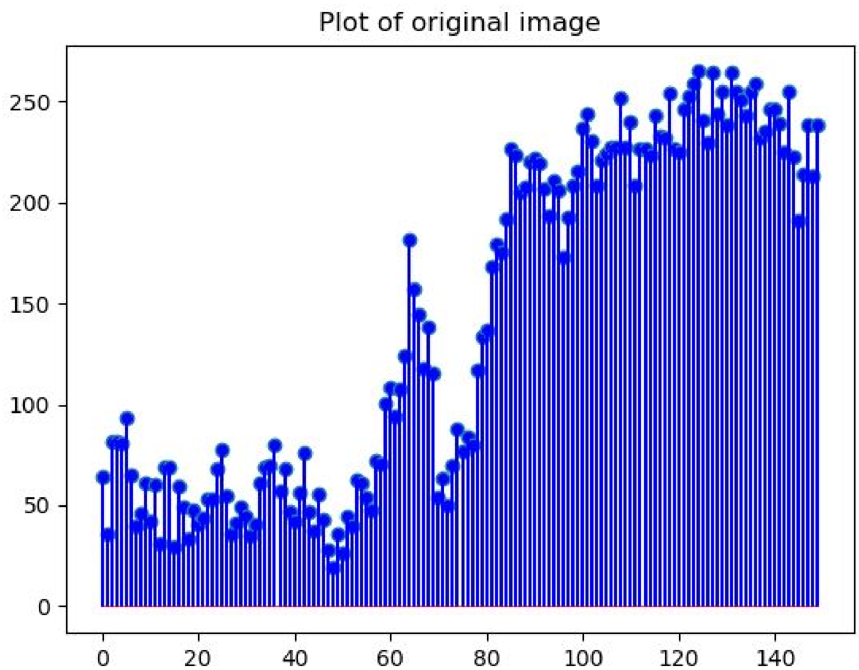
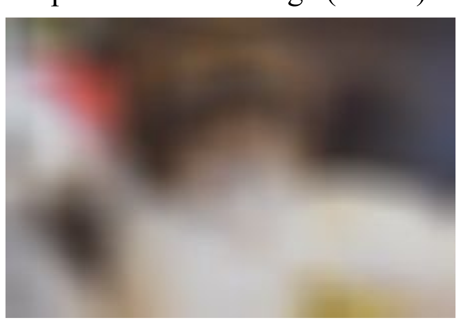
Matthew Lewis
CSC 391 Project #1

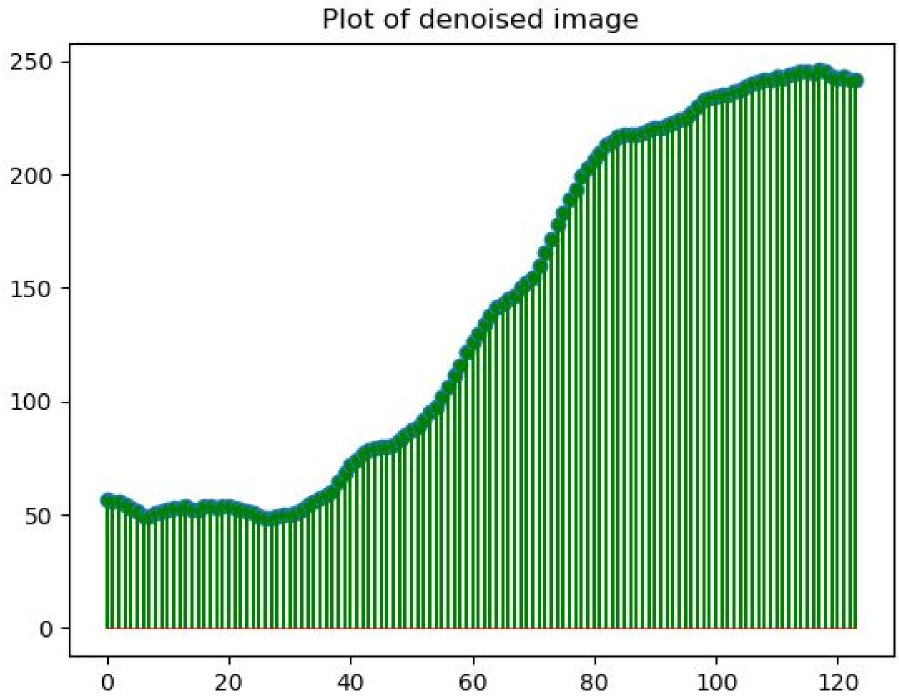
3.1

Original Image



Spatial Filtered Image (27x27)





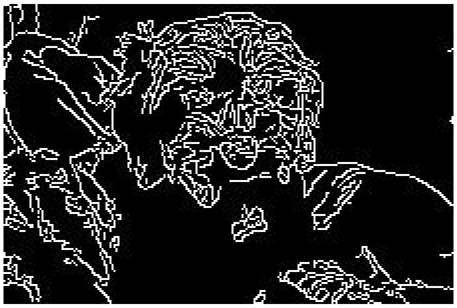
3.2.1

Gaussian filtered image (27x27)

The Gaussian filtered image has the advantage in resolution over the spatially filtered image. I used a k filter of 27x27 for this example. However, due to its higher resolution, the Gaussian filtered image is also more noisy than the spatially filtered image. This creates a tradeoff, one in which the spatial filter is more useful for simply denoising an image, but the Gaussian filter also denoises the image while keeping a higher degree of resolution.

3.2.2

Edge detected original puppy image



Edge detected spatially filtered image

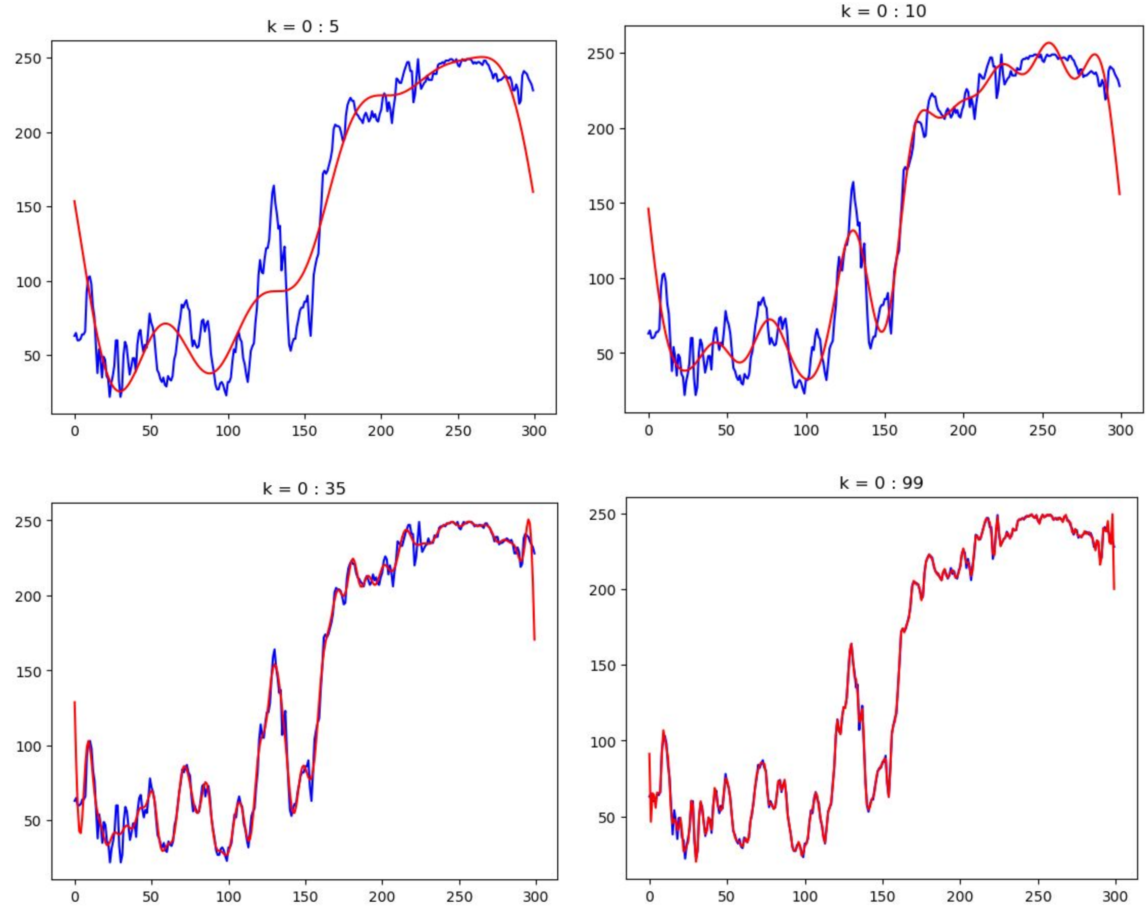
Original landscape image

Edge detected landscape image

After applying the edge filter to these images I was amazed at its ability to accurately detect edges in the images. The original puppy image looks perfectly edge detected. Not surprisingly, when I applied edge detection to the denoised puppy image, a black image was produced with no edges detected due to the lack of resolution in the spatially filtered image. The landscape image also looks beautiful after the edge detection filter was applied, and I do not think that I am able to come up with a better way of detecting images than the cv2 Cany Edge Detection function.

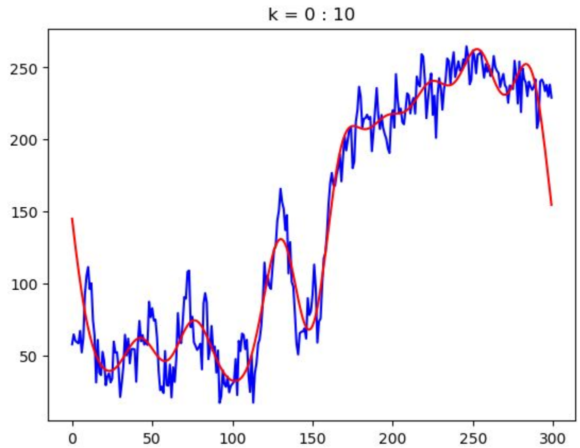
4.1

Frequency analysis

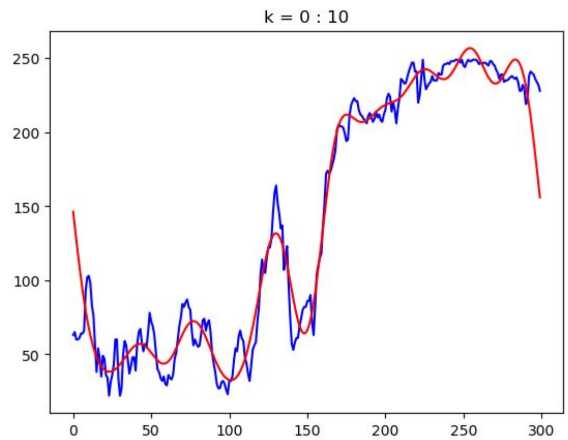


As the Fourier coefficient increases, the column data and frequency data of the image begin to mirror each other more closely. This k value provides a more accurate Fourier function as it increases, as I have shown with examples of k = 5, k = 10, k = 35, and k = 99.

Noisy Dog and corresponding plot

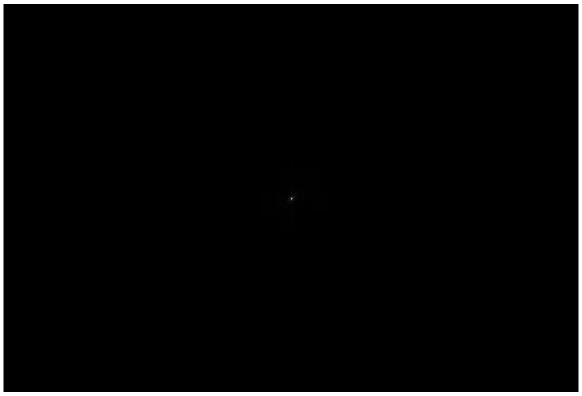


Normal dog and corresponding plot

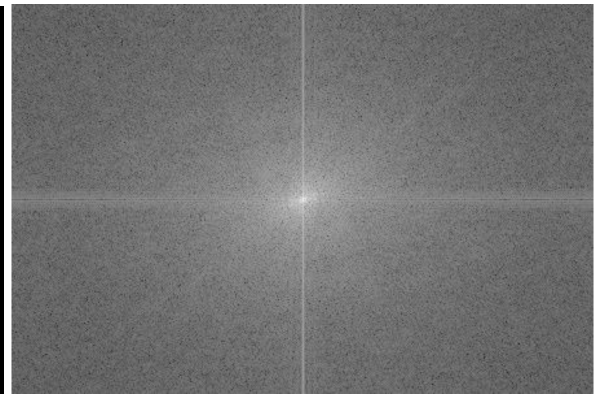


It is apparent that the frequency of the noisy dog image is much more extreme. It fluctuates more severely, evidenced by the lack of correlation between the frequency data and column data in its graph. Below, in mapping a 2D image of the Magnitude of the dog picture, you can see the magnitude shown. However, this image is unclear and appears to be a black square with one tiny white dot in the middle. Thus, it is useful to compute this as the logarithm of the magnitude plus one to better visually comprehend the 2D Fourier image of the dog.

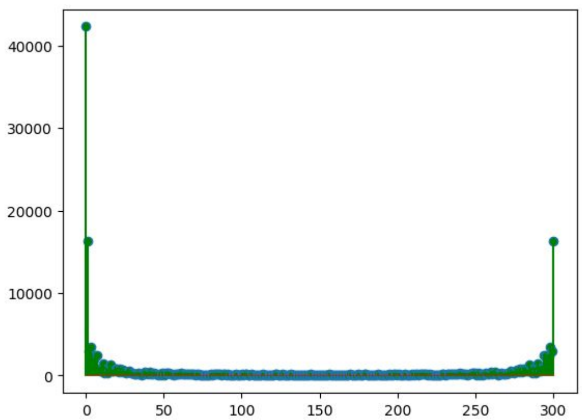
Fourier plot of the Magnitude

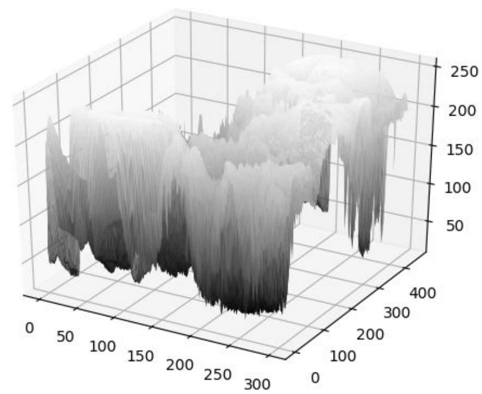


Fourier plot of the Logarithm of the Magnitude + 1



Both of these graphs represent the frequency of the normal dog image, one represented in 1D and one represented on a 3D plane. These help represent the range of frequencies in the image, and representing these values in a 3D plot is what I personally found most helpful in understanding the concept of plotting Fourier transforms.

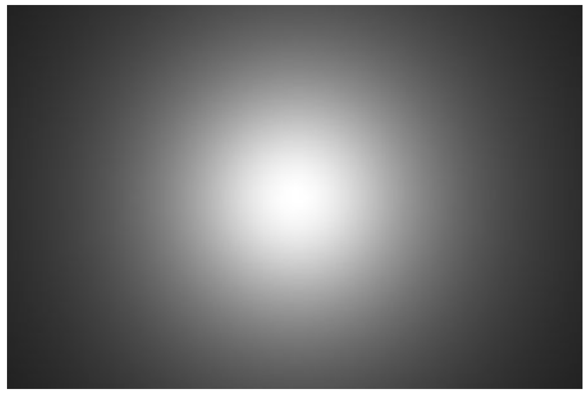




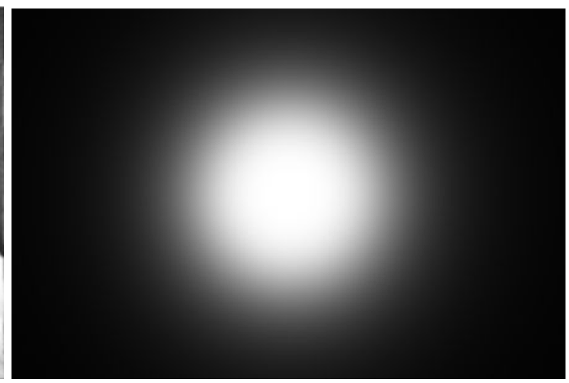
5.1

As n increases, a few different things happen. First, the Butterworth low pass filter grows closer to the ideal filter. Also, the resulting image from that filter becomes less and less clear, but this is due to the removal in high frequencies resulting from the use of the low pass filter.

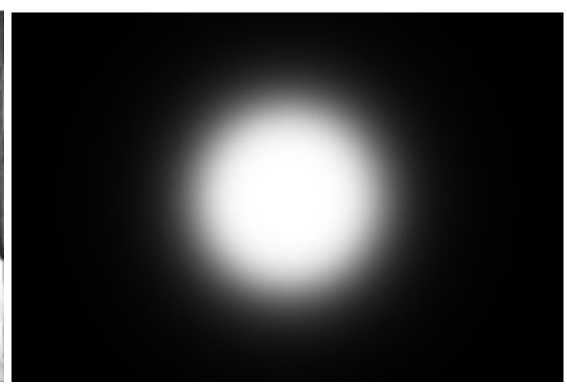
N = 1

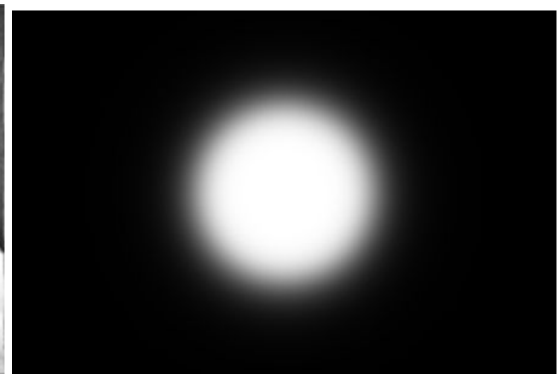
N = 2

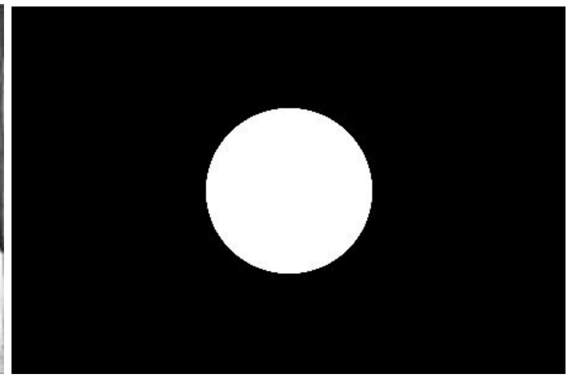
N = 3

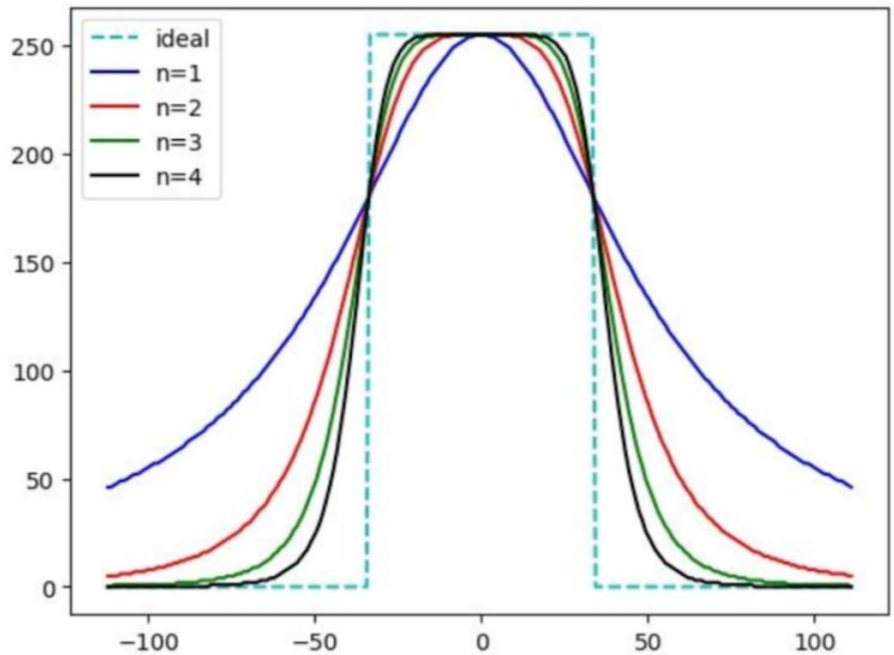
N = 4

N = 1000 (Ideal low pass)

Graphing the low pass values can help us to understand the effect of the Butterworth filter. When I tried to graph the n = 1000 value, it was unable to be plotted on this graph. That is understandable, considering the nearly ideal nature of the n = 1000 value and the fact that the ideal graph is impossible to replicate with a rational function. The low pass filter is so useful because of its ability to keep low frequencies while filtering out high frequencies and effectively removing noise.



ideal
n=1
n=2
n=3
n=4
250
200
150
100
50
0
−100
−50
0
50
100