

Visión Computacional para imágenes y video (Gpo 10)

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6. Otsu Thresholding

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Thresholding is used to create a binary image from a grayscale image

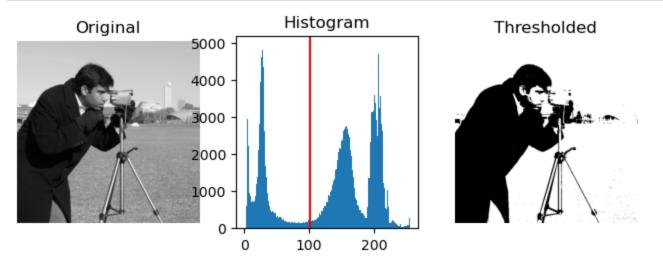
Importing Libraries

```
In [1]: import matplotlib.pyplot as plt
    from skimage import data
    from skimage.filters import threshold_otsu
    from skimage.filters import threshold_multiotsu
    import numpy as np
    import cv2
```

Single Thresholding

We illustrate how to apply one of these thresholding algorithms. Otsu's method [2]_ calculates an "optimal" threshold (marked by a red line in the histogram below) by maximizing the variance between two classes of pixels, which are separated by the threshold. Equivalently, this threshold minimizes the intra-class variance.

```
image = data.camera()
In [2]:
        thresh = threshold otsu(image)
        binary = image > thresh
        fig, axes = plt.subplots(ncols=3, figsize=(8, 2.5))
        ax = axes.ravel()
        ax[0] = plt.subplot(1, 3, 1)
        ax[1] = plt.subplot(1, 3, 2)
        ax[2] = plt.subplot(1, 3, 3, sharex=ax[0], sharey=ax[0])
        ax[0].imshow(image, cmap=plt.cm.gray)
        ax[0].set title('Original')
        ax[0].axis('off')
        ax[1].hist(image.ravel(), bins=256)
        ax[1].set title('Histogram')
        ax[1].axvline(thresh, color='r')
        ax[2].imshow(binary, cmap=plt.cm.gray)
        ax[2].set title('Thresholded')
        ax[2].axis('off')
        plt.show()
```



If you are not familiar with the details of the different algorithms and the underlying assumptions, it is often difficult to know which algorithm will give the best results. Therefore, Scikit-image includes a function to evaluate thresholding algorithms provided by the library. At a glance, you can select the best algorithm for your data without a deep understanding of their mechanisms.

```
In [3]: from skimage.filters import try_all_threshold
  img = data.page()
  fig, ax = try_all_threshold(img, figsize=(10, 8), verbose=False)
  plt.show()
```

Original

Region-based segmentation

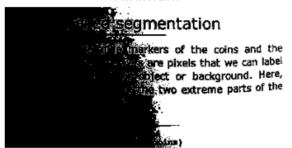
Let us first determine markers of the coins and the background. These markers are pixels that we can label unambiguously as either object or background. Here, the markers are found at the two extreme parts of the histogram of grey values:

markers = np.zeros_like(coins)

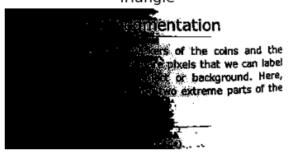
Li

on-based segmentation ist determine markers of the coins and the These markers are pixels that we can label to a seither object or background. Here, are found at the two extreme parts of the servy values:

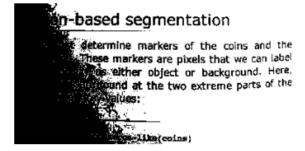
Minimum



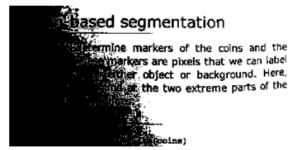
Triangle



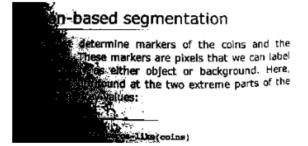
Isodata



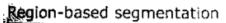
Mean



Otsu



Yen



the first determine markers of the coins and the ground. These markers are pixels that we can label biguously as either object or background. Here, arkers are found at the two extreme parts of the time of grey values:

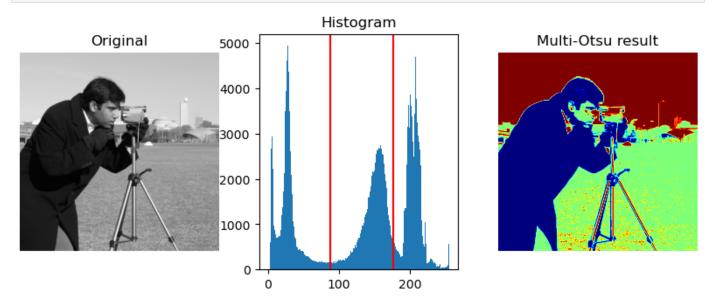
pr = np.zeros_like(coins)

Multi Thresholding

The multi-Otsu threshold is a thresholding algorithm that is used to separate the pixels of an input image into several different classes, each one obtained according to the intensity of the gray levels within the image.

Multi-Otsu calculates several thresholds, determined by the number of desired classes. The default number of classes is 3: for obtaining three classes, the algorithm returns two threshold values. They are represented by a red line in the histogram below.

```
# The input image.
In [4]:
        image = data.camera()
        # Applying multi-Otsu threshold for the default value, generating
        # three classes.
        thresholds = threshold multiotsu(image)
        # Using the threshold values, we generate the three regions.
        regions = np.digitize(image, bins=thresholds)
        fig, ax = plt.subplots(nrows=1, ncols=3, figsize=(10, 3.5))
        # Plotting the original image.
        ax[0].imshow(image, cmap='gray')
        ax[0].set title('Original')
        ax[0].axis('off')
        # Plotting the histogram and the two thresholds obtained from
        # multi-Otsu.
        ax[1].hist(image.ravel(), bins=255)
        ax[1].set title('Histogram')
        for thresh in thresholds:
            ax[1].axvline(thresh, color='r')
        # Plotting the Multi Otsu result.
        ax[2].imshow(regions, cmap='jet')
        ax[2].set title('Multi-Otsu result')
        ax[2].axis('off')
        plt.subplots adjust()
        plt.show()
```



Excersises

In this exercise we worked with different images, experimenting with a couple of use cases for the single and multi-thresholding algorithms on different images.

Single thresholding consists of binarizing an image, usually on black and white and apply detect a threshold where pixel will be separated based on its intensity value. If the value of the pixel is higher than the threshold they will be marked as white else, they will be considered black pixels.

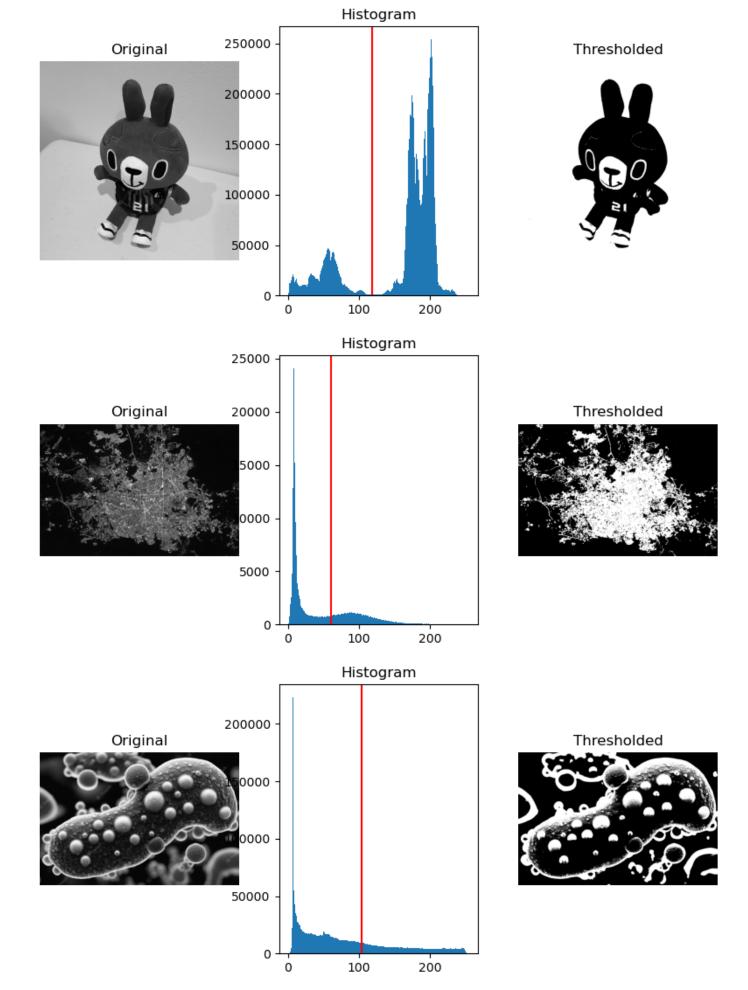
On the other hand, Otsu Multi thresholding it's a technique which allows us to split the image on multiple regions using multiple thresholds for pixel values.

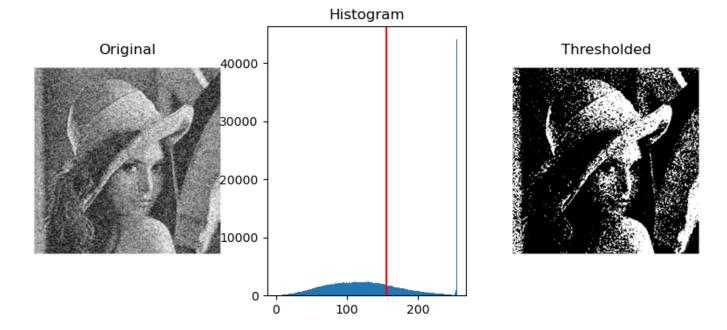
In our examples we take 3 use cases for image thresholding algorithms: edge detection on object photos, satellite images and medical/lab images. We believe that using these examples will lead us to a better understanding of the algorithms' functionality.

```
In [5]: # We start by saving the filepaths to our example images into a list.
imgs_toRead = ['data/bunny_5.jpg', 'data/satelite2.jpg', 'data/microscope.jpeg', 'data/l
```

Single Tresholding

```
# Then we replicate the single thresholding algorithm into a new function
In [6]:
        # to be able to reuse it as we want by just passing an image as a parameter
        def single tresh(image):
            thresh = threshold otsu(image)
            binary = image > thresh
            fig, axes = plt.subplots(ncols=3, figsize=(10, 4))
            ax = axes.ravel()
            ax[0] = plt.subplot(1, 3, 1)
            ax[1] = plt.subplot(1, 3, 2)
            ax[2] = plt.subplot(1, 3, 3, sharex=ax[0], sharey=ax[0])
            ax[0].imshow(image, cmap=plt.cm.gray)
            ax[0].set title('Original')
            ax[0].axis('off')
            ax[1].hist(image.ravel(), bins=256)
            ax[1].set title('Histogram')
            ax[1].axvline(thresh, color='r')
            ax[2].imshow(binary, cmap=plt.cm.gray)
            ax[2].set title('Thresholded')
            ax[2].axis('off')
            plt.show()
        # Using our list of filepaths we import the files and send it to our created function he
        for img in imgs toRead:
            single tresh(cv2.cvtColor(cv2.imread(img), cv2.COLOR BGR2GRAY))
```

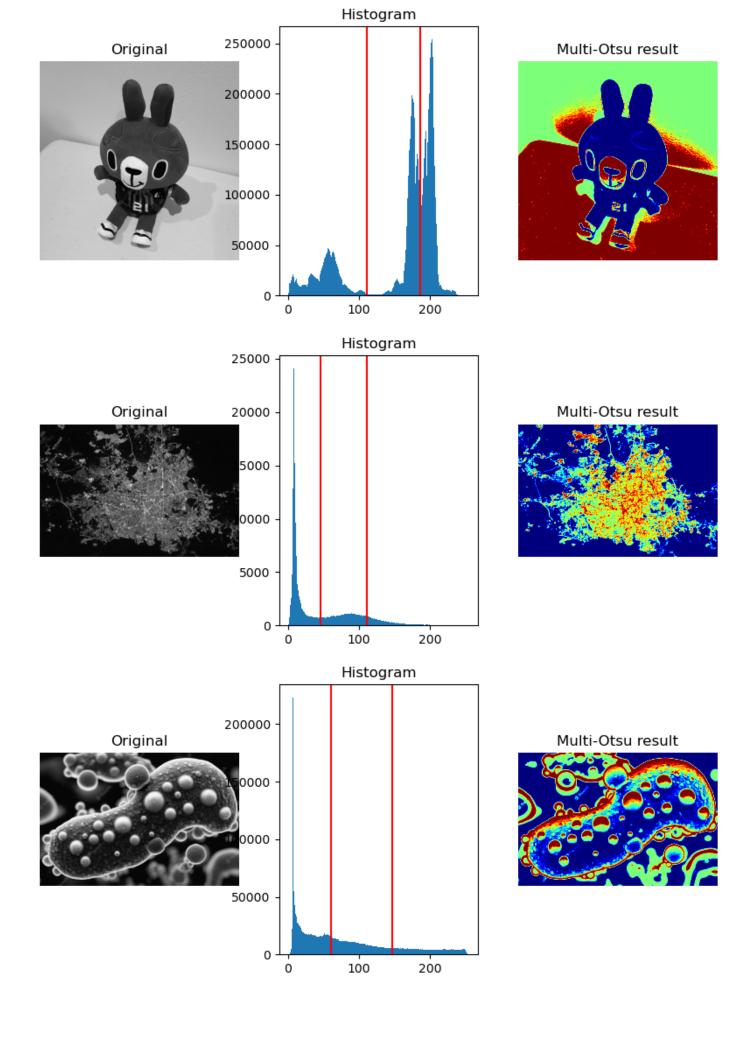


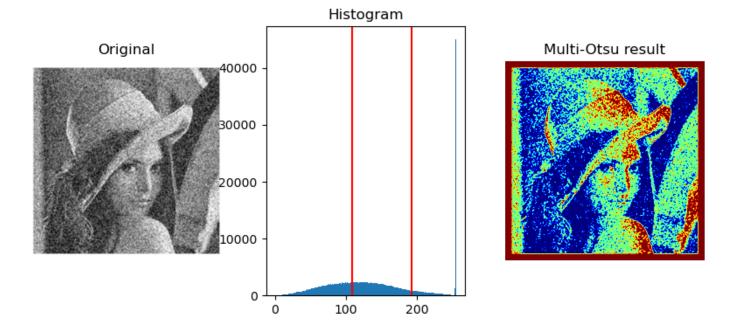


We can observe how single thresholding although is a simple technique and it doesn't always provides with the best results for complex image segmentation could provide us with a first preprocessing step in simpler applications.

Multi Tresholding

```
# Then we repeat the process for the multi thresholding algorithm
In [7]:
        # Replicating the alogorithm into a new function that will take only an image as a param
        def multi tresh(image):
            thresholds = threshold multiotsu(image)
            regions = np.digitize(image, bins=thresholds)
            fig, ax = plt.subplots(nrows=1, ncols=3, figsize=(10, 4))
            ax[0].imshow(image, cmap='gray')
            ax[0].set title('Original')
            ax[0].axis('off')
            ax[1].hist(image.ravel(), bins=255)
            ax[1].set title('Histogram')
            for thresh in thresholds:
                ax[1].axvline(thresh, color='r')
            ax[2].imshow(regions, cmap='jet')
            ax[2].set title('Multi-Otsu result')
            ax[2].axis('off')
            plt.subplots adjust()
            plt.show()
        for img in imgs toRead:
            multi tresh(cv2.cvtColor(cv2.imread(img), cv2.COLOR BGR2GRAY))
```





As we can observe after applying both algorithms the multi-thresholding could be considered a more advanced image processing technique than the simple one. By splitting our images into multiple regions not just one, we are able to detect more objects into an image.

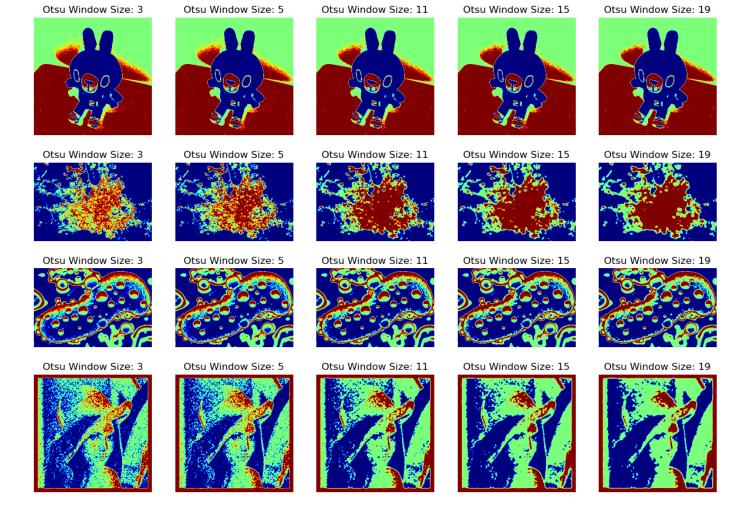
We believe that applying the single thresholding algorithm to an image with 2 clear histogram high points (e.g., the bunny image) can yield better results than the multi thresholding algorithm. However, when there are more complex images, with multiple high histogram values is better to use the later one.

Some of the disadvantages of the single thresholding algorithm against the multi thresholding we could identify are:

- Robustness to light changes in an image, as we see on the satellite image, some details are lost on the single thresholding implementation while on the multi thresholding we can see more details (streets).
- Adaptability to noisy images, as we can see on Lena's image, the single thresholding algorithm loses some details on the image due to its binary nature.

Different Size Windows

```
def multipleWIndowSize(image):
In [8]:
           wsizes = [3,5, 11, 15, 19]
           fig, ax = plt.subplots(nrows=1, ncols=len(wsizes), figsize=(15, 6))
            for i, size in enumerate(wsizes):
               gaus img = cv2.GaussianBlur(image, (size, size), 0)
                thresholds = threshold multiotsu(gaus img)
                img ots = np.digitize(gaus img, bins=thresholds)
                #img ots = cv2.adaptiveThreshold(gaus img, 255, cv2.ADAPTIVE THRESH GAUSSIAN C,
                ax[i].imshow(img ots, cmap='jet')
                ax[i].set title(f'Otsu Window Size: {size}')
                ax[i].axis('off')
            plt.subplots adjust()
            plt.show()
       for img in imgs toRead:
            multipleWIndowSize(cv2.imread(img , 0))
```



Conclusion

Otsu algorithm is a useful thresholding technique that we can leverage to implement image segmentation on grayscale images with regions of interest based on the level of intensity of the pixels contained in the image. By being able to select the optimal threshold to separate such regions and obtained a better result.

On this exercise we learn that the simple thresholding is a fast and easy to implement technique to get familiar with the algorithm, however, it could not be appropriate to implement it on complex images with irregular lightning or noise. On the other hand, the multi-thresholding Otsu technique it's a more advanced technique that could be useful for the previous issues mentioned on the single thresholding algorithm, although it can be harder and costly to implement.

Last but not least, we observe the implementation of the adaptative thresholding algorithm in which we used different window sizes to smooth the image and then apply the algorithm to obtain the thresholds on this smoothed image, this allowed us to observed different results on the different images we have and we could observe how the textures and the illumination are a key factor to take into consideration when applying a segmentation algorithm.

These techniques are powerful tools that can be used on multiple real-life applications, and it will be up to the developer to decide which technique will adapt best to its needs.

References

[1] Gonzalez, R. C., & Woods, R. E. (2018). Digital image processing (Fourth edition.). Pearson.

- [2] Senthilkumaranand, N., Vaithegi S. (2016). Image Segmentation by using thresholding techniques for medical images. CSEIJ.
- [3] Otsu's method for image thresholding explained and implemented. Muthu.Co. https://muthu.co/otsus-method-for-image-thresholding-explained-and-implemented/
- [4] Wang, Y. (2018). Improved OTSU and adaptive genetic algorithm for infrared image segmentation. 2018 Chinese Control And Decision Conference (CCDC), 5644–5648.