

## Image Segmentation

This report will cover my programming assignment 5 for CAP 5415 (Computer Vision).

### Implementation

The program implements the following methods:

1. **Grayscale loading** – load an image and represent it as a NumPy matrix.
2. **Histogram computation** – calculate the intensity distribution of pixel values.
3. **Class probability calculation** – compute cumulative probabilities for each potential threshold.
4. **Mean intensity calculation** – determine the mean intensity for foreground and background classes.
5. **Between-class variance** – compute  $\sigma^2_b$  to measure separation between classes.
6. **Threshold optimization** – find the threshold that maximizes between-class variance.
7. **Binarization** – apply the threshold to segment the image into binary output.

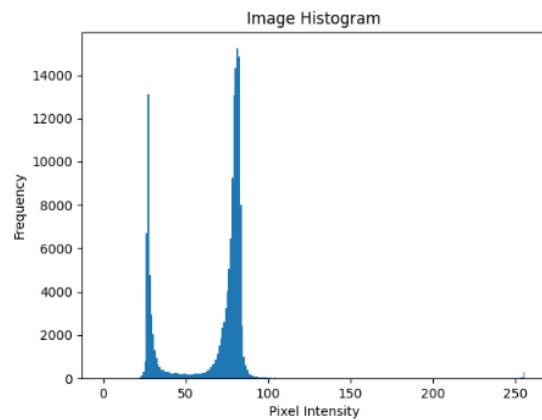
**Note:** a user can manually select their own threshold for testing. More details and step to replicate can be found on [this](#) repository.

The **Otsu Thresholding** algorithm followed the following pseudo-code:

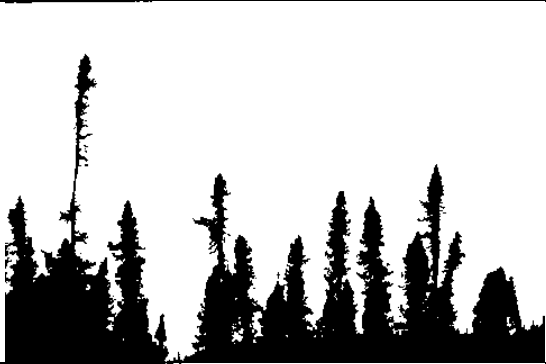
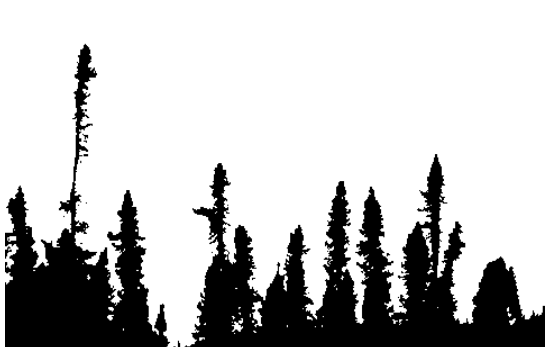
```
1: Input: Histogram  $H_I$ , max intensity  $G_{\max}$ , step size  $T_0$ 
2: Initialize:  $u = T_0$ ,  $T = u$ ,  $S_{\max} = 0$ 
3: while  $u < G_{\max}$  do
4:   Step 1: Compute Class Probabilities ( $P_1, P_2$ )
5:    $P_1 = \sum_{i=0}^u p(i)$ ,  $P_2 = \sum_{i=u+1}^{G_{\max}} p(i)$ 
6:   Step 2: Compute Class Means ( $\mu_1, \mu_2$ )
7:    $\mu_1 = \frac{1}{P_1} \sum_{i=0}^u i \cdot p(i)$ ,  $\mu_2 = \frac{1}{P_2} \sum_{i=u+1}^{G_{\max}} i \cdot p(i)$ 
8:   Step 3: Compute Between-Class Variance
9:    $\sigma_b^2(u) = P_1 P_2 (\mu_1 - \mu_2)^2$ 
10:  Step 4: Update Optimal Threshold
11:  if  $\sigma_b^2(u) > S_{\max}$  then
12:     $S_{\max} = \sigma_b^2(u)$ 
13:     $T = u$ 
14:  end if
15:   $u = u + T_0$ 
16: end while
17: Return  $T$ 
```

## Results

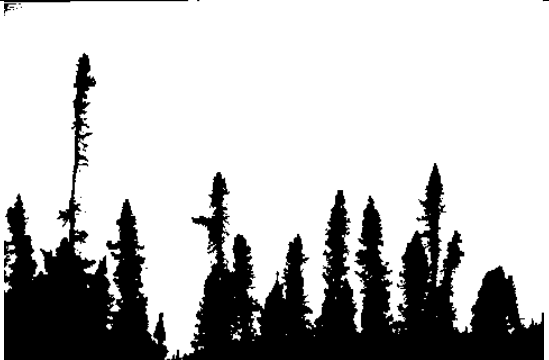

Image 238011.jpg



This image was one of the easier to segment because there was a very clear distinction between the foreground and background. We can see two clear peaks in the histogram, indicating the image consists of majority two colors.

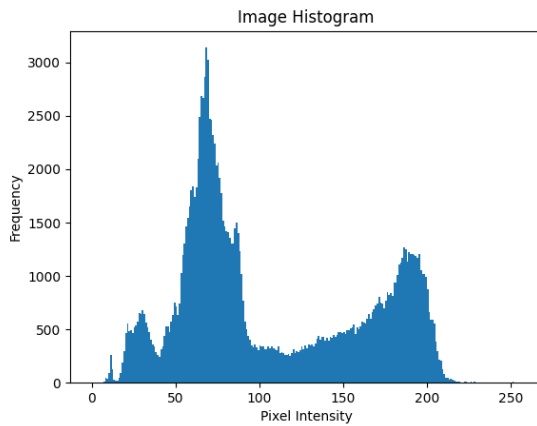
Manual Threshold 50	
Manual Threshold 55	

## Results

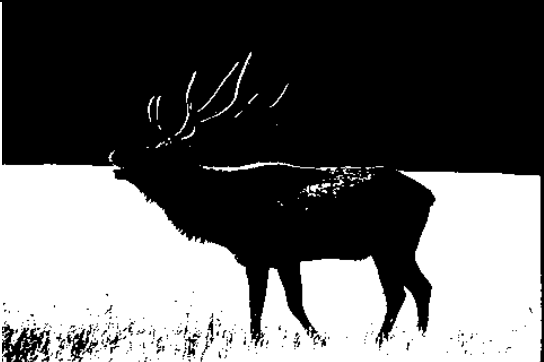

Manual Threshold 60	
Otsu Threshold 54	

## Results

### Image 41004.jpg

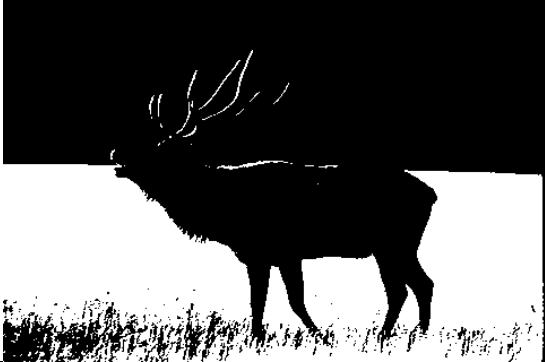



This image was significantly more difficult than the previous, since it contained many more different shades of different colors. For example, the grass in the front was a darker shade than the rest of the grass, and certain furs on the animal was a brighter color than the rest, making it very difficult to perfectly segment a specific feature.

Manual Threshold 115	
Manual Threshold 120	

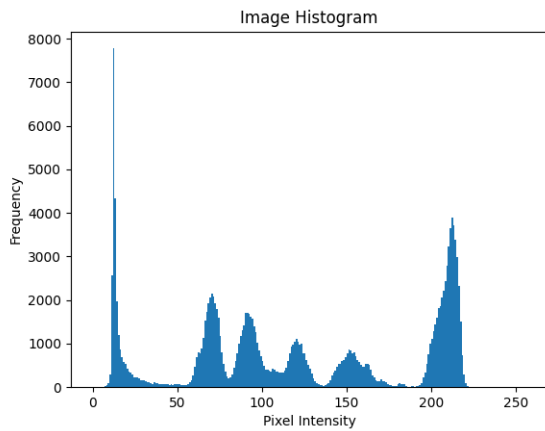
The table displays two thresholded versions of the deer image. The first row, labeled 'Manual Threshold 115', shows a binary image where the deer and its antlers are black against a white background. The second row, labeled 'Manual Threshold 120', shows a similar binary image, but with slightly different contrast and noise levels, particularly in the foreground grass area.

## Results

Manual Threshold 130	
Otsu Threshold 119	

## Results


### Image 55067.jpg



I believe this image is a perfect example of “Otsu thresholding doesn’t always work.” This image arguably gives over 6 different segments, and for best results, the user would have to manually indicate where they want to segment. For example, to separate the sky from the mountains, the ideal threshold would be at about 175, whereas Otsu predicted 131.

Manual Threshold 170	<p>The image shows the result of thresholding at 170. The sky is white, and the mountains and foreground are black. The mountains are mostly black, with some white speckles on the peaks.</p>
Manual Threshold 175	<p>The image shows the result of thresholding at 175. The sky is white, and the mountains and foreground are black. The mountains are mostly black, with some white speckles on the peaks.</p>

## Results

Manual Threshold 180	
Otsu Threshold 131	