Application of Statistics into the Medical Diagnosis

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Abstract

Advancements in medical imaging continue to reshape the way that doctors diagnose and treat patients' diseases. In this report we are going to take a glance at brain tumor images that were acquired from an optical fluorescence microscope imaging system employing a 488 nanometer argon laser. The report will offer an in depth investigation into the variance that happens at completely different depths of the brain tumor images. The variance, calculated using the Otsu algorithm, is displayed next to the brain image for every respective depth of brain tumor pictures.

I. Introduction

Everyone understands the severity of cancer and the effects that it can have on the body. However, many individuals don't understand that innovations in medical imaging and diagnosing will have an enormous impact on the ultimate success or failure of fighting a disease. Cancer is no longer the death sentence that it once was, partly as a result of the medical field's ability to diagnose it at an early stage. In the medical field, the first step to treatment is via identification. An early and correct diagnosis will save people's lives by permitting them to get the treatment that they need to start fighting the disease before it has an opportunity to spread. Even though medical analysis in imaging is presently at a peak, there is still much more work to be done in order to advance medical imaging systems to a subsequent level. Currently, Magnetic Resonance Imaging (MRI) and Positron Emission tomography (PET) are the most effective available imaging strategies. However, these imaging systems have a limited ability to exactly single out cancer tissue from healthy tissue. The ability to differentiate the two in diagnosis is extraordinarily necessary because it permits doctors to visualize the distinction between the two types of tissue and have a stronger plan of action to treat the cancer. Being able to discover the tumor margins in cancerous tissue would be monumental in using non-invasive techniques to help in the surgical removal of tumors. By viewing the images in

contrast and accurately pinpointing the tumor margin, doctors are able to be more precise with the surgical removal of the cancerous tissue and lower the likelihood of cancer recurrence. Different kinds of imaging strategies are presently being developed as well. Some examples of these imaging systems that allow surgeons to visualize the tissue margins and structures while operating are optical coherence tomography, imaging with terahertz waves, inverse scattering, and margin illumination using optical imaging agents. In this project, the imaging system used will be an optical light microscope imaging system where tumors were illuminated by a 488 nanometer argon laser to accumulate raw auto-fluorescent pictures. Tumor cells appear as white spots on these brain tumor images. Using the Otsu method, we were able to realize the variance within every class and also the variance between classes. In this report, we are going to take a glance at an image at different depths and graph the variance at every depth.

II. Problem Definition

The Otsu method was named after its creator Nobuyuki Otsu. The Otsu method is one of several binarization algorithms and involves iterating through all the possible threshold values and calculating a measure of spread for the pixel level of intensity. One main purpose of the Otsu method is to notice the threshold value wherever the sum of foreground and background spreads is at its minimum. Here, the problem is that the raw image of the tumor isn't clearly outlined enough for us to see it fully - we want the clearest image possible so the surgeons will do their best work. We processed the raw image by utilizing a histogram and the Otsu technique to highlight cancer in the raw image. Overall, we set up a threshold for the raw image and anything that was below the parameters would be taken out - if the image was above the threshold then it'd be highlighted. By applying this principle to our raw image by using the Otsu technique we have successfully highlighted the cancer image and separated the less important data. The processed image will now

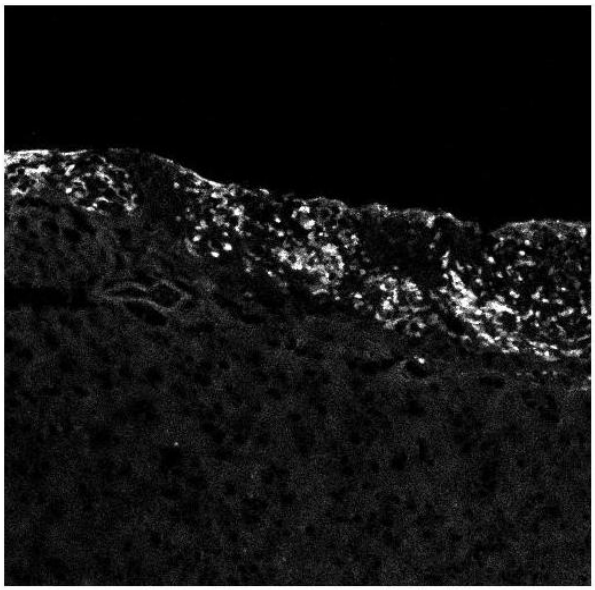
look like the cancer is more intensely highlighted compared to the raw image. For us to do this, we need to properly outline our parameters, the variance, the sample size, and the population mean.

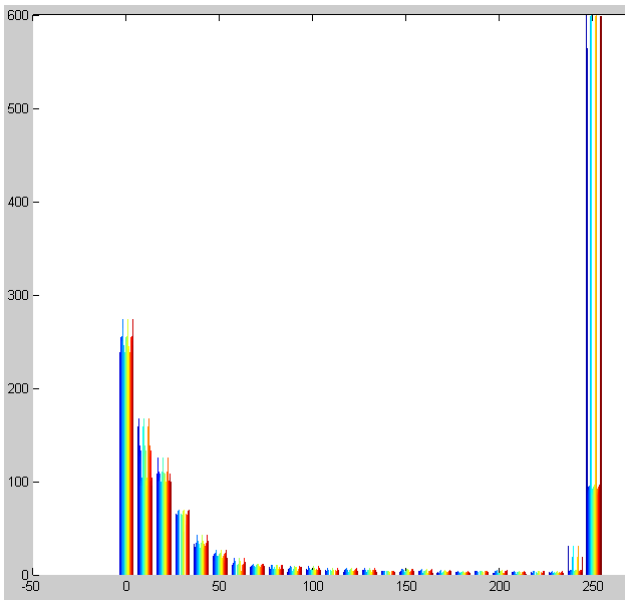
III. Unprocessed Images

Code used:

```
y=imread('file name.jpg');
x = 0:10:260;
figure(1)
imshow(y);
figure(2)
imshow(y);
hist(y,x);
```

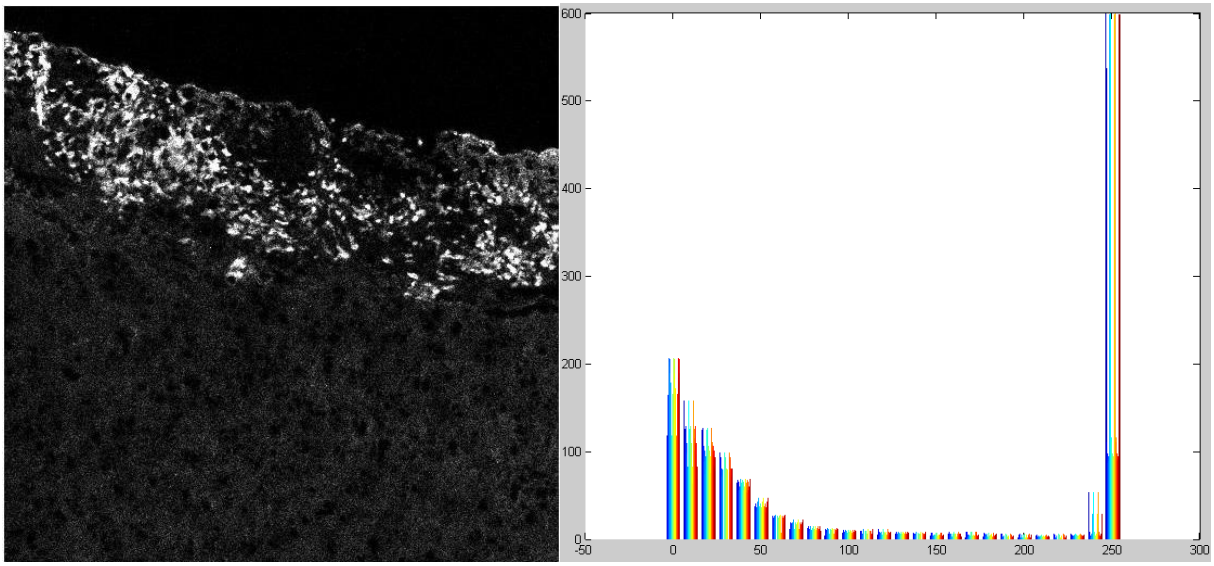
Tumor Depth at 10um





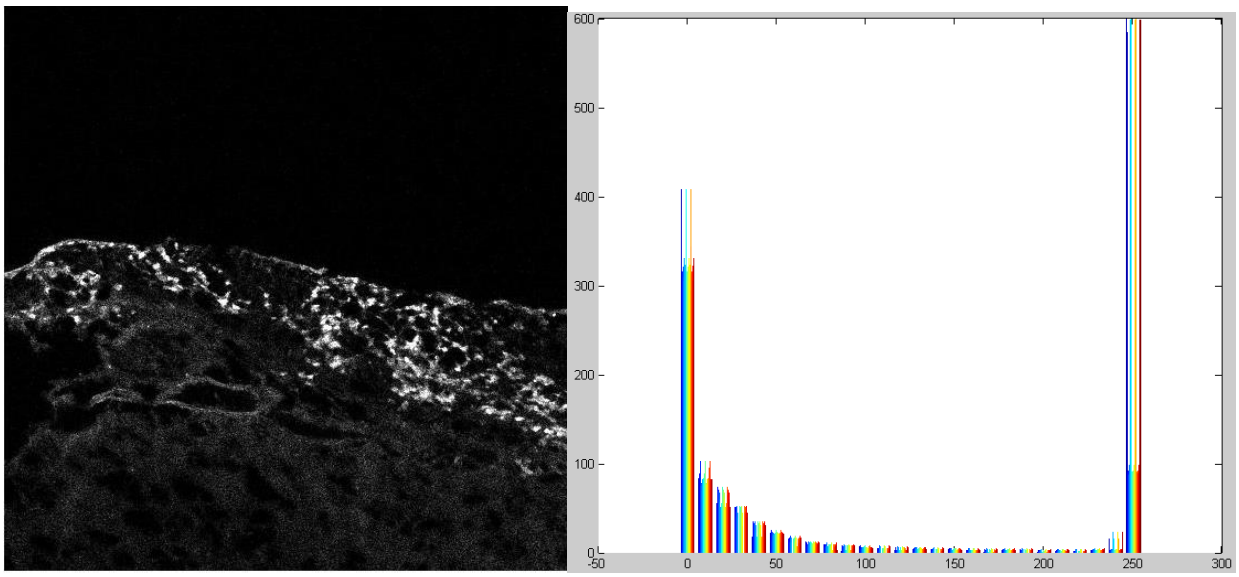
Observations/Analysis: Here the amplitude starts at a range of 200-300 and slowly decreases. On the tail of the graph there is a small jump ~20 and then there is a huge spike that shoots past 600+.

Tumor Depth at 30um



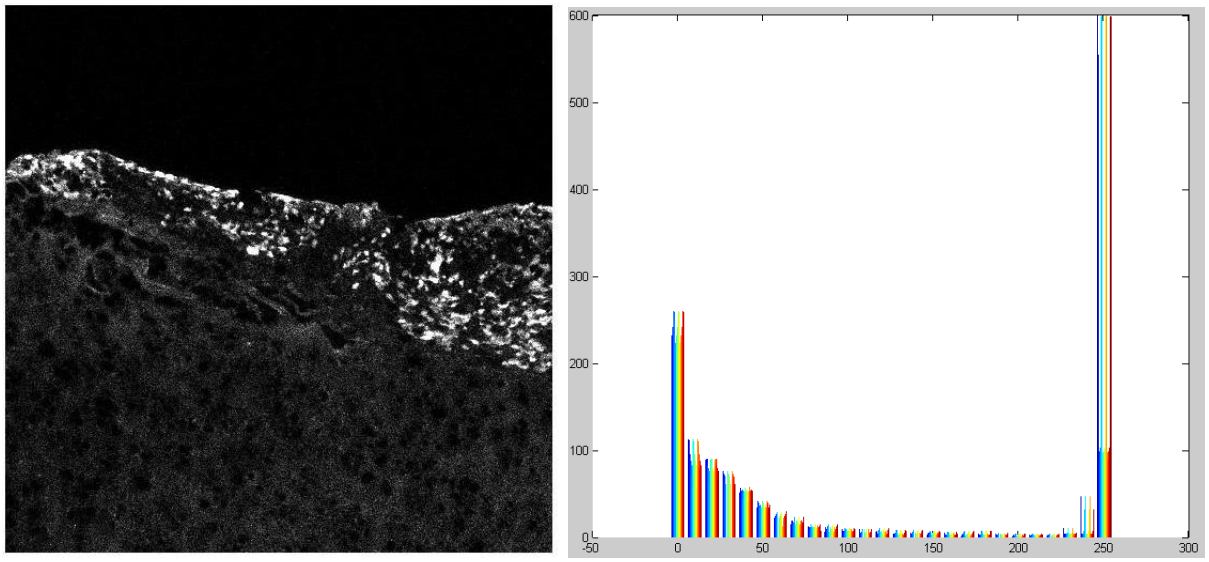
Observations/Analysis: The difference between this graph and the prior graph is that in this graph, the amplitude starts at around 200 and the tail of this graph is slightly higher compared to the tumor depth at 10um. It is slightly higher at the first jump and the second jump is still just as high.

Tumor Depth at 40um



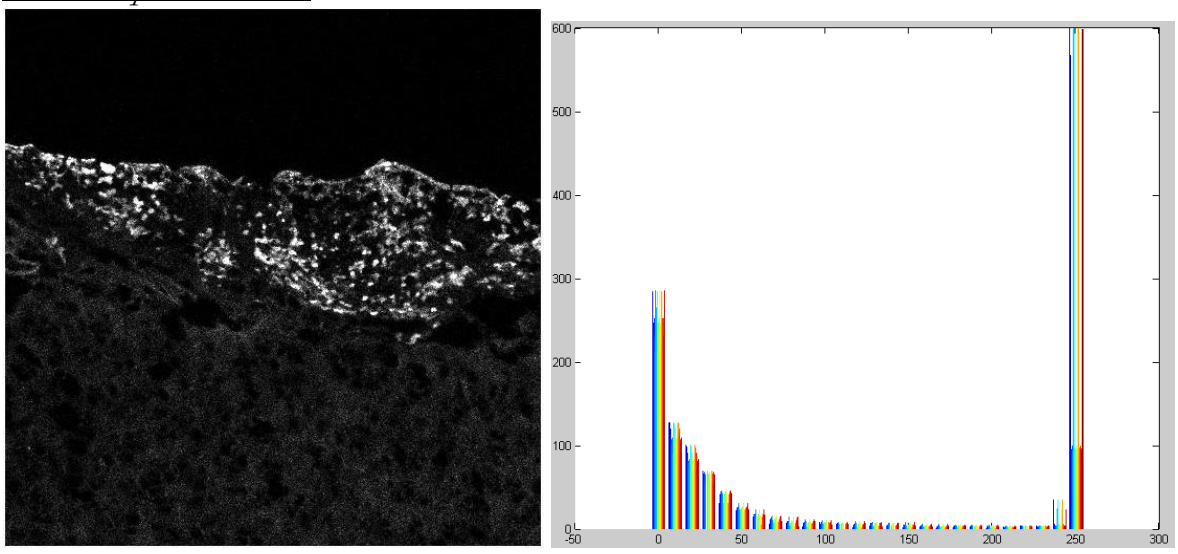
Observations/Analysis: This histogram starts close to around 400 amplitude and then drop off is much greater from 400 to close to around 100 and then it has a decreasing slope. Here the tail of the graph is the lowest so far, ~10.

Tumor Depth at 60um



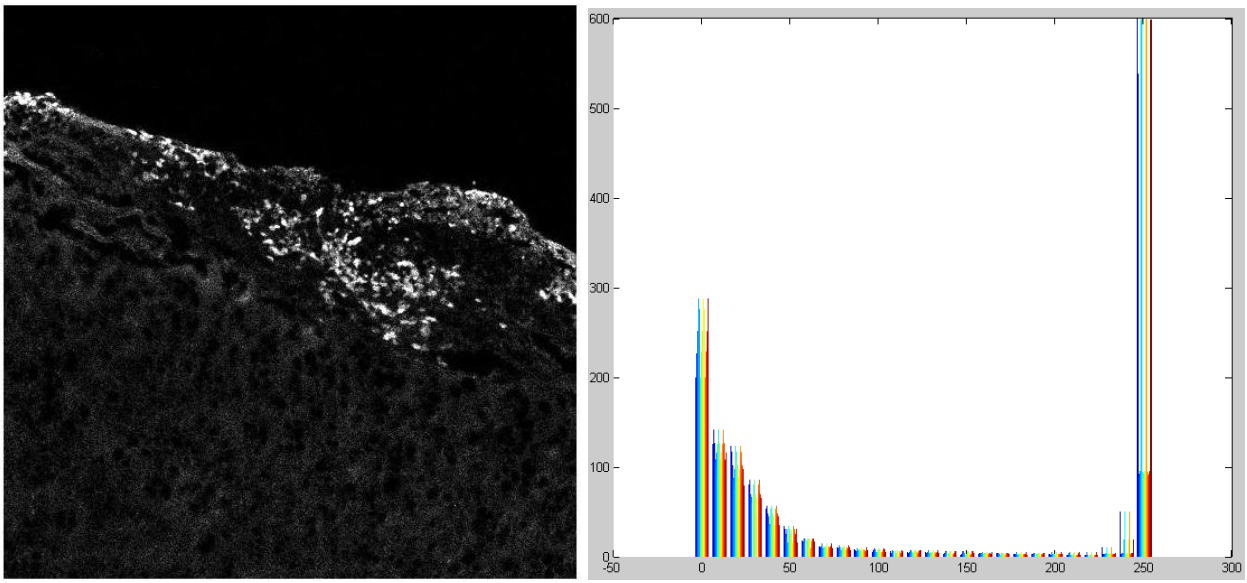
Observations/Analysis: Here the amplitude start is an average (200-300) but the drop off here is from ~200 to ~100 and the tail jump is close to ~30.

Tumor Depth at 100um



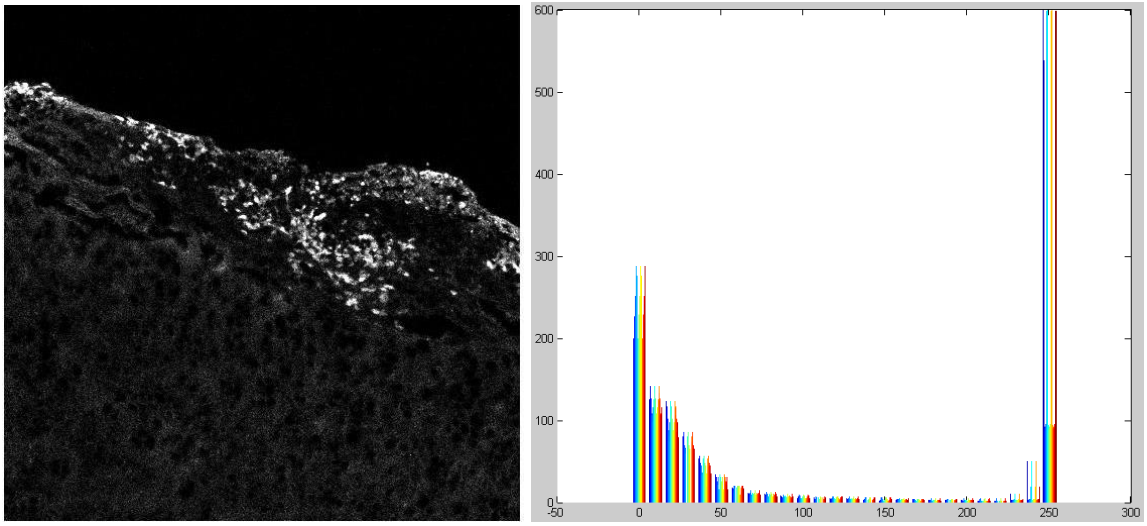
Observations/Analysis: Here the start is roughly average to what we found, and the drop off is slightly higher while the tail is roughly ~30.

Tumor Depth at 110um



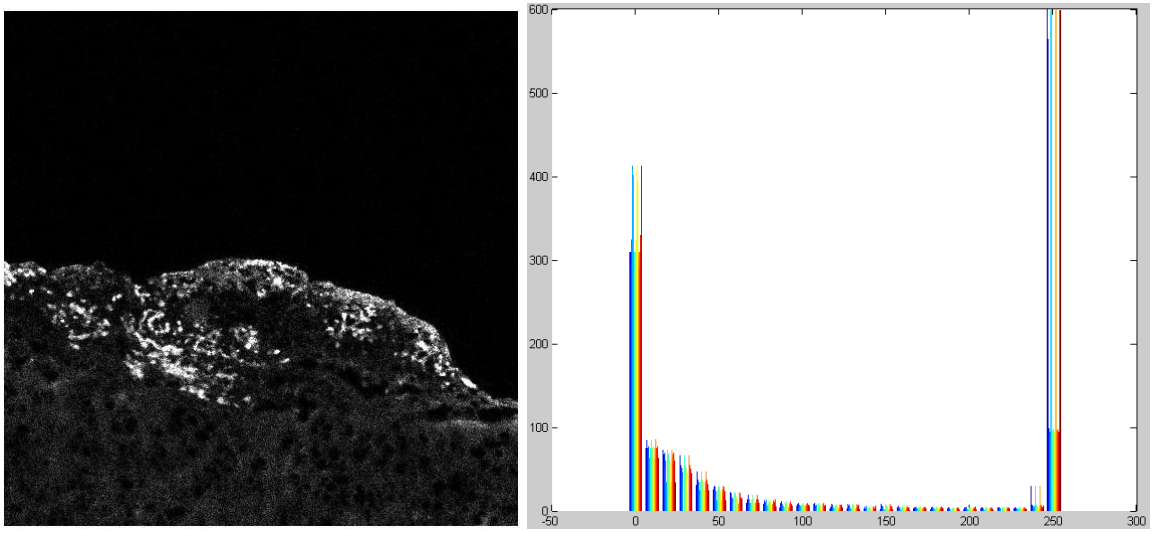
Observations/Analysis: Here the starting amplitude is roughly average (200-300 range), but here the drop off varies be being slightly higher than the previously seen. And the increments of dissension are marginally larger. Just as before we see a slight jump and an huge spike near the 250 marker.

Tumor Depth at 120um



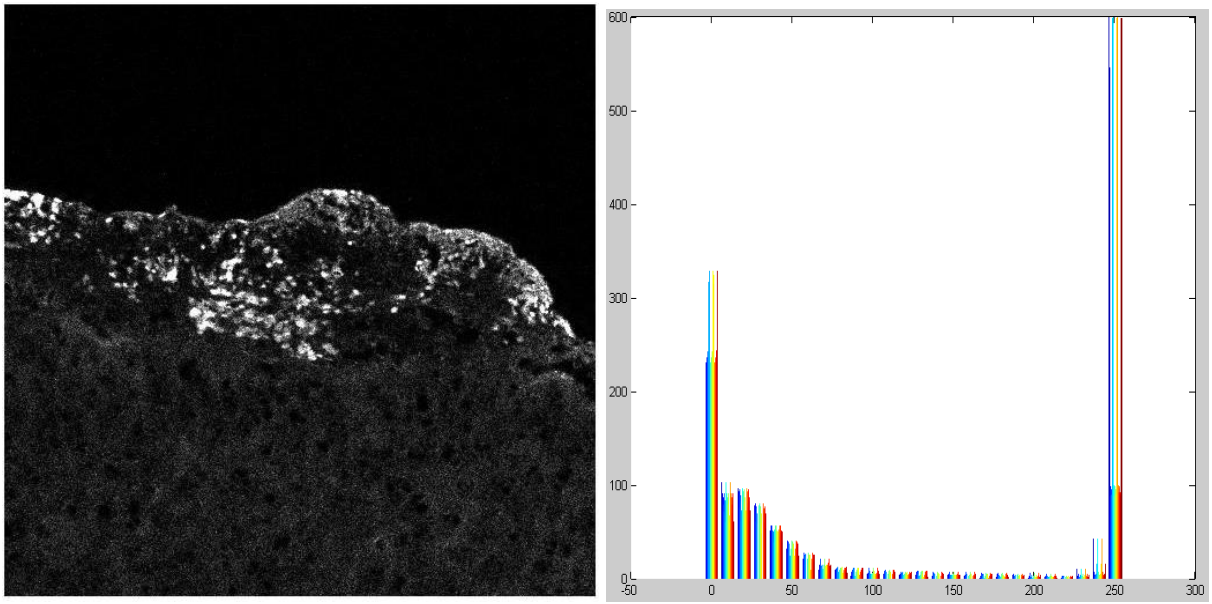
Observations/Analysis: There is not much different at for this histogram from the previous ones except that on the tail there is only a slight spike before the major jump.

Tumor Depth at 140um



Observations/Analysis: Here on the histogram we see a major jump in the 300-400 range of amplitude, and the drop off between the start is radically different. Just as the histogram for the tumor at 120 um there is a lack of spike before the end.

Tumor Depth at 150um



Observations/Analysis: Finally we see the histogram at 150um depth and we can observe that there is radical difference between the start and the rest of the graph. In the case we see that there is a there is actually a slight increase before the steady decline of the graph.

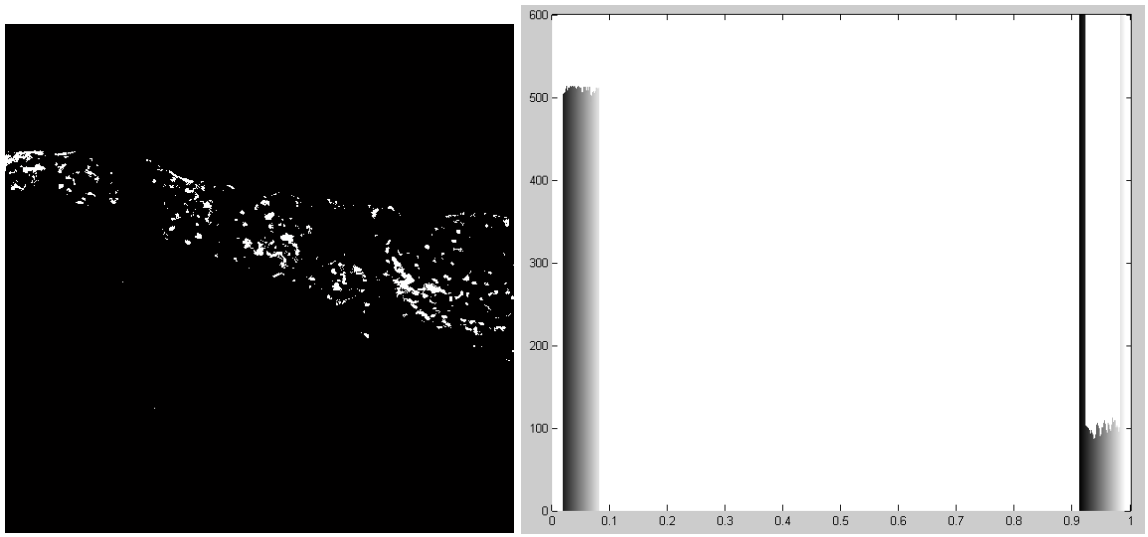
IV. Processed Images

Since we wanted a more clear and defined image we had to use some type of method that would help us get this. Here we used the Otsu method, in order to highlight the cancer cells. What we did was first we took the raw image and convert it into its histogram on MATLAB. Once we had the histogram for each image, we then put it through the Otsu method on MATLAB to be processed. Our coding for using the Otsu method is provided below.

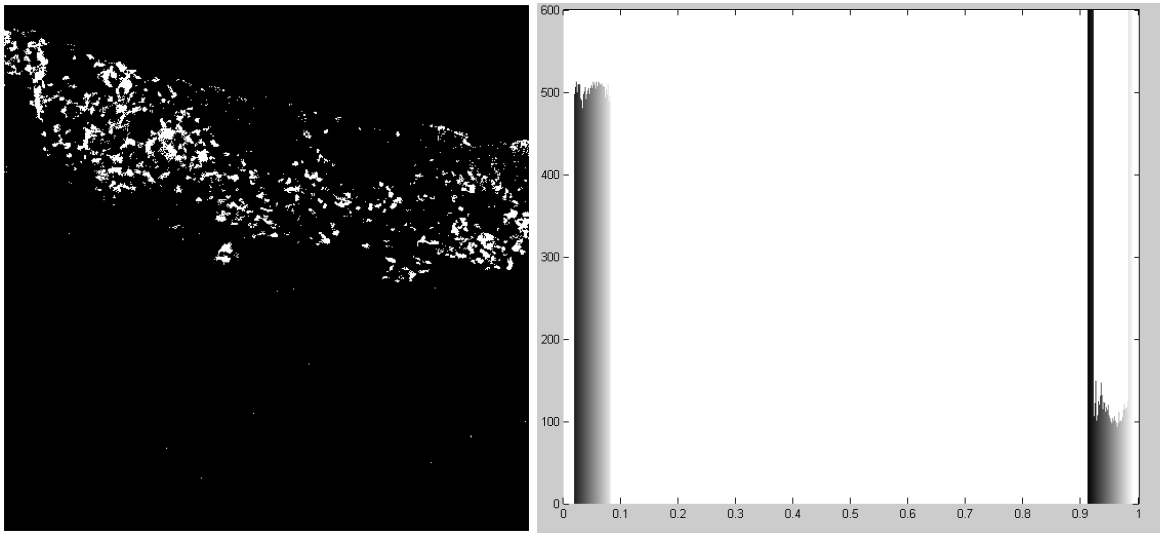
Code Used:

```
im=mean(double(imread('image150.jpg')),3);

[height width]=size(im);
pixels=height*width;

bins=[0:255]+0.5;
N=hist(reshape(im,pixels,1),bins);

%normalising the bin frequencies to make probabilities
Nnorm=N/sum(N);
%cumulative probability
theta=cumsum(Nnorm);
mu=cumsum(Nnorm.*[0:255]);
%Repeat on the image
%evaluate sigB2 over the t range
sigB2=(mu-mu(256)*theta).^2./(theta.*(1-theta));

%find the maximum value and the index where it is (this is the
Otsu threshold)
[p ot]=max(sigB2);

%thresholding
x=(im>ot);
figure(1)
imshow(x)
figure(2)
imshow(x)
hist(x);
```

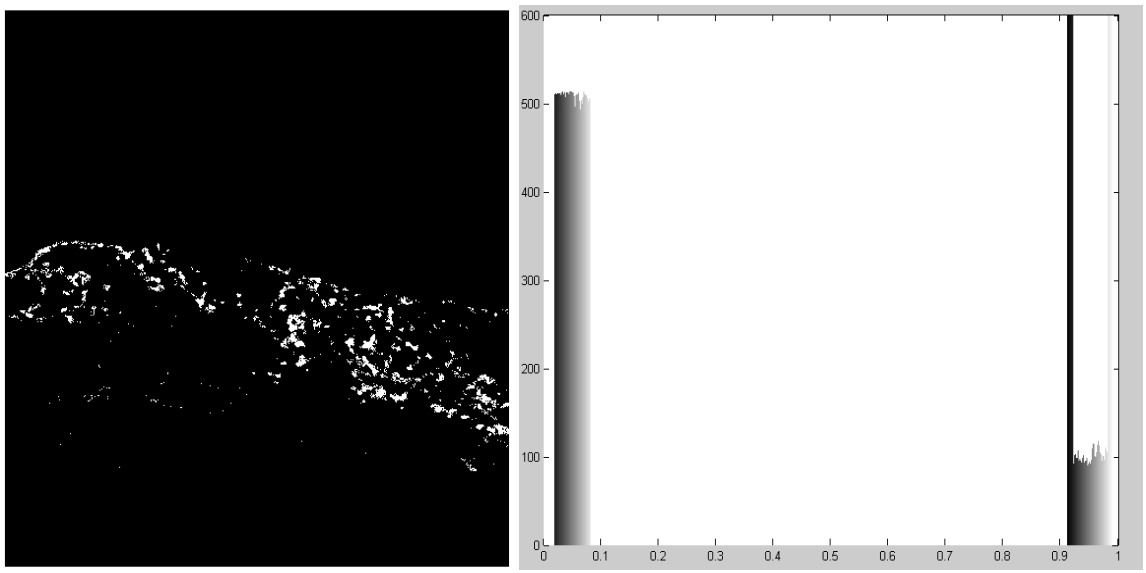
Tumor Depth at 10um



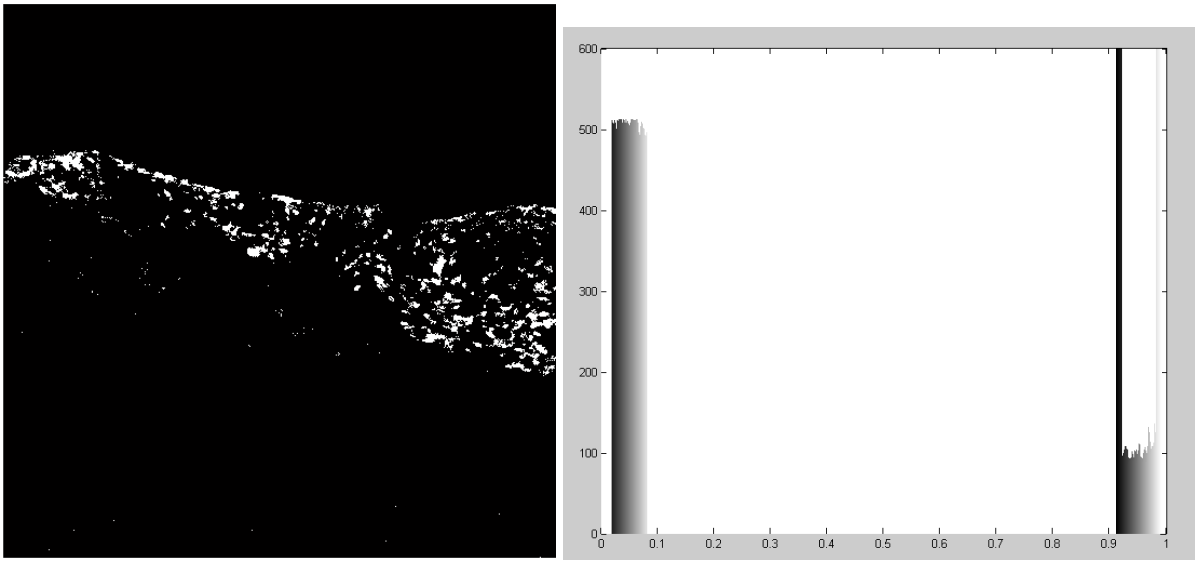
Tumor Depth at 30um



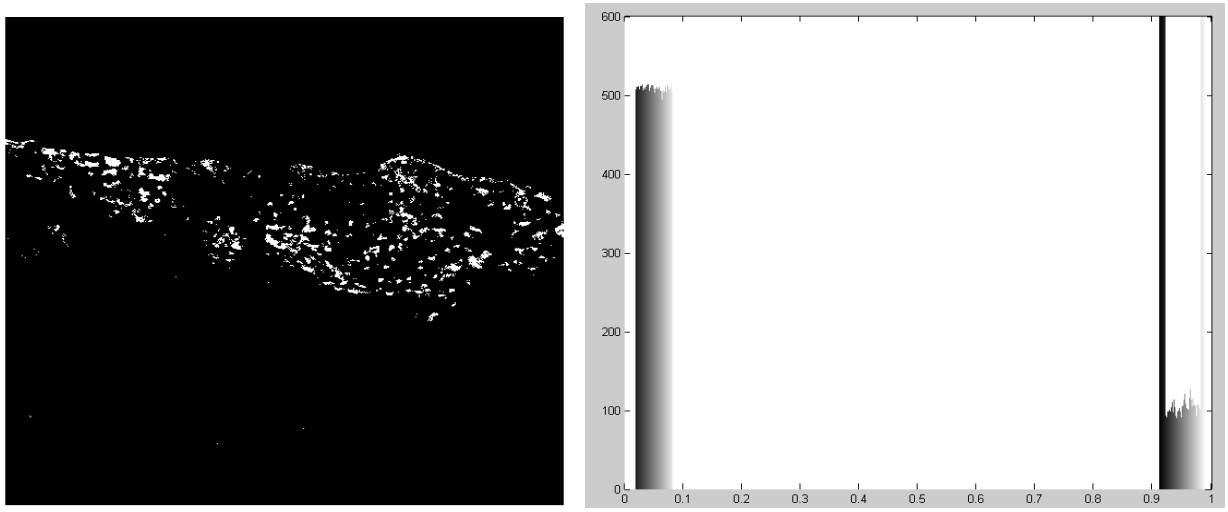
Tumor Depth at 40um



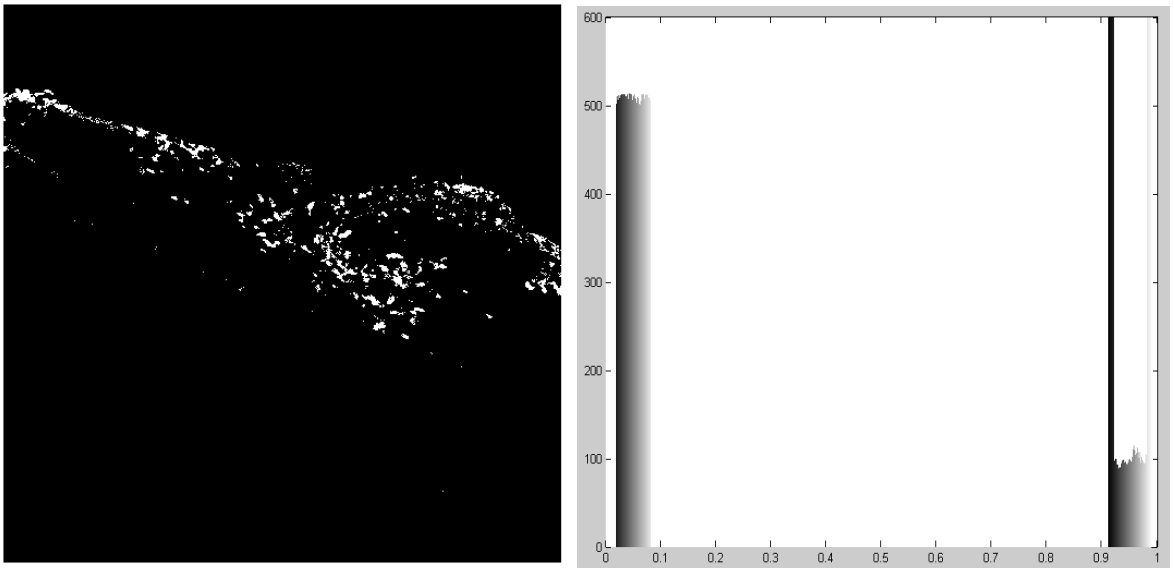
Tumor Depth at 60um



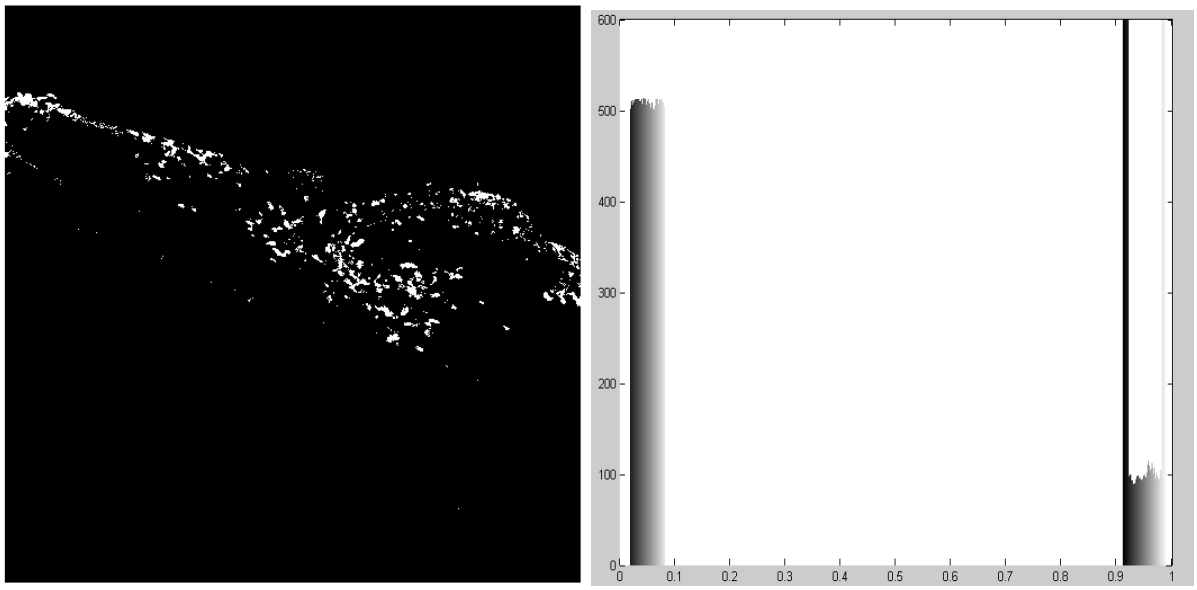
Tumor depth at 100um



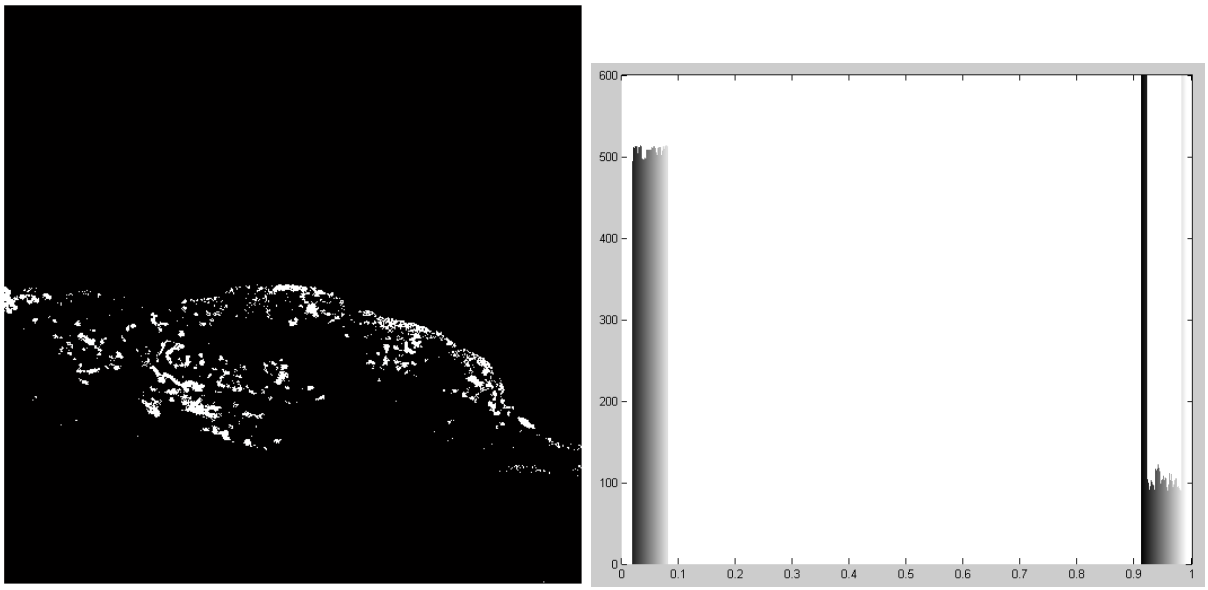
Tumor Depth at 110um



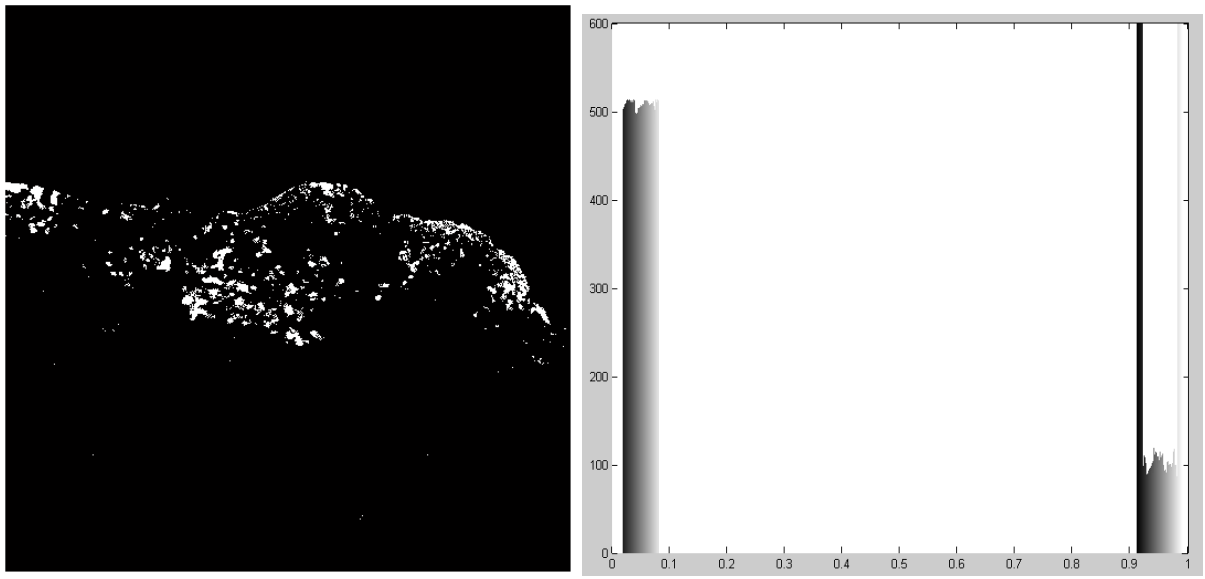
Tumor Depth at 120um



Tumor Depth at 140um



Tumor Depth at 150um



V. Discussion

Using the Otsu method, one could come up with several issues. The major problem with thresholding is that we tend to consider only the intensity, not any relationships between the pixels. There is no guarantee that the pixels identified by the thresholding method are contiguous. There's a possibility that we may miss isolated pixels inside the region. These possibilities are more possible as the noise gets worse, because it's more possible that a pixel's intensity will not represent the traditional intensity within the region. When we use thresholding, it sometimes loses too much data from a region or gets too many extraneous background pixels. The Otsu method can be used for several various things, but what we found most important is that it might be used to enhance tumor images. The enhancement of tumor images will help doctors and surgeons to exactly determine what the problem is and what the required procedure should be.

Attached on top of are the pictures of tumors at varied depths. Here we first took the raw image and its histogram, and processed it by using the Otsu method. Once we processed it, we now

get a clear image of where precisely the cancer is located on the tumor. In the real world we'd pass this image onto a surgeon, so that they can see the areas of interest more clearly. It can do this by taking the raw image of the cancer and highlighting the realm of interest, in this case the cancer cells that the surgeons plan of removing. The downside to this is that by altering the image the surgeon will lose the overall outline of the image, thus lacking the ability to examine how the cells are connected to one another – therefore, we advocate that surgeons look at both unprocessed and processed images. This way, surgeons can see visually how the cancerous region will look during surgery, while additionally being able to reference processed images to tailor their surgery. As these processed images become more information-packed, surgeons will have an easier time removing cancerous tissue while leaving healthy tissue behind.

VI. Conclusion

This project was the most practical application of our acquired knowledge at Manhattan College. By using algorithms and theory we had previously learned and applying them to a real-world problem, we are able to adequately prepare ourselves for the industry. Knowing theory is all fine and dandy, but without any applications experience that knowledge becomes useless.

The Otsu algorithm is a powerful method that can process images and use cluster-based thresholding to segment an image for processing. This assumes that the image contains two classes of pixels, and then calculates the optimal thresholding that would separate each class. The result is an image with two classes of pixels that has a minimized spread and maximized inter-class variance. However, this method is only one-dimensional, and therefore is only useful for specific images.

By processing images of tumors with Otsu's Method, we are able to highlight the difference between cancerous cells and healthy cells within that tumor – this way, surgeons remove only what they need to, allowing the patient to recover faster. As image processing within the medical field

grows stronger, the information that it can provide grows even faster. With more accurate data, surgeons and specialists can more accurately diagnose a patient, removing the need for unnecessary tests, saving both the patient and hospital money. Image processing also allows specialists to diagnose cancer earlier, resulting in quicker surgeries and a lower mortality rate.

Overall, the rise in image processing has directly led to a rise in longevity. By being able to detect cancer with a high sensitivity and earlier, patients no longer have to question their doctor's diagnoses and can receive tailored treatment faster. Patients will recover fast, less money will be spent on both ends, and the overall health of society will grow.