Otsu’s Thresholding with OpenCV

What is Image Thresholding?

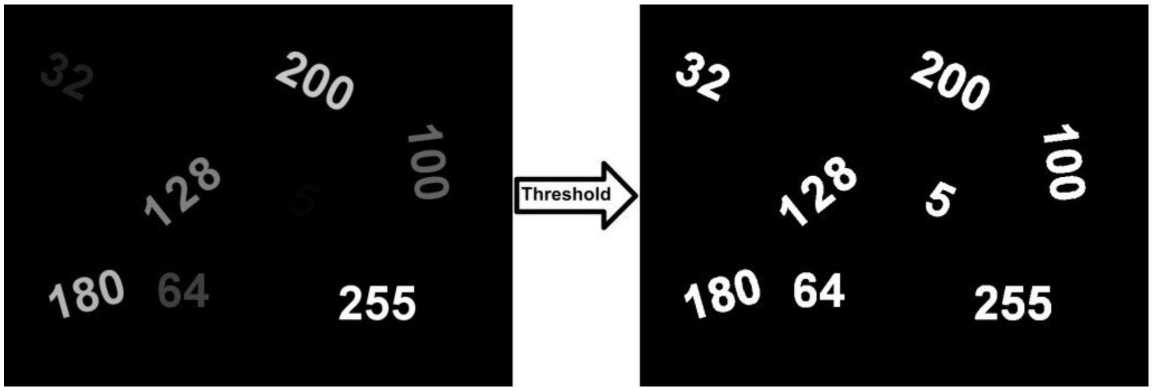


Image thresholding is used to binarize the image based on pixel intensities. The input to such thresholding algorithm is usually a grayscale image and a threshold. The output is a binary image.

If the intensity of a pixel in the input image is greater than a threshold, the corresponding output pixel is marked as white (foreground), and if the input pixel intensity intensity is less than or equal to the threshold, the output pixel location is marked black (background).

Image thresholding is used in many applications as a pre-processing step. For example, you may use it in medical image processing to reveal tumor in a mammogram or localize a natural disaster in satellite images.

A problem with simple thresholding is that you have to manually specify the threshold value. We can manually check how good a threshold is by trying different values but it is tedious and it may break down in the real world.

So, we need a way to automatically determine the threshold. The Otsu’s technique named after its creator Nobuyuki Otsu is a good example of auto thresholding.

Before we jump into the details of the technique let’s understand how image thresholding relates to image segmentation.

Image thresholding vs. Image Segmentation

Image segmentation refers to the class of algorithms that partition the image into different segments or groups of pixels.

In that sense, image thresholding is the simplest kind of image segmentation because it partitions the image into two groups of pixels — white for foreground, and black for background.

The figure below shows different types of segmentation algorithms:

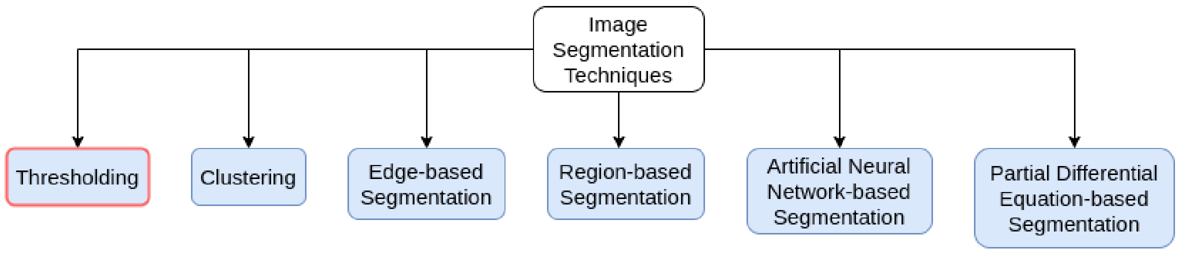


Image Segmentation Techniques
Thresholding
Clustering
Edge-based Segmentation
Region-based Segmentation
Artificial Neural Network-based Segmentation
Partial Differential Equation-based Segmentation

Pic. 1: Highlevel classification of image segmentation approaches

You can see image thresholding (shown using a red bounding box) is a type of image segmentation.

Image thresholding be future sub-divided into the **local** and **global** image thresholding algorithms.

In global thresholding, a single threshold is used globally, for the whole image.

In local thresholding, some characteristics of some local image areas (e.g. the local contrast) may be used to choose a different threshold for different parts of the image.

Otsu's method is a global image thresholding algorithm.

Otsu's Thresholding Concept

Automatic global thresholding algorithms usually have following steps.

1. Process the input image
2. Obtain image histogram (distribution of pixels)
3. Compute the threshold value T
4. Replace image pixels into white in those regions, where saturation is greater than T and into the black in the opposite cases.

Usually, different algorithms differ in step 3.

Let's understand the idea behind Otsu's approach. The method processes image histogram, segmenting the objects by minimization of the variance on each of the classes. Usually, this technique produces the appropriate results for bimodal images. The histogram of such image contains two clearly expressed peaks, which represent different ranges of intensity values.

The core idea is separating the image histogram into two clusters with a threshold defined as a result of minimization the weighted variance of these classes denoted by $\sigma_w^2(t)$.

The whole computation equation can be described as: $\sigma_w^2(t) = w_1(t)\sigma_1^2(t) + w_2(t)\sigma_2^2(t)$, where $w_1(t), w_2(t)$ are the probabilities of the two classes divided by a threshold t, which value is within the range from 0 to 255 inclusively.

As it was shown in the Otsu's paper there are actually two options to find the threshold. The first is to minimize the within-class variance defined above $\sigma_w^2(t)$, the second is to maximize the between-class variance using the expression below: $\sigma_b^2(t) = w_1(t)w_2(t)[\mu_1(t) - \mu_2(t)]^2$, where μ_i is a mean of class i.

The probability P is calculated for each pixel value in two separated clusters C_1, C_2 using the cluster probability functions expressed as: $w_1(t) = \sum_{i=1}^{t} P(i)$,
$w_2(t) = \sum_{i=t+1}^{I} P(i)$

It should be noted that the image can presented as intensity function $f(x, y)$, which values are gray-level. The quantity of the pixels with a specified gray-level i denotes by i. The general number of pixels in the image is n.
Thus, the probability of gray-level i occurrence is: $P(i) = \frac{n_i}{n}$.

The pixel intensity values for the C_1 are in $[1, t]$ and for C_2 are in $[t + 1, I]$, where I is the maximum pixel value (255).

The next phase is to obtain the means for C_1, C_2, which are denoted by $\mu_1(t), \mu_2(t)$ appropriately: $\mu_1(t) = \sum_{i=1}^{t} \frac{iP(i)}{w_1(t)}$,

$\mu_2(t) = \sum_{i=t+1}^{I} \frac{iP(i)}{w_2(t)}$

Now let's remember the above equation of the within-classes weighted variance. We will find the rest of its components (σ_1^2, σ_2^2) mixing all the obtained above ingredients: $\sigma_1^2(t) = \sum_{i=1}^{t} [i - \mu_1(t)]^2 \frac{P(i)}{w_1(t)}$,

$\sigma_2^2(t) = \sum_{i=t+1}^{I} [i - \mu_2(t)]^2 \frac{P(i)}{w_2(t)}$.

It should be noted that if the threshold was chosen incorrectly the variance of some class would be large. To get the total variance we simply need to summarize the within class and between-class variances: $\sigma_T^2 = \sigma_w^2(t) + \sigma_b^2(t)$, where $\sigma_b^2(t) = w_1(t)w_2(t)[\mu_1(t) - \mu_2(t)]^2$. The total variance of the image (σ_T^2) does not depend on the threshold.

Thus, the general algorithm's pipeline for the between-class variance maximization option can be represented in the following way:

1. calculate the histogram and intensity level probabilities
2. initialize $w_i(0), \mu_i(0)$
3. iterate over possible thresholds: $t = 0, ..., max\_intensity$
    - update the values of w_i, μ_i, where w_i is a probability and μ_i is a mean of class i

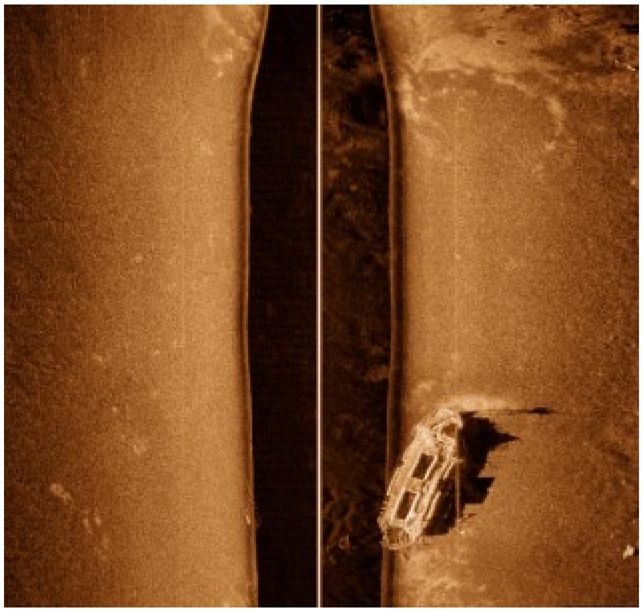
- calculate the between-class variance value $\sigma_b^2(t)$

4. the final threshold is the maximum $\sigma_b^2(t)$ value

Otsu's Binarization Application

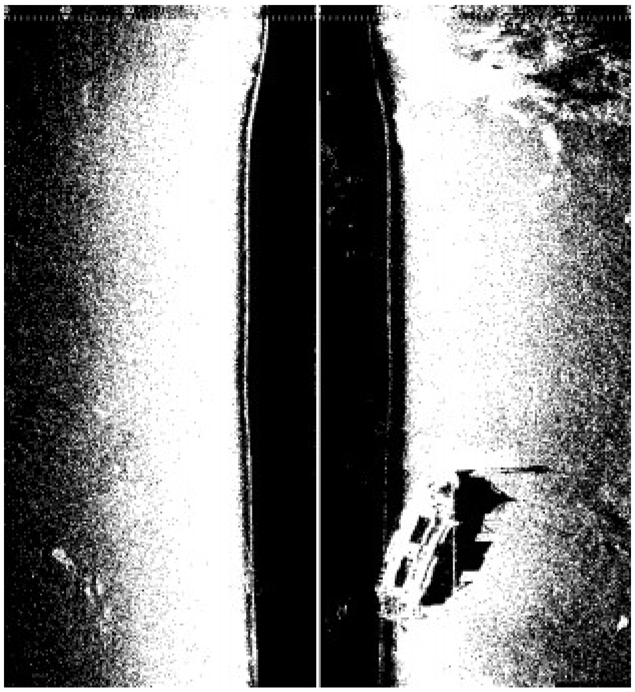
You could ask what is the real case where Otsu's approach could be applied? Despite the fact that the method was announced in 1979, it still forms the basis of some complex solutions. Let's take as an example an urgent task of robotic mapping, concluding in accurate spatial representation of any environment covered by a robot. This information is key for a properly robot autonomous functioning. The non-trivial case is underwater surface mapping described in the article "An improved Otsu threshold segmentation method for underwater simultaneous localization and mapping-based navigation".

The authors provide improved Otsu's method as one of the approaches for estimation of the underwater landmark localization. Advantages of such an approach are precise real-time segmentation of underwater features and proven performance in comparison with threshold segmentation methods. Let's view its idea more precisely using the provided in the article side-scan sonar (SSS) shipwreck image example. Modern SSS systems can cover large areas of the sea bottom performing two-dimensional realistic images. Thus, their background contains the regions of sludge and aquatic animals in form of spots usually <= 30 pixels (this further will be used as a parameter denoted by N_{30}).



Pic. 2: SSS sea bottom image

They distort correct image processing due to the similarity of their gray level to certain zones of foreground objects. Classical Otsu's technique results in the segmented image with these artifacts as we can see below:

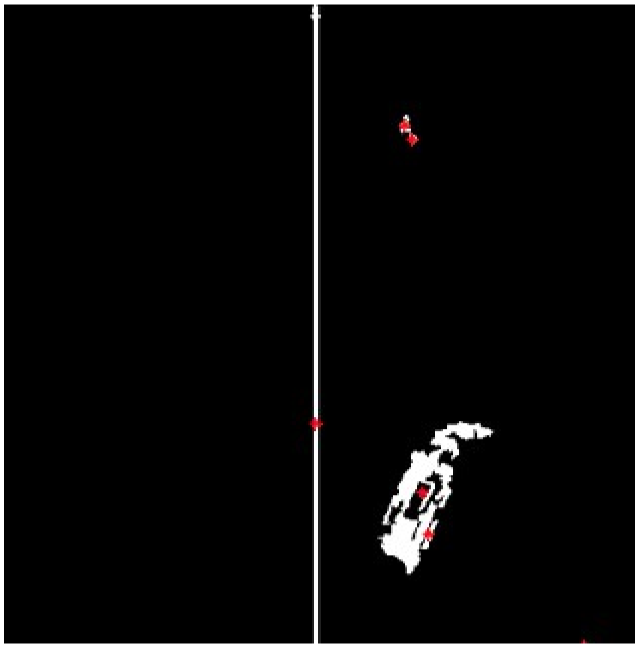


Pic. 3: SSS sea bottom image

The method based on Otsu's binarization was developed to deal with this spot challenge constraining the search range of the appropriate segmentation threshold for foreground object division. The improved Otsu's method pipeline is the following:

1. Obtain Otsu's threshold T
2. Apply Canny edge detection to compute N_{30}
3. if $N_{30} > 300$ compute final T value.

The result is clear wrecked ship separation from the background:



Pic. 4: Improved Otsu's result

Method Implementation

Let's implement Otsu's method on our own. It will look similar to threshold_otsu solution from the scikit-learn library, so feel free to use it as a reference. The function is built around maximization of the between-class variance (as we remember there is also minimization option) as OpenCV getThreshVal_Otsu.

The below image is used as input:

Pic. 5: Input image

Now let's go through the following necessary points in order to achieve the result.

1. Read Image.

First, we need to read image in a grayscale mode and its possible improvement with a Gaussian blur in order to reduce the noise:

```
# Read the image in a grayscale mode
image = cv2.imread(img_title, 0)

# Apply GaussianBlur to reduce image noise if it is required
if is_reduce_noise:
    image = cv2.GaussianBlur(image, (5, 5), 0)
```

In our case the image is quite qualitative, hence we set is_reduce_noise flag to False.

2. Calculate the Otsu's threshold.

The below code block represents the main algorithm computation part concluding in the threshold obtaining. The precise explanations of the lines can be found in the comments:

```
# Set total number of bins in the histogram
bins_num = 256

# Get the image histogram
hist, bin_edges = np.histogram(image, bins=bins_num)

# Get normalized histogram if it is required
if is_normalized:
    hist = np.divide(hist.ravel(), hist.max())

# Calculate centers of bins
bin_mids = (bin_edges[:-1] + bin_edges[1:]) / 2.

# Iterate over all thresholds (indices) and get the probabilities w1(t), w2(t)
weight1 = np.cumsum(hist)
weight2 = np.cumsum(hist[::-1])[::-1]

# Get the class means mu0(t)
mean1 = np.cumsum(hist * bin_mids) / weight1
# Get the class means mu1(t)
mean2 = (np.cumsum((hist * bin_mids)[::-1]) / weight2[::-1])[::-1]

inter_class_variance = weight1[:-1] * weight2[1:] * (mean1[:-1] -
mean2[1:]) ** 2

# Maximize the inter_class_variance function val
index_of_max_val = np.argmax(inter_class_variance)

threshold = bin_mids[:-1][index_of_max_val]
print("Otsu's algorithm implementation thresholding result: ", threshold)
```

3. Results.

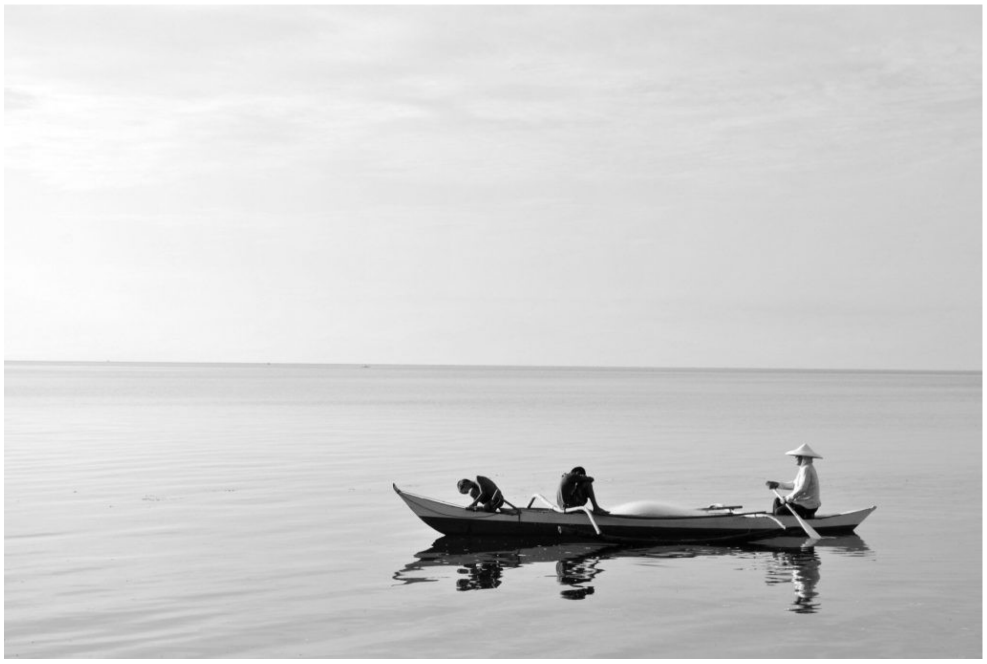
The execution result is:

```
Otsu's algorithm implementation thresholding result: 131.982421875
```

Now we better understand the algorithm’s essence after its whole pipeline implementation. Let’s explore how we can obtain the same result using the already implemented threshold method from the OpenCV library.

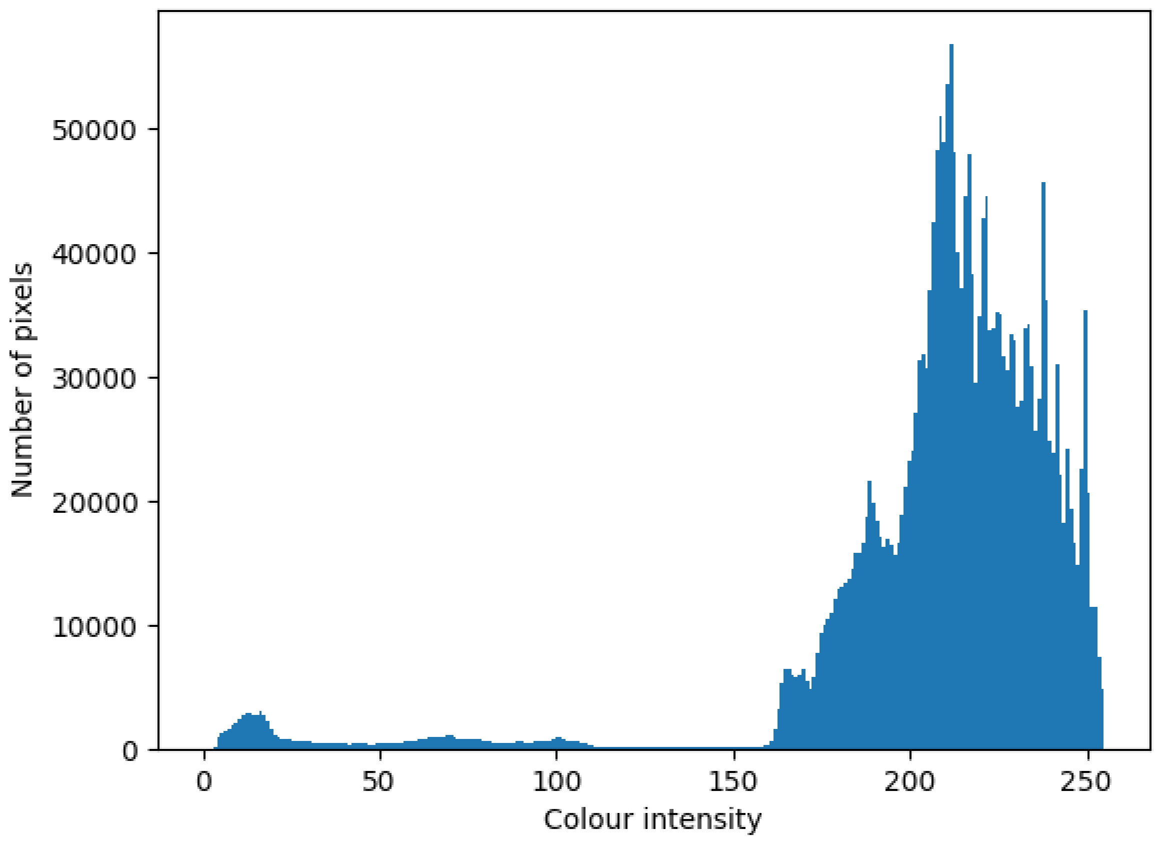
1. Read Image.

The first step is the same – image loading in a grayscale mode with a possible noise reduction. Let’s visualize the results of the preprocessed image and its histogram:



Pic. 6: Preprocessed image

In the below image histogram we can see clearly expressed mono peak and its near region and slightly expressed peak at the beginning of the scale:



Pic. 7. Image histogram

2. Calculate the Otsu's threshold.

To apply Otsu's technique we simply need to use OpenCV threshold function with set THRESH_OTSU flag:

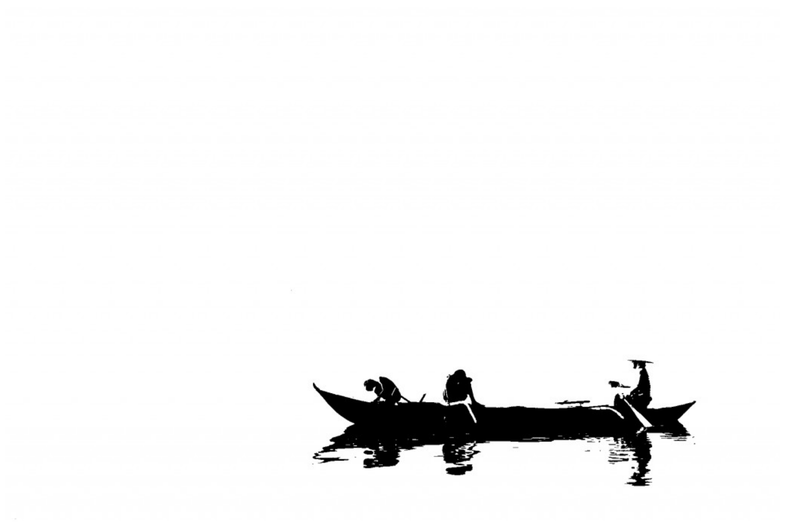
```
# Applying Otsu's method setting the flag value into
cv.THRESH_OTSU.
# Use a bimodal image as an input.
# Optimal threshold value is determined automatically.
otsu_threshold, image_result = cv2.threshold(
     image, 0, 255, cv2.THRESH_BINARY + cv2.THRESH_OTSU,
)
print("Obtained threshold: ", otsu_threshold)
```

3. Results.

The threshold value is near the obtained above in a handmade case (131.98):

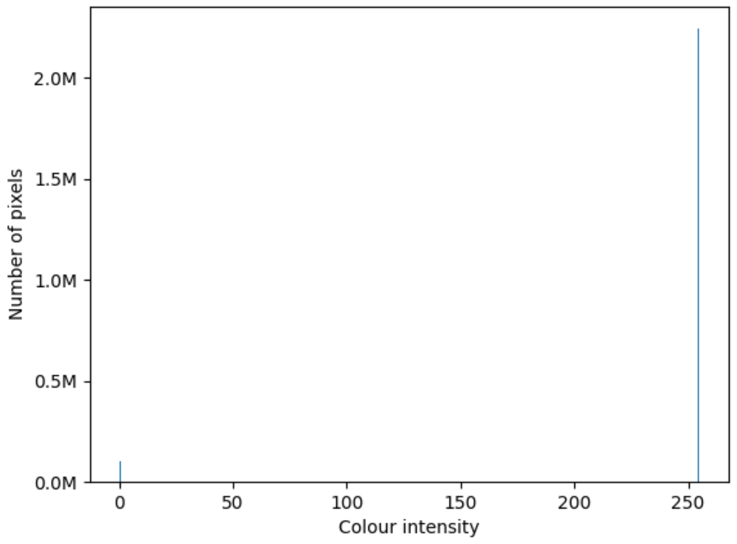
```
Obtained threshold:  132.0
```

Now let’s view the final binarized image after Otsu’s method application:



Pic. 8: Otsu’s method result

We can clearly observe that the background and the main objects in the picture were separated. Let’s draw a histogram for the obtained binarized image:



Pic. 9: Otsu’s method result