6_segmentation_otsu_Guillermo

March 11, 2024

- 1 Maestría en Inteligencia Artificial Aplicada
- 2 TC 4033: Visión computacional para imágenes y video
- 3 Tecnológico de Monterrey
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- 4 # 6. Otsu Thresholding
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Thresholding is used to create a binary image from a grayscale image

4.3 Importing Libraries

```
[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
```

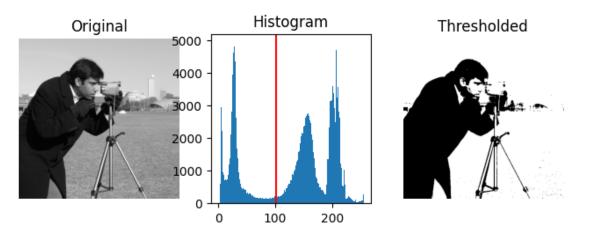
4.4 Single Thresholding

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.

```
[4]: image = data.camera()
     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()
```

<ipython-input-4-ce81723eaa7b>:9: MatplotlibDeprecationWarning: Auto-removal of
overlapping axes is deprecated since 3.6 and will be removed two minor releases
later; explicitly call ax.remove() as needed.

ax[2] = plt.subplot(1, 3, 3, sharex=ax[0], sharey=ax[0])



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.

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



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:

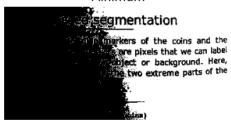
arkers = np.zeros_like(coins)

on-based segmentation

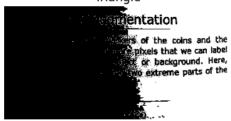
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ica_lika(coins)

Minimum



Triangle



Isodata

n-based segmentation

etermine markers of the coins and the riese markers are pixels that we can label as either object or background. Here, found at the two extreme parts of the values:

Mean

Based segmentation

parkers of the coins and the parkers are pixels that we can label tiper object or background. Here, the two extreme parts of the

Otsu

n-based segmentation

etermine markers of the coins and the Phese markers are pixels that we can label the selfther object or background. Here, cound at the two extreme parts of the values:

Yen

Region-based segmentation

rus 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 am of grey values:

mr. = ap.zeros_like(coins)

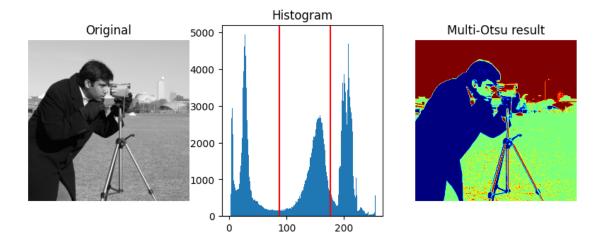
```
[6]: # TODO: Slide image for segmentation, alpha blerding
```

4.5 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.

```
[7]: # The input image.
     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()
```



5 Ejercicio

6 1.

Experimenta con diferentes imagenes ademas de las provistas en en Colab, identifica imagenes con diferentes backgrounds y estilos, cuales son las limitaciones de single thresholding contra el algoritmo de Otsu

Comenzamos creando una función para aplicar el método de otsu para 1 solo threshold:

```
[8]: def single_tres_otsu(img):
         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.subplots_adjust()
plt.show()
```

Cargamos 6 imágenes utilizadas en actividades previas:

```
[9]: image_1 = cv2.imread('/content/image_1.jpg', cv2.IMREAD_GRAYSCALE)
image_2 = cv2.imread('/content/image_2.jpg', cv2.IMREAD_GRAYSCALE)
image_3 = cv2.imread('/content/image_3.jpg', cv2.IMREAD_GRAYSCALE)
image_4 = cv2.imread('/content/image_4.jpg', cv2.IMREAD_GRAYSCALE)
image_5 = cv2.imread('/content/image_5.jpg', cv2.IMREAD_GRAYSCALE)
image_6 = cv2.imread('/content/image_6.jpg', cv2.IMREAD_GRAYSCALE)
images = []
images = []
```

Aplicamos median filter a un par de ellas para mejor funcionamiento:

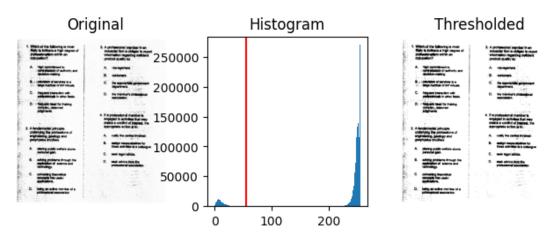
```
[10]: images[0] = cv2.medianBlur(images[0], 5)
images[1] = cv2.medianBlur(images[1], 5)
#images[4] = cv2.medianBlur(images[4], 5)
#images[5] = cv2.medianBlur(images[5], 5)
```

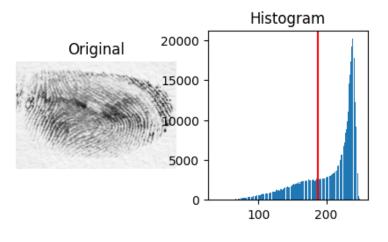
Aplicamos el método a cada una:

```
[11]: for image in images: single_tres_otsu(image)
```

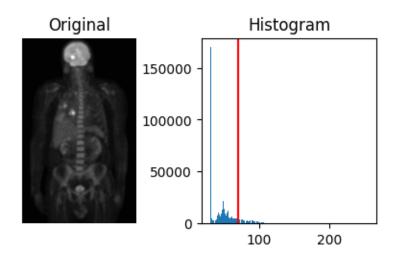
<ipython-input-8-1577835ef629>:9: MatplotlibDeprecationWarning: Auto-removal of
overlapping axes is deprecated since 3.6 and will be removed two minor releases
later; explicitly call ax.remove() as needed.

ax[2] = plt.subplot(1, 3, 3, sharex=ax[0], sharey=ax[0])

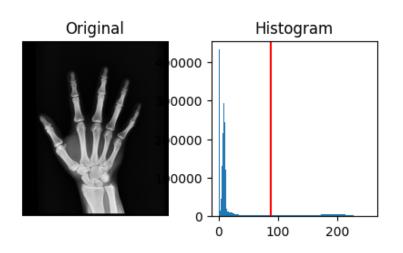




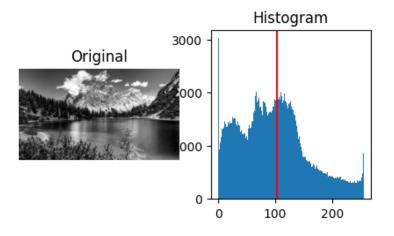


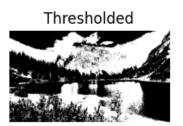


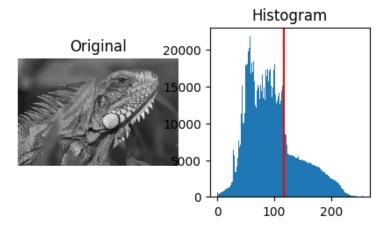














Ahora generamos una función para aplicar le método de threshold múltiple:

```
[12]: def multi_tres_otsu(image):
    thresholds = threshold_multiotsu(image)
    regions = np.digitize(image, bins=thresholds)

fig, ax = plt.subplots(nrows=1, ncols=3, figsize=(10, 3.5))

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')

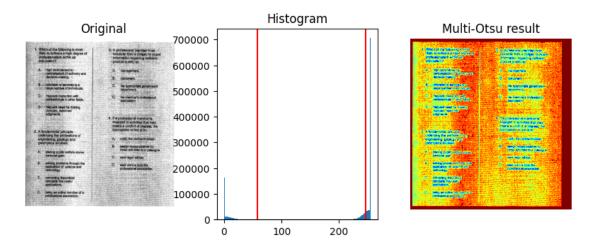
plt.subplots_adjust()

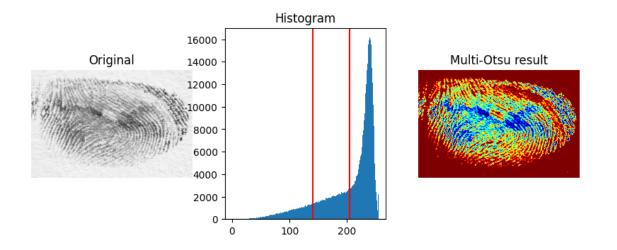
plt.show()
```

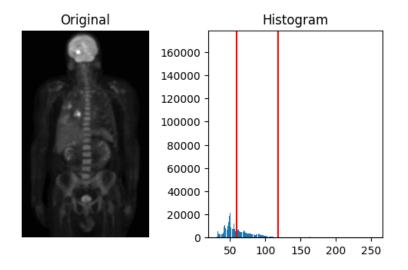
Lo aplicamos a las mismas imágenes:

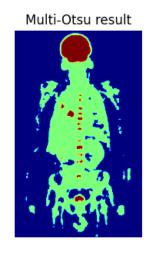
```
[13]: images = [image_1, image_2, image_3, image_4, image_5, image_6]
```

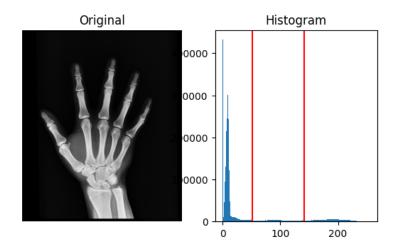
```
[14]: for image in images:
    multi_tres_otsu(image)
```



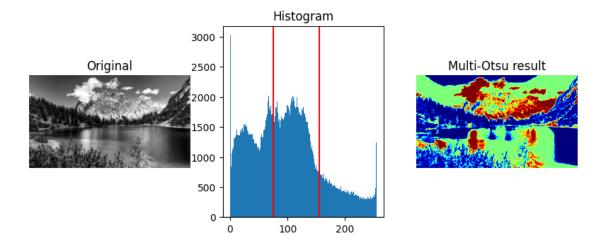


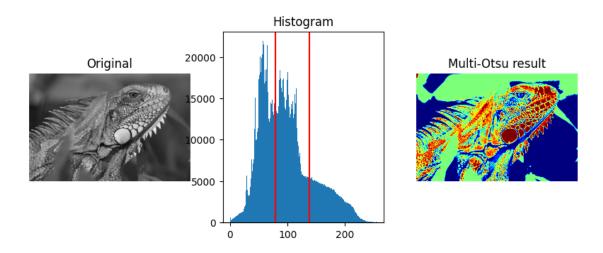












7 2. (Opcional)

Como en un proyecto previo, es posible aplicar Otsu para ventanas de diferentes tamaños, obteniendo mejores resultados. Realiza esta implementacion y ve como mejoran los resultados con el ejemplo de la hoja de papel.

Función para Otsu general

```
[15]: def otsu_proc(image):
    thresh = threshold_otsu(image)
    binary = image > thresh
    return binary
```

Imagen sobre la cuál vamos a trabajar

[17]: imagen = data.page()

Dividimos la imagen en 4 ventanas

```
[18]: (h, w) = imagen.shape[:2]
# compute the center coordinate of the image
(cX, cY) = (w // 2, h // 2)
```

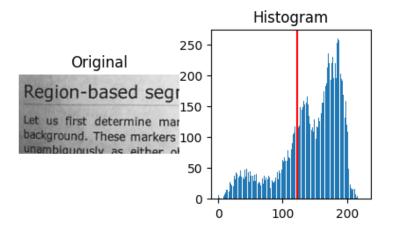
```
[19]: topLeft = imagen[0:cY, 0:cX]
topRight = imagen[0:cY, cX:w]
bottomLeft = imagen[cY:h, 0:cX]
bottomRight = imagen[cY:h, cX:w]
```

```
[20]: images_w = []
images_w = [topLeft, topRight, bottomLeft, bottomRight]
```

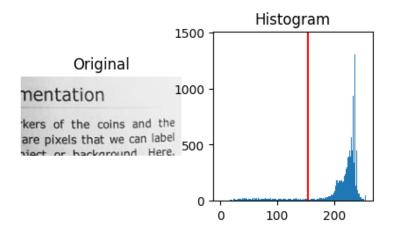
```
[21]: for image in images_w: single_tres_otsu(image)
```

<ipython-input-8-1577835ef629>:9: MatplotlibDeprecationWarning: Auto-removal of
overlapping axes is deprecated since 3.6 and will be removed two minor releases
later; explicitly call ax.remove() as needed.

ax[2] = plt.subplot(1, 3, 3, sharex=ax[0], sharey=ax[0])



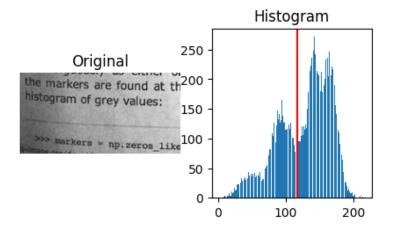
Thresholded Region-based segr Lus first determine mar erround. These markers blowersty as either of

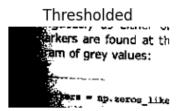


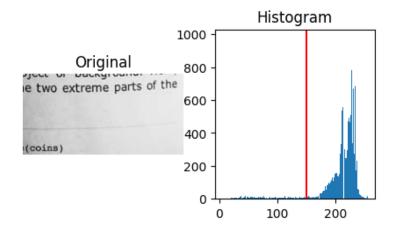
Thresholded

nentation

'kers of the coins and the are pixels that we can label afect on background. Here.







Thresholded se two extreme parts of the

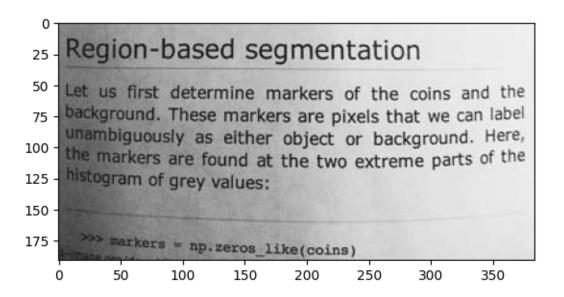
(coins)

```
[22]: otsu_img = []
      for image in images_w:
        otsu_img.append(otsu_proc(image))
[24]: from PIL import Image
      image_tl = Image.fromarray(otsu_img[0])
      image_tr = Image.fromarray(otsu_img[1])
      image_bl = Image.fromarray(otsu_img[2])
      image_br = Image.fromarray(otsu_img[3])
[25]: #resize, first image
      image1 = image_tl
      image2 = image_tr
      image3 = image_bl
      image4 = image_br
      image1_size = image_tl.size
      image2_size = image_tr.size
      image3_size = image_bl.size
      image4_size = image_br.size
      new_image = Image.new('RGB',(2*image1_size[0], 2*image1_size[1]))
      new_image.paste(image1,(0,0))
      new_image.paste(image2,(image1_size[0],0))
      new_image.paste(image3,(0,image1_size[1]))
      new_image.paste(image4,(image1_size[0],image2_size[1]))
     new_image.save("/content/merged_image.jpg","JPEG")
```

Imagen Original

```
[26]: plt.imshow(imagen, cmap='gray')
```

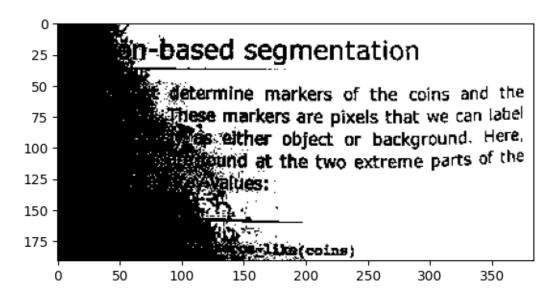
[26]: <matplotlib.image.AxesImage at 0x7ee97cf7eb30>



Segmentación OTSU general

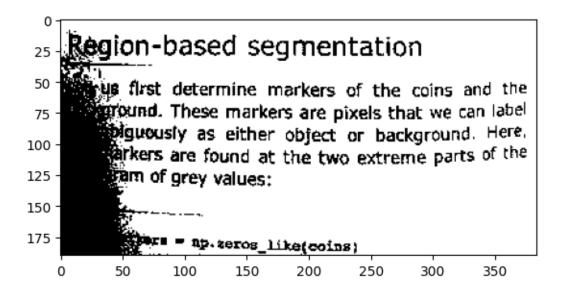
```
[27]: plt.imshow(otsu_proc(imagen), cmap='gray')
```

[27]: <matplotlib.image.AxesImage at 0x7ee97a446c20>



Segmentación OTSU por ventanas (4)

```
[28]: plt.imshow(new_image)
```



8 Conclusiones

El método de otsu es una técnica de thresholding automática que se utiliza para determinar uno o varios umbrales optimo al separar los pixeles de una imagen en clases distintas. Este método es bueno en su eficiencia al hacer el cálculo, y ayuda al no tener que establecerlo anualmente. Además de que tiene buena adaptabilidad para la distribución de intensidades en iluminación y contraste. Generalmente es utilizado en aplicaciones de segmentación de imágenes, donde se requiere separar objetos de interés de un fondo.

Una nota particular con la primera imagen y con 1 solo umbral, fue que el ruido que tenia la imagen no lo permitía funcionar bien. Por lo se soluciono aplicando un median filter. Seguido, fue posible convertir la imagen a una imagen binaria donde la identificación del texto fuera mucho mas sencilla.

Al observar la diferencia entre las imágenes con 1 solo umbral, y con 3 clases, fue posible como variaba la distribución de intensidades entre las imágenes. Sin embargo, es claro notar que, dependiendo de la imagen, estas pueden requerir cierto pre-procesamiento de imagen para adaptarlas al método. Ya que es sensible al ruido.

Adicionalmente, al realizar la segmentación de Otsu por ventana, podemos observar que se puede obtener una mejor definición del threshold óptimo en esa ventana, permitiendo obtener imágenes mejor segmentadas.

9 Referencias

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- OpenCV. (n.d.). Image Thresholding. Retrieved from OpenCV: https://docs.opencv.org/4.x/d7/d4d/tutorial_py_thresholding.html

[]: