Medical Image Enhancement

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Introduction

Medical images can greatly benefit from image enhancement methods: noise reduction, histogram equalization and image sharpening are some examples of techniques that aid in the efficient interpretation of such data. Not only discussing Gaussian and median filters and their application for noise removal, In this project, I also introduce image enhancement techniques including histogram equalization, image sharpening and design MATLAB scripts and functions that implement them.[1] Medical chest X-ray are used as examples in this project.

Contrast augmentation

(Note that, in this report, the wordings that describe the questions are from the course material by Dr. Albu and I will give the appropriate citation at the end of each corresponding paragraph. On the other hand, all figures, tables, methods implementation, statistics, analysis, explanations and conclusions are all from my personal work.) Important features of an image might be difficult to identify if its pixel intensities are not well distributed (i.e., it has low contrast). These images are characterized by the concentration of most of their information in one end of a histogram (excessively dark or bright images). By applying a transformation function that generates a more uniform intensity distribution, one is actually enhancing the visibility of the image. A typical global transformation that aims to do that is called histogram equalization.[1]

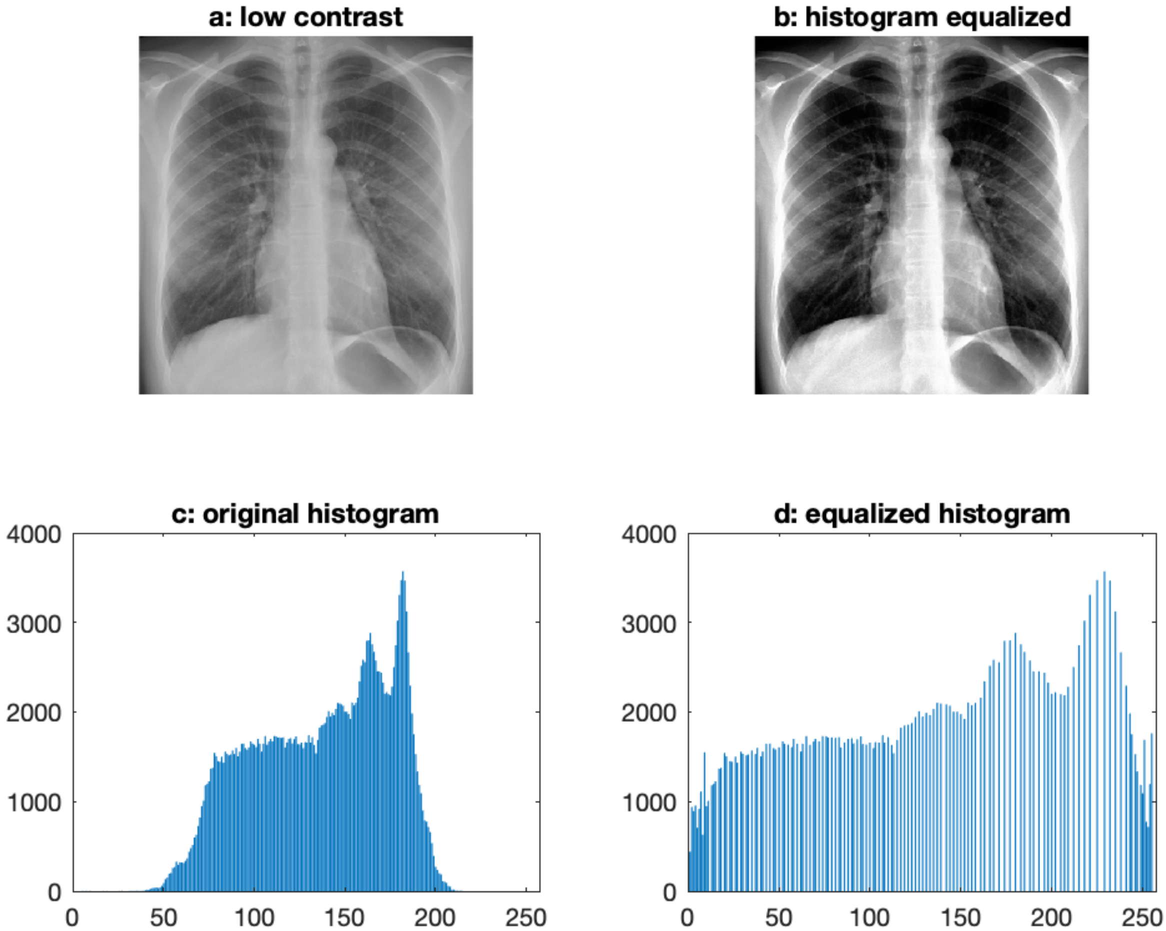

Figure 1: images and histograms for ChestXray

Figure 1 shows the comparisons for the images and the histograms of the original ChestXray and the equalized-histogram ChestXray.

We use Matlab functions to run both Histogram Equalization and Adaptive Histogram Equalization (AHE) on the same image and report the re- sults. Save the result of AHE as '3-AdaptHistogramEqualized.png' and present the histograms of the image after AHE as 'AdaptEqualizedHistogram.png'.

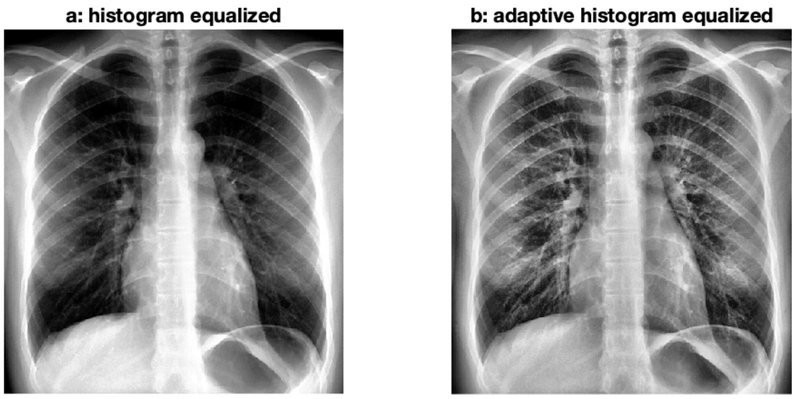

Figure 2: images for equalized histogram and adaptive equalized histogram of ChestXray

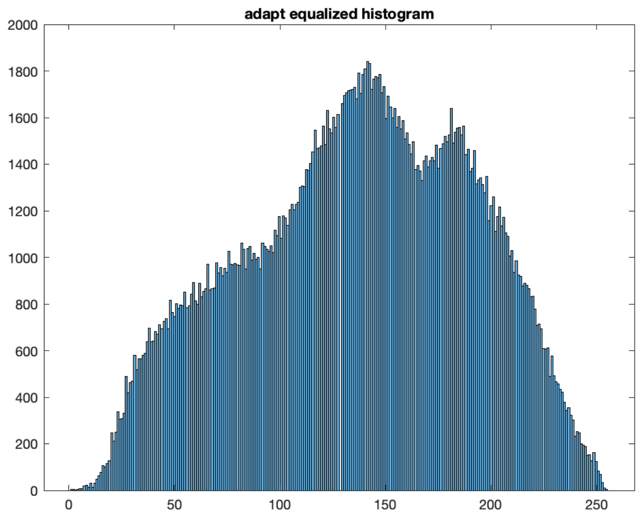

Figure 3: adaptive equalized histogram for ChestXray

Figure 2 shows the comparison for equalized histogram and adaptive equalized histogram of ChestXray. Figure 3 shows the adaptive equalized histogram for ChestXray.

Histogram Equalization is a technique used to improve contrast in images. It accomplishes this by effectively spreading out the most frequent intensity values, i.e. stretching out the intensity range of the image. This method usually increases the global contrast of images when its usable data is represented by close contrast values. This allows for areas of lower local contrast to gain a higher contrast. In other words, Histogram

Equalization expands the range of global pixel intensities of an image given the lower limit and the upper limit of the intensity a pixel can reach. From Figure 2a, we could observe that the contrast of ChestXray is considerably enhanced.

Adaptive Histogram Equalization differs from ordinary histogram equalization in the respect that the adaptive method computes several histograms, each corresponding to a distinct section of the image, and uses them to redistribute the lightness values of the image. It is therefore suitable for improving the local contrast and enhancing the definitions of edges in each region of an image. From Figure 2b, we could observe that most specific details of ChestXray are clearer and more distinct than the equalized-histogram one.

Ordinary histogram equalization uses the same transformation derived from the image histogram to transform all pixels. This works well when the distribution of pixel values is similar throughout the image. However, when we need to process an image that contains regions that are significantly lighter or darker than most of the image, the contrast in those regions will not be sufficiently enhanced using ordinary histogram equalization. In this type of cases, we need to use adaptive histogram equalization.

We report the transformation curve of the intensity values for histogram equalization and explain what it means.

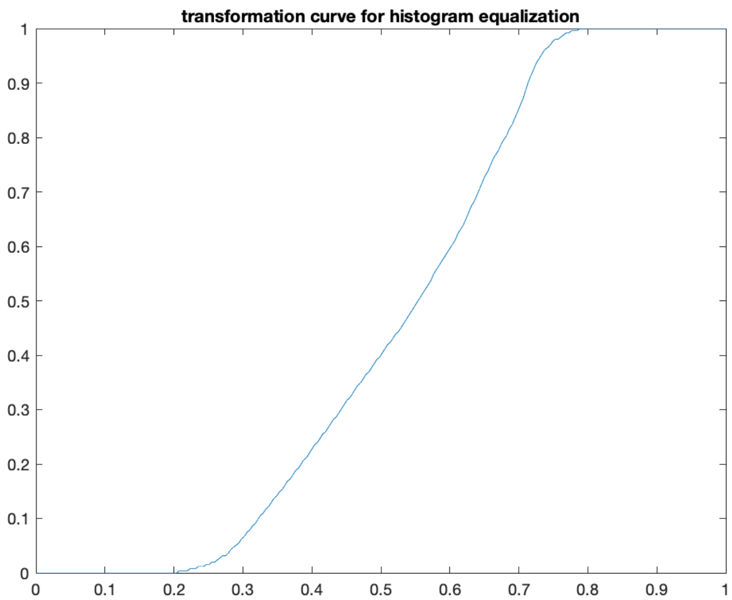

Figure 4: transformation curve for histogram equalization

Figure 4 shows the transformation curve for histogram equalization for ChestXray. I have normalized the pixel intensities to $[0, 1]$. We could consider this curve as the cumulative distribution function of the histogram. This curve reflects the change of the histogram of ChestXray in Figure 2(a) mapping to the entire range a pixel can reach, i.e., $[0, 255]$. In other words, this curve is a mapping that reflects the cumulative probability of all up to the current pixel intensity. We could stretch out the intensity range of the image to the entire range, i.e., $[0, 255]$, by conducting a mapping transformation using this curve. For example, in this figure, the input value is mainly between $[0.2, 0.8]$, while the output value is mainly between $[0, 1]$. 0.2 corresponds to 50 in Figure 1(c), almost the lowest pixel intensity of the image, while 0.8 corresponds to 200 in Figure 1(c), almost the highest pixel intensity of the image. The pixel with the highest intensity 200 in the image, upon the transformation, would have a new intensity of 255.

Image Smoothing

Images with enhanced edges (i.e., sharpened) better highlight features that can guarantee an effective medical interpretation. In this section we will investigate two sharpening strategies: 1) using a classical sharpening operator, and 2) using a Laplacian of Gaussian (LoG)-based operator. The first approach is sometimes referred to as an unsharp filter: a technique that use an unsharp (or smoothed) version of the image in the enhancement process.[1]

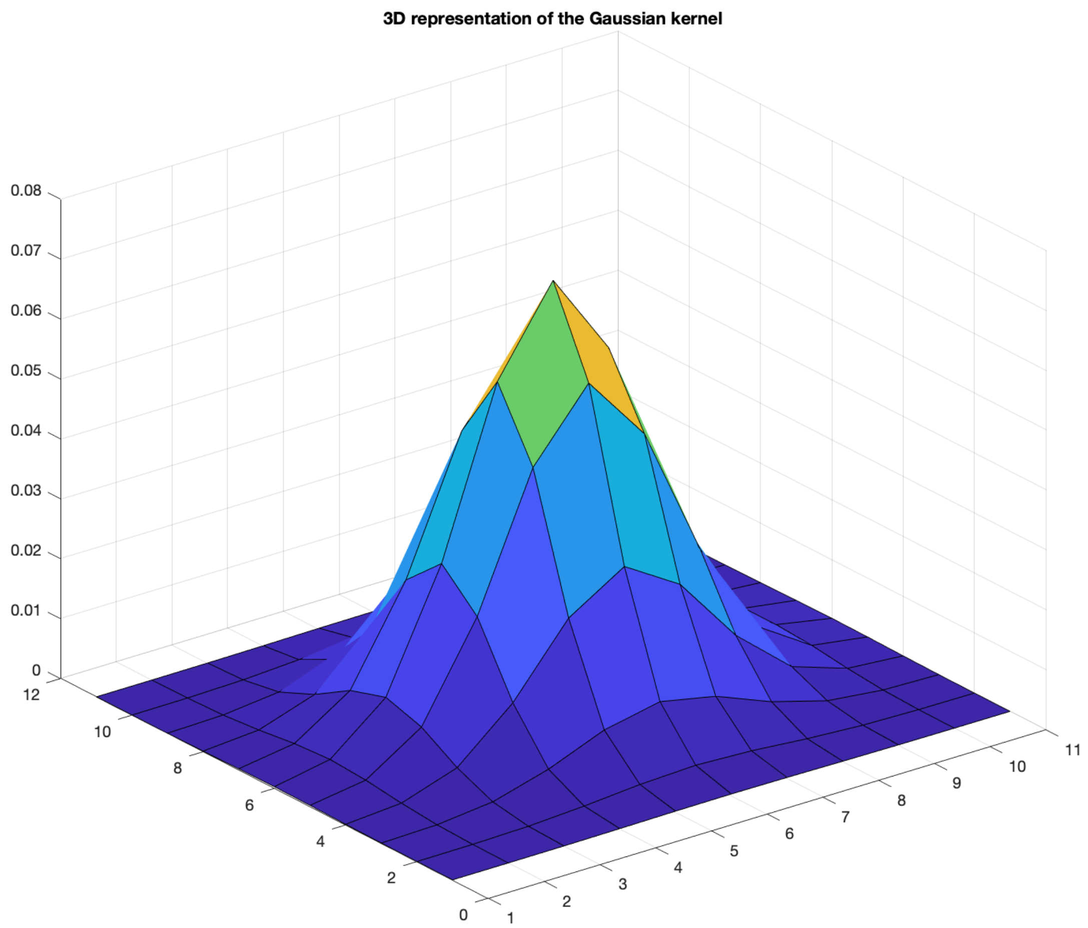

Figure 5: 3D representation of the Gaussian kernel with size = 11 and $\sigma = 1.5$

Figure 5 shows the complete 3D representation of the Gaussian kernel with size = 11 and $\sigma = 1.5$. We could clearly observer that the graph is much same as the graph of the probability density function of a continuous bivariate normal distribution.

The sum of values of this Gaussian kernel is around 1.

We applied that kernel in the original grayscale ChestXray image using convolution. Figure 6 shows the comparison between the original ChestXray and the smoothed version using the Gaussian kernel we just obtained.

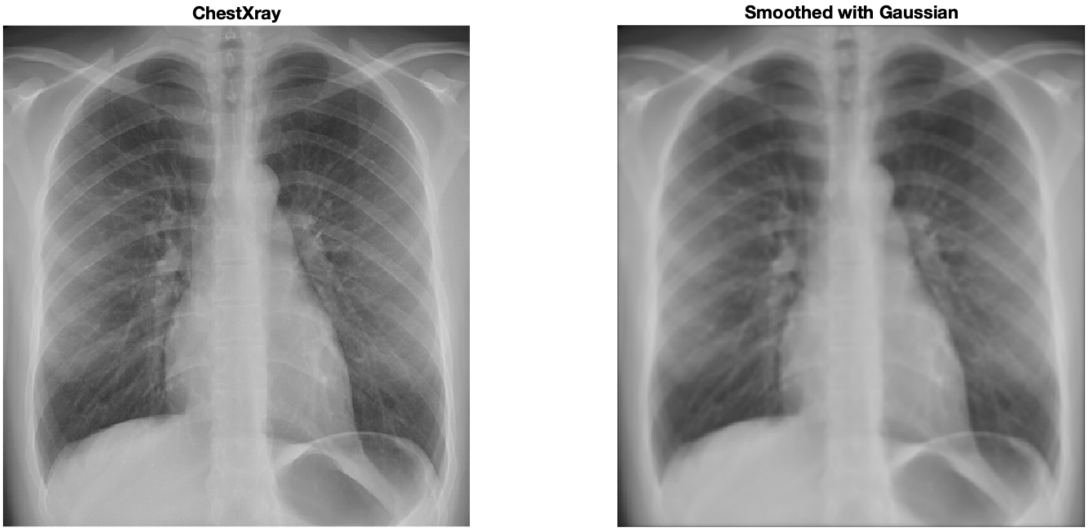

Figure 6: Comparison between the original ChestXray and the smoothed version using Gaussian kernel with size $= 11$ and $\sigma = 1.5$

Use the myGaussian function to calculate and report the sum of values from a Gaussian kernel with wsize $= 5$ and $= 2$.
The sum of values from a Gaussian kernel with size $= 5$ and $\sigma = 2$ is around 0.63 and is not unity with the answer in (a). Given the continuous Gaussian equation:

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

it could be verified the integral

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} G_k(x, y)\, dxdy = 1. \tag{2}$$

However, given that our Gaussian smoothing operator is just a discrete approximation of continuous Gaussian function, in order to make the sum of all values of the filter $= 1$, we need to perform normalization to the kernel after we have calculated all finite values for the kernel. The normalized value at location(x, y) of the kernel, $G(x, y)$, is computed by

$$G(x, y) = \frac{G_k(x, y)}{\sum_x \sum_y G_k}. \tag{3}$$

I have modified ***myGaussian.m*** to make sure that the sum of values from a Gaussian kernel is 1.

Image Sharpening

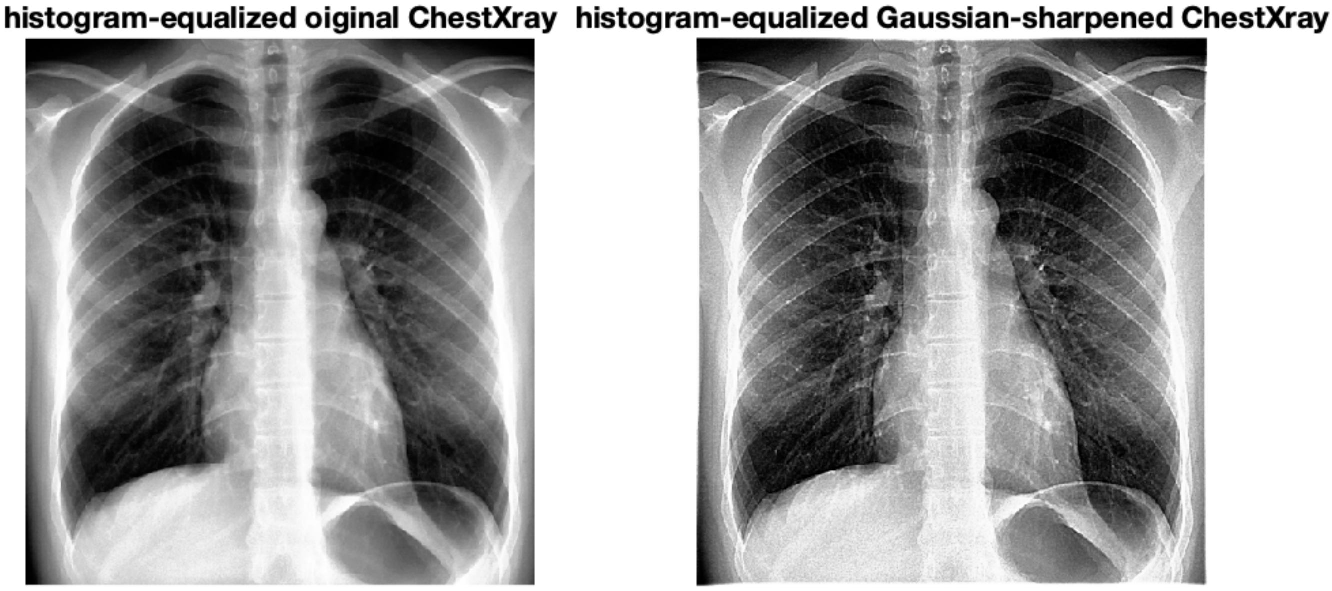

Figure 7: histogram-equalized images

Figure 7 shows the comparison between the histogram-equalized original ChestXray and the histogram-equalized sharpened ChestXray. Though the left image, upon histogram-equalization, shows many details, the Gaussian-sharpened right image with histogram-equalization highlights way more sharpened edges and features.

Laplacian of Gaussian Calculation and Usage

LoG edge detector combines Gaussian and Laplacian functions, both smooths and detects the edges in an image. An approximation of its effect can be obtained by subtracting two images smoothed with Gaussian kernels using different (‘Difference of Gaussian’).

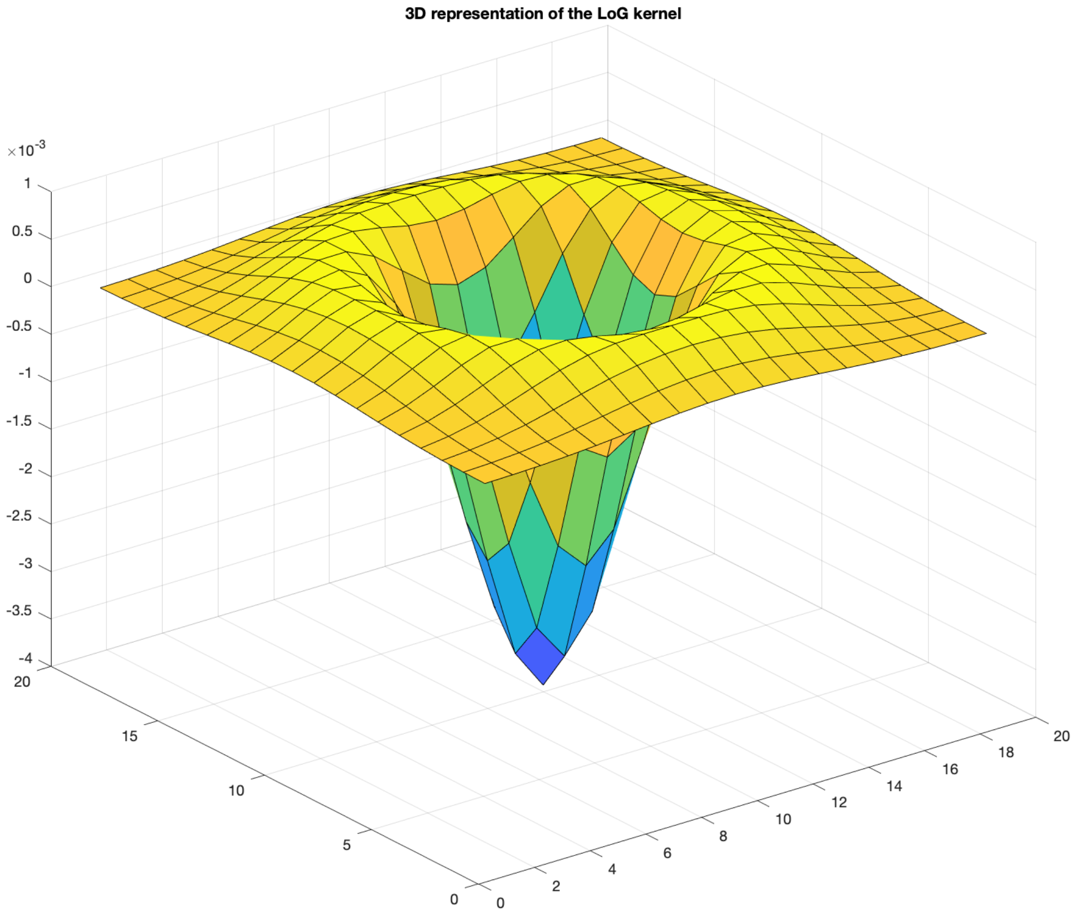

Figure 8: 3D representation of the LoG kernel with size = 19 and σ = 3

Figure 8 shows the complete 3D representation of the Laplacian of Gaussian kernel with size = 19 and σ = 3.

We implement the LoG-based sharpening operation described in Figure 3. In order to do so, first create an LoG kernel with the myLoG func- tion, wsize = 9 and = 0.6. Then, use convolution to apply this kernel in the original image and calculate the edge image. Use the myHistEq function to en- hance both the LoG-sharpened and original images. Present both outputs (i.e., histogram-equalized original and LoG-sharpened images) and save the sharp- ened one as '6-SharpenedwithLoG.png'.

Figure 9 shows the comparison between the histogram-equalized original ChestXray and the histogram-equalized LoG-sharpened ChestXray. Though the left image, upon histogram-equalization, shows many details, the LoG-sharpened right image with histogram-equalization highlights way more sharpened edges and features.

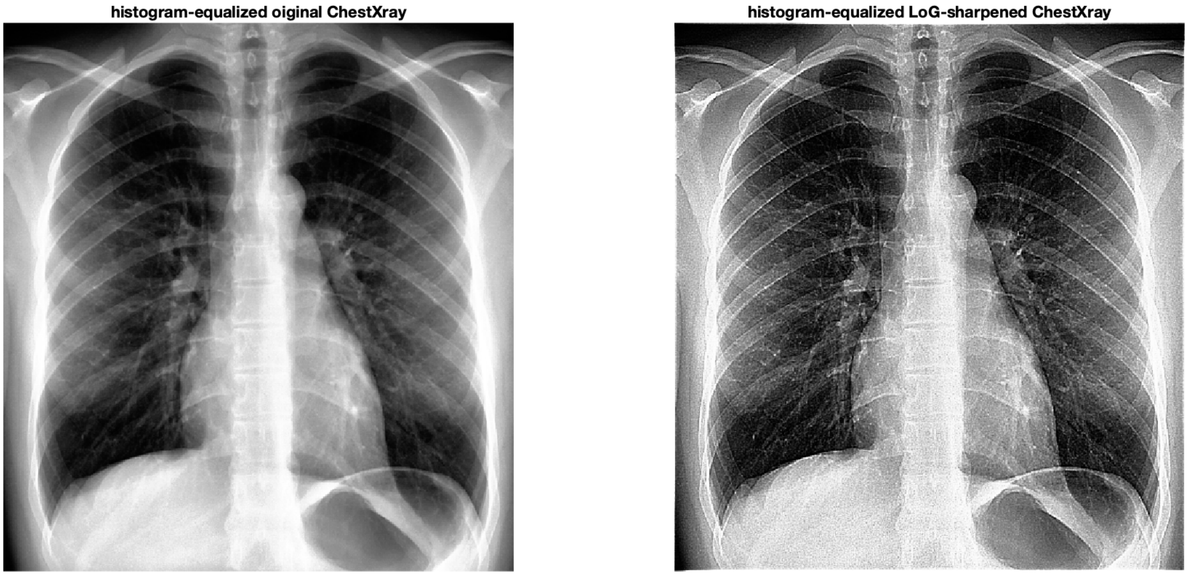

Figure 9: histogram-equalized images

Conclusion

In this project, I not only discussed Gaussian and median filters and their application for noise removal, but also introduced image enhancement techniques including histogram equalization, image sharpening and design MATLAB scripts and functions that implement them. Medical chest X-ray are used as examples in this project.

References

[1] A. Albu, *Ece435: Medical image processing course materials.*