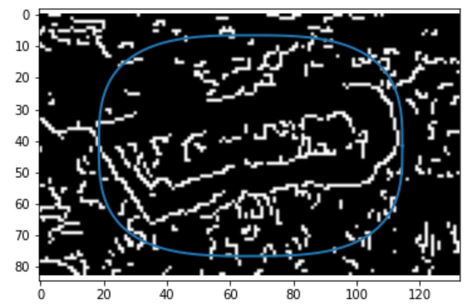


Figure 39: Detecting the sternum in Scan 2 using Hough Transform, with Lame parameter 3

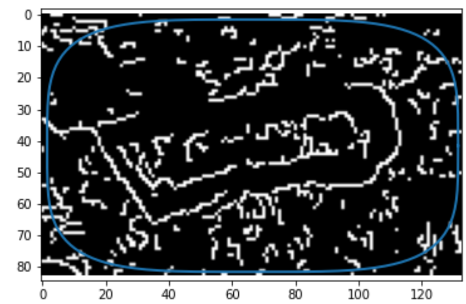


Figure 40: Detecting the sternum in Scan 2 using Hough Transform, with Lame parameter 4

Summary and Observations

- Since we have reduced the number of parameters by fixing the center and orientation, Hough transform is not able to fit the curves very well.

- If the number of dimensions were not limited, the Lame curve would be able to generalize to curves of any orientation and center.
- **Scan 1:**
  - Lame curves of dimensions 1, 2, and 4 were able to detect the strenum pretty closely.
  - Lame curve of dimension 3 was not suitable for this image, which is evident from Fig. 35.
- **Scan 2:**
  - To analyse the performance of the Hough tranform, the image for Scan 2 was selected as one which had a few false edges.
  - In this case, Lame curves of dimensions 1 and 3 were able to identify the sternum to some extent, whereas those of dimensions 2 and 4 did not work well.

SUMMARY

The image processing pipeline used in the assignment is summarized below:

- **Acquisition:** CT Images were used for the analysis.
- **Enhancement:** Filtering using gaussian filter.
- **Feature Extraction:** Edge detection using canny detectors, and feature extraction using Hough transform.