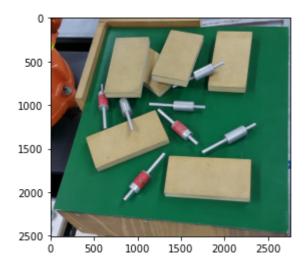
Segmentación

A partir de la imagen de bloques encontrar, mediante alguno de los métodos mencionados o combinación de ellos (inclusive pueden utilizar operaciones morfológicas como las vistas anteriormente) la mejor segmentación de los bloques respecto del resto de las piezas.

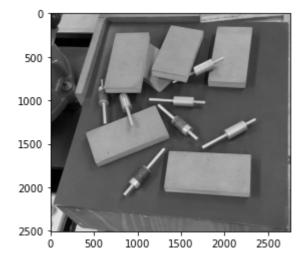
```
In [1]: %matplotlib inline
import numpy as np
import cv2 as cv
import matplotlib.pyplot as plt
```

```
ing = cv.imread('piezas.png')
img = cv.cvtColor(img, cv.COLOR_BGR2RGB)
plt.figure()
plt.imshow(img)
```

Out[2]: <matplotlib.image.AxesImage at 0x7f66590cdb80>



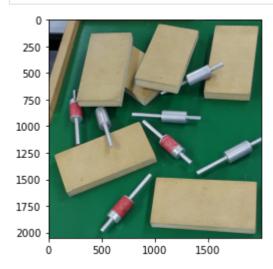
```
In [3]: grayImg = cv.cvtColor(img, cv.COLOR_BGR2GRAY)
    plt.imshow(grayImg, cmap='gray')
    plt.show()
```



Recortamos la imágen para obtener solo los bloques y no todo el fondo innecesario

```
In [4]: cutoutImg = img[100:2150, 350:2350]
    plt.imshow(cutoutImg)
```

plt.show()

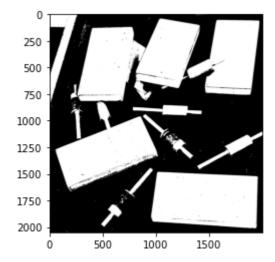


In []:

Watershed

```
In [5]: gray = cv.cvtColor(cutoutImg,cv.COLOR_BGR2GRAY)
    ret, thresh = cv.threshold(gray,0,255,cv.THRESH_BINARY+cv.THRESH_OTSU)
    plt.figure()
    plt.imshow(thresh,cmap='gray')
```

Out[5]: <matplotlib.image.AxesImage at 0x7f6657f70340>

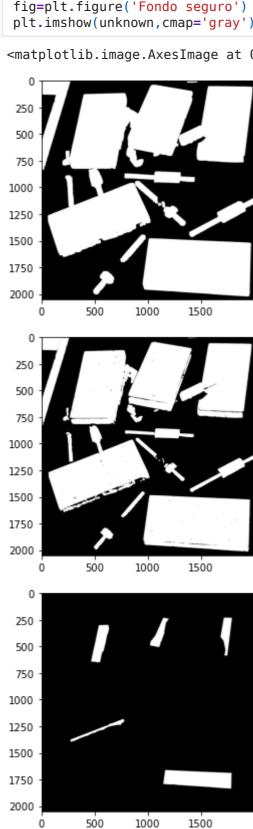


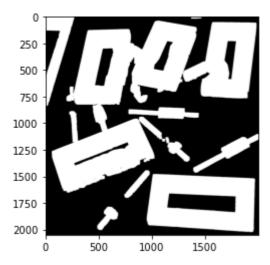
```
In [6]: kernel = np.ones((6,6),np.uint8)
    opening = cv.morphologyEx(thresh,cv.MORPH_OPEN,kernel, iterations = 2)
    sure_bg = cv.dilate(opening,kernel,iterations=3)
    closing = cv.morphologyEx(opening,cv.MORPH_CLOSE,kernel, iterations = 2)
    dist_transform = cv.distanceTransform(closing,cv.DIST_L2,5)
    ret, sure_fg = cv.threshold(dist_transform,0.7*dist_transform.max(),255,0)
    sure_fg = np.uint8(sure_fg)
    unknown = cv.subtract(sure_bg,sure_fg)

fig=plt.figure('Sure_BG')
    plt.imshow(sure_bg,cmap='gray')
```

```
fig=plt.figure('Opening')
plt.imshow(opening,cmap='gray')
fig=plt.figure('Sure FG')
plt.imshow(sure_fg,cmap='gray')
fig=plt.figure('Fondo seguro')
plt.imshow(unknown,cmap='gray')
```

<matplotlib.image.AxesImage at 0x7f6657e00280> Out[6]:

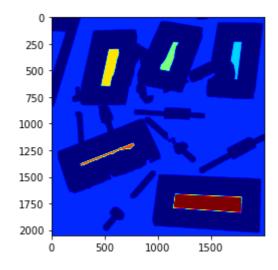




```
In [7]: ret, markers = cv.connectedComponents(sure_fg)
    markers = markers+1
    markers[unknown==255] = 0

plt.figure()
    plt.imshow(markers,cmap='jet')
```

Out[7]: <matplotlib.image.AxesImage at 0x7f6657d418e0>

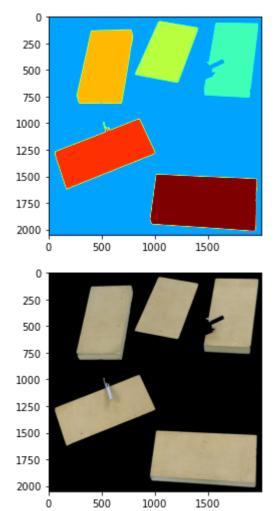


```
In [8]: watershed = cutoutImg.copy()
    markers = cv.watershed(watershed,markers)
    watershed[markers == 1] = [0,0,0]

    plt.figure()
    plt.imshow(markers,cmap='jet')

    plt.figure()
    plt.imshow(watershed,cmap='jet')
```

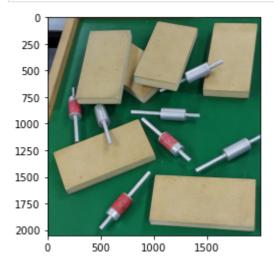
Out[8]: <matplotlib.image.AxesImage at 0x7f6657ce1220>



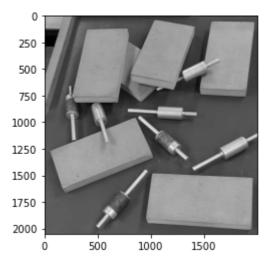
In []:

K Means

In [9]: plt.imshow(cutoutImg)
plt.show()



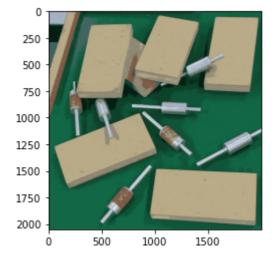
```
In [10]: grayImg = cv.cvtColor(cutoutImg, cv.COLOR_BGR2GRAY)
    plt.imshow(grayImg, cmap='gray')
    plt.show()
```



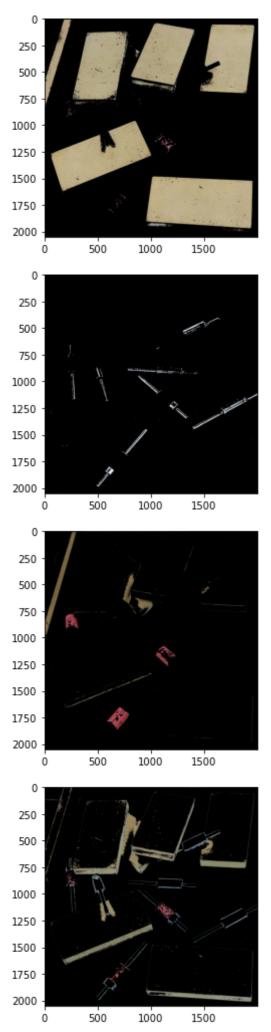
```
In [11]: Z = cutoutImg.reshape((-1,3))
Z = np.float32(Z)

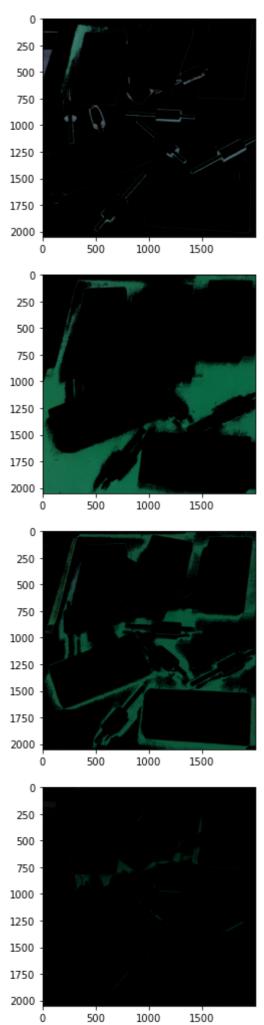
criteria = (cv.TERM_CRITERIA_EPS + cv.TERM_CRITERIA_MAX_ITER, 50, 0.5)
K = 10

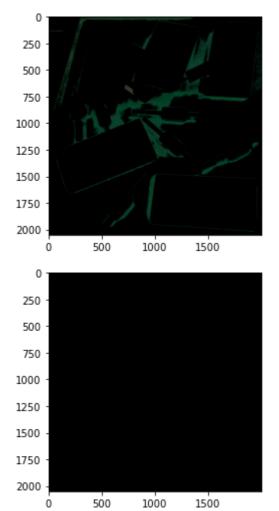
ret,label,center=cv.kmeans(Z,K,None,criteria,10,cv.KMEANS_RANDOM_CENTERS)
```



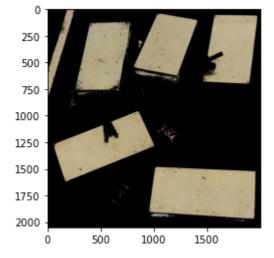
```
In [13]: copy = cutoutImg.copy()
    copy = copy.reshape((-1, 3))
    for cluster in range(1,11):
        clusterCopy = copy.copy()
        clusterCopy[label != cluster] = [0, 0, 0]
        clusterCopy = clusterCopy.reshape(cutoutImg.shape)
        plt.imshow(clusterCopy)
        plt.show()
```







```
In [17]: cluster = 1
    kmeans = cutoutImg.copy()
    kmeans = kmeans.reshape((-1, 3))
    kmeans[label != cluster] = [0, 0, 0]
    kmeans = kmeans.reshape(cutoutImg.shape)
    plt.imshow(kmeans)
    plt.show()
```



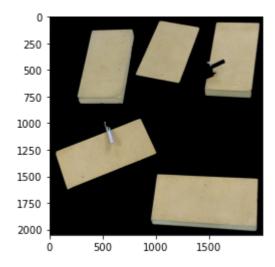
In []:

Conclusiones

Comparamos ambos resultados:

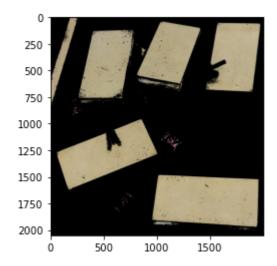
```
In [18]: ## Watershed
    plt.figure()
    plt.imshow(watershed,cmap='jet')
```

Out[18]: <matplotlib.image.AxesImage at 0x7f6657e346a0>



```
In [19]: ##Kmeans
   plt.figure()
   plt.imshow(kmeans)
```

Out[19]: <matplotlib.image.AxesImage at 0x7f6657d0e850>



Se puede ver como el resultado obtenido por watershed es mejor, y más performante además para este tipo de imágen.