Image Binarization/ Thresholding - Assingment 2

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Import modulus

In [5]:
```
import cv2 as cv
print( cv.__version__ )
import numpy as np
from matplotlib import pyplot as plt
```

```
4.5.3
```

Load images

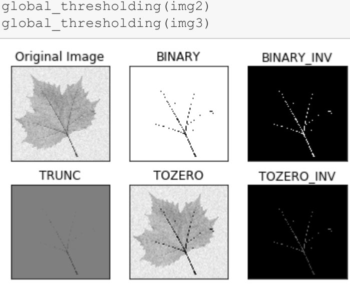
In [7]:
```
img1 = cv.imread('imgs/noisy_leaf.jpg',0)
img2 = cv.imread('imgs/panda.jpg',0)
img3 = cv.imread('imgs/panda2.jpg',0)
```

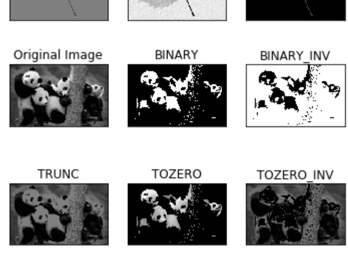
1. Global Thresholding

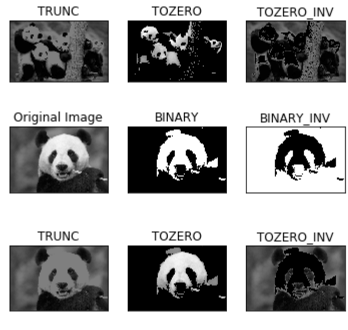
In Glbal thresholding we arbitary select threshold value T. Output result is varying with respect to the threshold we give. One of draw back is we don't know the optimal threshold value.

In [16]:
```
# Experiment with different THRESHOLD_TYPES
# 127 -
# 255 - Max value
def global_threshold(img):
    ret,thresh1 = cv.threshold(img,127,255,cv2.THRESH_BINARY)
    ret,thresh2 = cv.threshold(img,127,255,cv2.THRESH_BINARY_INV)
    ret,thresh3 = cv.threshold(img,127,255,cv2.THRESH_TRUNC)
    ret,thresh4 = cv.threshold(img,127,255,cv2.THRESH_TOZERO)
    ret,thresh5 = cv.threshold(img,127,255,cv2.THRESH_TOZERO_INV)

    titles = ['Original Image','BINARY','BINARY_INV','TRUNC','TOZERO','TOZERO_INV']
    images = [img, thresh1, thresh2, thresh3, thresh4, thresh5]
    for i in range(6):
        plt.subplot(2,3,i+1),plt.imshow(images[i],'gray',vmin=0,vmax=255)
        plt.title(titles[i])
        plt.xticks([]),plt.yticks([])
    plt.show()
```

In [15]:
```
global_thresholding(img1)
global_thresholding(img2)
global_thresholding(img3)
```







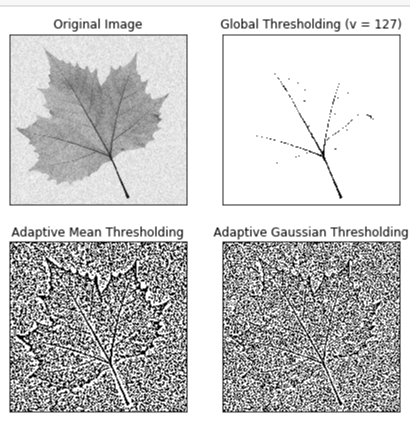
2. Adaptive Thresholding

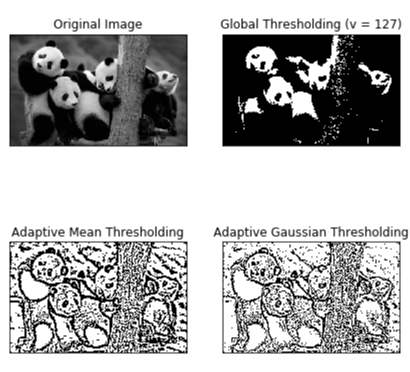
Uneven illumination factors can affect global thresholding (different ighting conditions in different regions). Adaptive thresholding can be used as a solution. Here we split image into squares/regions and check whether variance of each square exceed 100. If it exceed that value that particular square need to threshold seperatly. Algorithm determines the threshold for a pixel based on a small region around it. So we get different thresholds for different regions of the same image

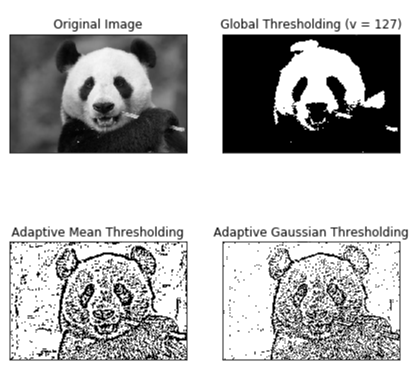
Adaptive thresholding calculate as mean of block size vs Adaptive thresholding calculate as weighted sum of block size

In [59]:
```
def adaptive_threshold(img):
    ret,thresh1 = cv.threshold(img,127,255,cv.THRESH_BINARY)

    thresh2 = cv.adaptiveThreshold(img,255,cv.ADAPTIVE_THRESH_MEAN_C,cv.THRESH_BINARY,11,2)
    thresh3 = cv.adaptiveThreshold(img,255,cv.ADAPTIVE_THRESH_GAUSSIAN_C, cv.THRESH_BINARY,11,2)
    titles = ['Original Image', 'Global Thresholding (v = 127)','Adaptive Mean Thresholding', 'Adaptive Gaussian Thresholding']
    images = [img, thresh1, thresh2, thresh3]
    plt.subplots(figsize=(7, 7))
    for i in range(4):
        plt.subplot(2,2,i+1),plt.imshow(images[i],'gray')
        plt.title(titles[i])
        plt.xticks([]),plt.yticks([])
    plt.show()
```

In [60]:
```
adaptive_threshold(img1)
adaptive_threshold(img2)
adaptive_threshold(img3)
```







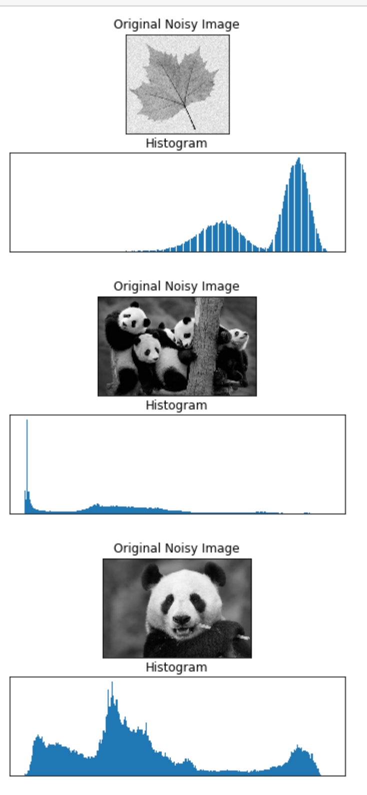
3. Otsu Method

Otsu Binarization technique can be idealy apply to images that is bimodal which is images we can see two distinct distribution in piel histogram. What Otsu method do is it finds the minimum point that we can seperate these two distribution. It will automatically gives optimal threshold value.

Image Intensity Histogram

In [19]:
```
def plot_intensity_hist(img):
    plt.subplot(2,1,1), plt.imshow(img,cmap = 'gray')
    plt.title('Original Noisy Image'), plt.xticks([]), plt.yticks([])
    plt.subplot(2,1,2), plt.hist(img.ravel(), 256)
    plt.title('Histogram'), plt.xticks([]), plt.yticks([])

    plt.show()
```

In [20]:
```
plot_intensity_hist(img1) # bimodal image
plot_intensity_hist(img2)
plot_intensity_hist(img3)
```



Implementation of Otsu method

source : https://www.meccanismocomplesso.org/en/otsu-s-method-for-image-binarization-thresholding/

In [56]:
```
def otsu_1(img):
    #blur = cv2.GaussianBlur(img,(5,5),0) # to reduce image noise
    # find normalized_histogram, and its cumulative distribution function
    hist = cv2.calcHist([img],[0],None,[256],[0,256])
    hist_norm = hist.ravel()/hist.sum()
    Q = hist_norm.cumsum()
    bins = np.arange(256)
    fn_min = np.inf
    thresh = -1
    for i in range(1,256):
        p1,p2 = np.hsplit(hist_norm,[i]) # probabilities
        q1,q2 = Q[i],Q[255]-Q[i] # cum sum of classes
        if q1 == 0:
            q1 = 0.00000001
        if q2 == 0:
            q2 = 0.00000001
        b1,b2 = np.hsplit(bins,[i]) # weights
        # finding means and variances
        m1,m2 = np.sum(p1*b1)/q1, np.sum(p2*b2)/q2
        v1,v2 = np.sum(((b1-m1)**2)*p1)/q1,np.sum(((b2-m2)**2)*p2)/q2
        # calculates the minimization function
        fn = v1*q1 + v2*q2
        if fn < fn_min:
            fn_min = fn
            thresh = i
    # find otsu's threshold value with OpenCV function
    ret, otsu = cv.threshold(img,0,255,cv.THRESH_BINARY+cv.THRESH_OTSU)
    print("Threshold otsu implementation 1 - ",thresh,"Otsu OpenCV implementation - ",ret)
```

In [57]:
```
otsu_1(img1)
otsu_1(img2)
otsu_1(img3)
```

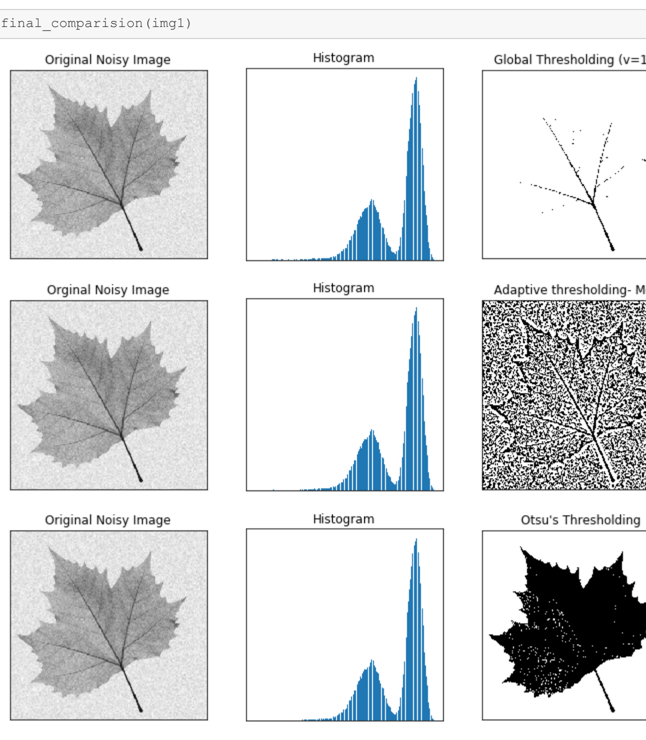
```
Threshold otsu implementation 1 -  204 Otsu OpenCV implementation -  202.0
Threshold otsu implementation 1 -  87 Otsu OpenCV implementation -  88.0
Threshold otsu implementation 1 -  143 Otsu OpenCV implementation -  138.0
```

After using Gaussian kernel to remove noise

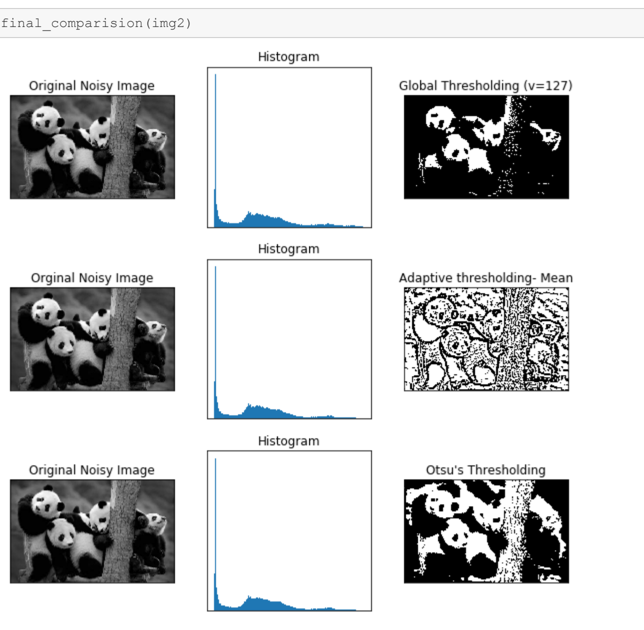
In [58]:
```
def final_comparision(img):

    ret,thresh1 = cv.threshold(img, 127,255,cv.THRESH_BINARY )

    thresh2 = cv.adaptiveThreshold(img,255,cv.ADAPTIVE_THRESH_MEAN_C,cv.THRESH_BINARY,11,2)
    ret3,thresh3 = cv.threshold(img,0,255,cv.THRESH_BINARY+cv.THRESH_OTSU)

    # plot all the images and their histograms
    images = [img, 0, thresh1,
              img, 0, thresh2,
              img, 0, thresh3]
    titles = ['Original Noisy Image','Histogram','Global Thresholding (v=127)',
              'Original Noisy Image','Histogram','Adaptive Thresholding- Mean',
              'Original Noisy Image','Histogram',"Otsu's Thresholding"]

    plt.subplots(figsize=(10, 10))
    for i in range(3):
        plt.subplot(3,3,i*3+1),plt.imshow(images[i*3],'gray')
        plt.title(titles[i*3]), plt.xticks([]), plt.yticks([])
        plt.subplot(3,3,i*3+2),plt.hist(images[i*3].ravel(),256)
        plt.title(titles[i*3+1]), plt.xticks([]), plt.yticks([])
        plt.subplot(3,3,i*3+3),plt.imshow(images[i*3+2],'gray')
        plt.title(titles[i*3+2]), plt.xticks([]), plt.yticks([])

    plt.show()
```

Compare result of different image thresholding techniques

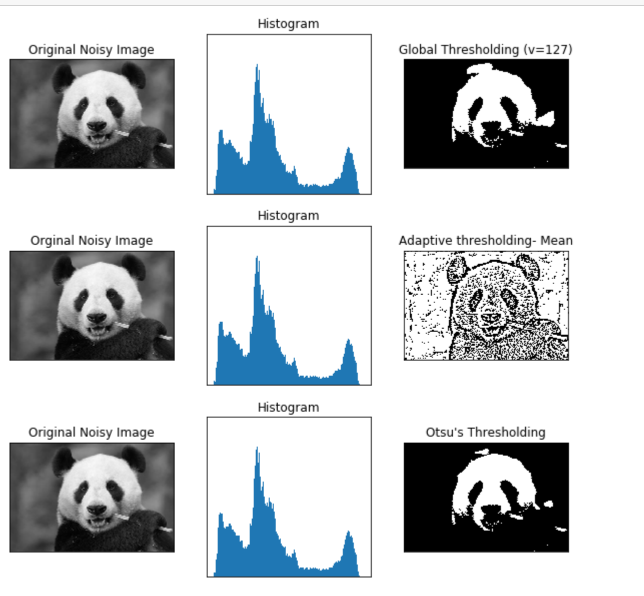
In [59]:
```
final_comparision(img1)
```



In [61]:
```
final_comparision(img2)
```



In [62]:
```
final_comparision(img3)
```



Discussion

Global thresholding, adaptive thresholding and otsu thresholding gave very different output images. In given input images Otsu thresholding thechnuqe identify foreground and background better than other two techniques. Here I have used one images which clearly has two distinct distribution of intensity While other images not. Otsu method works well in bimodal images.

Two other Image Binarization technique

Kitler Method - Global Binarization

The kilter method is used mixture of Gaussian distribution to find threshold value. In kilter Method the t is threshold that is used to segment the image into two parts background and foreground, both of the parts modelled by Gaussian distribution

$pB(t)$ and $pF(t)$, the $pmix(t)$ mixture of these two Gaussian distribution.

$$pmix(t) = \alpha pB(t) + (1-\alpha)pF(t)$$

Where α is determined by the portions of background and foreground in the image.

Niblack Method - Local binarizaation

A pixel-wise threshold is calculated by using a moving window on a grey-level image. Standard deviation s and mean m of every pixel in the window is calculated, and then threshold is computed by using these values as follows,

$$T=m+k*s$$

Where, T =threshold value

k = constant whose value lies between 0 and 1.

s = standard deviation

m = mean

Quality of binarization is defined by the value of k and the size of moving window.