CSE 344 Computer Vision Assignment 2

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In [2]:
```python
import numpy as np
import cv2
import matplotlib.pyplot as plt
from IPython.display import display
from PIL import Image
import skfuzzy as fuzz
from sklearn.metrics import silhouette_score
from tqdm import tqdm
from skimage.segmentation import slic
from skimage.segmentation import mark_boundaries
from skimage.util import img_as_float
from skimage import io
from scipy.spatial.distance import cdist
import scipy.stats
import copy
import math
from scipy.integrate import quad
from sklearn.cluster import KMeans
from scipy import ndimage
```

Question 1

Write a program to implement a region segmentation algorithm using the fuzzy c-means algorithm on normalized 'RGBxy' data of an image. Merge stray (isolated) pixels (or very-small regions) to their surrounding regions. [3 marks]

In [45]:
```python
img = cv2.imread("Cap1.PNG")
fig=plt.figure(figsize=(6, 6))
plt.imshow(cv2.cvtColor(img, cv2.COLOR_BGR2RGB))
plt.show()
```

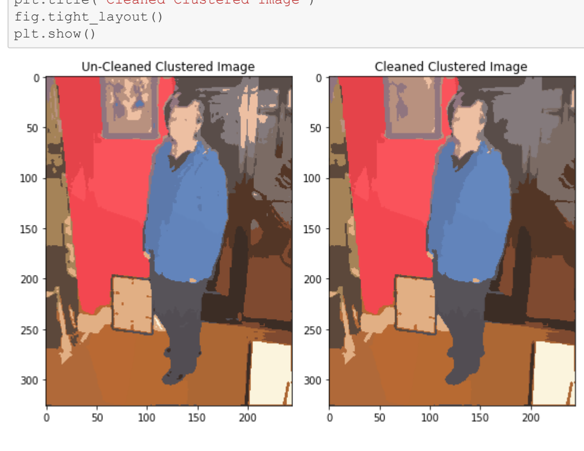
In [28]:
```python
img = np.array(img)[:,:,0:3]
img_data = np.zeros((img.shape[0], img.shape[1], 5))
for i in range(img.shape[0]):
    for j in range(img.shape[1]):
        img_data[i,j,0:3] = img[i,j]/255
        img_data[i,j,3] = i/img.shape[0]
        img_data[i,j,4] =  j/img.shape[1]
img_data = img_data.reshape(((img.shape[0]*img.shape[1], 5))).T
print(img_data.shape)
```

```
(5, 79544)
```

In [29]:
```python
fcm = fuzz.cluster.cmeans(img_data, 25, 2, error=0.05, maxiter=1000, init=None)
```

In [30]:
```python
def clean_image(img, plot = False):

    m,n = img.shape
    binary_maps = []

    if(plot):
        fig=plt.figure(figsize=(60, 60))
        columns = 5
        rows = len(np.unique(img))//5
        img = img + 1
        n = len(np.unique(img))
        for i in range(1,n+1):
            curr = copy.deepcopy(img)
            curr[curr != i] = 0
            curr[curr == i] = 1
            filled = ndimage.binary_fill_holes(curr).astype(int)
            idx = np.where(filled == 1)
            img[idx[0],idx[1]] = i
            fig.add_subplot(rows, columns, i)
            plt.imshow(filled.astype(int))
        fig.tight_layout()
        plt.show()

        return img-1

    img = img + 1
    n = len(np.unique(img))
    for i in range(1,n+1):
        curr = copy.deepcopy(img)
        curr[curr != i] = 0
        curr[curr == i] = 1
        filled = ndimage.binary_fill_holes(curr).astype(int)
        idx = np.where(filled == 1)
        img[idx[0],idx[1]] = i

    return img-1
```

In [33]:
```python
cluster_centers = fcm[0]
prob_matrix = fcm[1]
pred_matrix = np.argmax(prob_matrix, axis = 0)

pred_matrix = cluster_centers[pred_matrix]
clustered_image = pred_matrix[:,0:3]
clustered_image = clustered_image.reshape(((img.shape[0],img.shape[1], 3)))*255
clustered_image = clustered_image.astype(int)


pred_matrix = np.argmax(prob_matrix, axis = 0)
cleaned_img = clean_image(np.squeeze(pred_matrix).reshape(img.shape[0],img.shape[1]))
cleaned_clus_img = cluster_centers[cleaned_img][:,:,0:3]
cleaned_clus_img = cleaned_clus_img.reshape(((img.shape[0],img.shape[1], 3)))*255
cleaned_clus_img = cleaned_clus_img.astype(int)

fig=plt.figure(figsize=(8, 8))
columns = 2
rows = 1
fig.add_subplot(rows, columns, 1)
plt.imshow(clustered_image)
plt.title("Un-Cleaned Clustered Image")
fig.add_subplot(rows, columns, 2)
plt.imshow(cleaned_clus_img)
plt.title("Cleaned Clustered Image")
fig.tight_layout()
plt.show()
```



Question 2

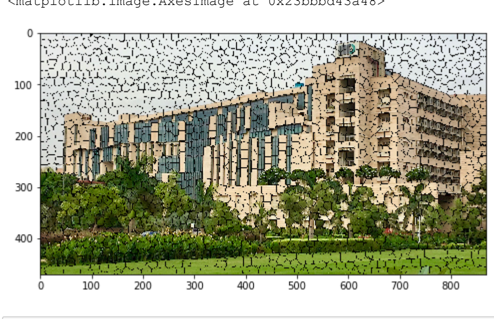
Write a program to obtain the spatial and contrast cues using SLIC superpixels of an image instead of pixels. [3 marks]

In [41]:
```python
img_path = '1558014721_E7jyWs_iiit_d.jpg'
image  = cv2.imread(img_path)
plt.figure(figsize = (8,8))
plt.imshow(cv2.cvtColor(image, cv2.COLOR_BGR2RGB))
print(image.shape)
```

```
(470, 870, 3)
```

In [36]:
```python
img = cv2.imread(img_path)
img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
#Initialize the slic item, the average size of super pixels is 20 (default is 10), and the smoothing factor is 20
slic = cv2.ximgproc.createSuperpixelSLIC(img,region_size=15,ruler = 20.0)
slic.iterate(40)     #Number of iterations, the greater the better
mask_slic = slic.getLabelContourMask() #Get Mask, Super pixel edge Mask==1
label_slic = slic.getLabels()        #Get superpixel tags
number_slic = slic.getNumberOfSuperpixels()  #Get the number of super pixels
mask_inv_slic = cv2.bitwise_not(mask_slic)
img_slic = cv2.bitwise_and(img,img,mask =  mask_inv_slic) #Draw the superpixel boundary on the original image
plt.figure(figsize = (8,8))
plt.imshow(img_slic)
```

Out[36]:
```
<matplotlib.image.AxesImage at 0x23bbbd43a48>
```



In [39]:
```python
def get_super_image(image, segments):

    m,n = segments.shape

    dict_ = {}
    centers = {}

    for i in range(m):
        for j in range(n):
            if(segments[i,j] not in dict_):
                dict_[segments[i,j]] = []
                centers[segments[i,j]] = []
                dict_[segments[i,j]].append(image[i,j])
                centers[segments[i,j]].append(np.array([i,j]))
            else :
                dict_[segments[i,j]].append(image[i,j])
                centers[segments[i,j]].append(np.array([i,j]))
    for key in list(dict_.keys()):
        dict_[key] = np.mean(np.array(dict_[key]), 0).astype(int)
        centers[key] = np.mean(np.array(centers[key]), 0).astype(int)

    slic_image = np.zeros((image.shape[0],image.shape[1],3))

    for i in range(m):
        for j in range(n):
            slic_image[i,j] =  dict_[segments[i,j]]
    slic_image = slic_image.astype(int)
    plt.figure(figsize = (8,8))
    plt.imshow(slic_image)
    plt.title("SLIC Image")

    return slic_image, dict_, centers
```

In [40]:
```python
slic_image, dict_pixels, dict_centers = get_super_image(img,label_slic)
```

Contrast Cue

Contrast cue represents the **visual feature uniqueness** on the single or multiple images. Contrast is one of the most widely used cues for measuring saliency in single image saliency detection algorithms, since the contrast operator simulates the human visual receptive fields. This rule is also valid in the case of cluster-based method for the multiple images, while the difference is that contrast cue on the cluster-level better represents the global correspondence relationship than the pixel/patch level.
The contrast cue $w^c(k)$ of cluster C^k is defined using its feature contrast to all other clusters:

$$w^c(k) = \sum_{i=1, i\neq k}^{K} (\frac{n^i}{N}||\nu^k - \mu^i||_2)$$

where a L2 norm is used to compute the distance on the feature space, n^i represents the pixel number of cluster C^i , and N denotes the pixel number of all images.

Spatial Cue

In human visual system, the regions near the image center draw more attention than the other regions. When the distance between the object and the image center increases, the attention gain is depreciating. This scenario is known as **'central bias rule'** in single image saliency detection. We extend this concept to the cluster-based method, which measures a global spatial distribution of the cluster.
The spatial cue $w^s(k)$ of cluster C^k is defined as:

$$w^s(k) = \frac{1}{n^k}\sum_{j=1}^{M}\sum_{i=1}^{N_j}[N(||z_i^k - o^j||^2|0,\sigma^2).\delta(b(p_i^j) - C^k)]$$

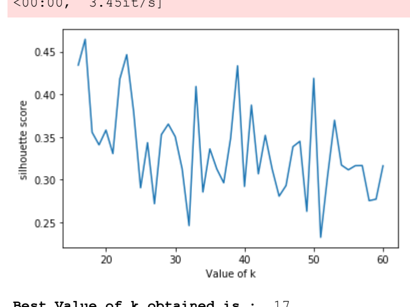
where $\delta(.)$ is the Kronecker delta function, o^j denotes the center of image I^j, and Gaussian kernel $N(\cdot)$ computes the Euclidean distance between pixel z_i^j and the image center o^j, the variance σ^2 is the normalized radius of images. And the normalization coefficient n^k is the pixel number of cluster C^k . Different from the single image model, our spatial cue w^s represents the location prior on the cluster-level, which is a global central bias on the multiple images. The same as the contrast cue, the spatial cue is also **valid on both single and multiple images**.

Reference : Cluster-Based Co-Saliency Detection

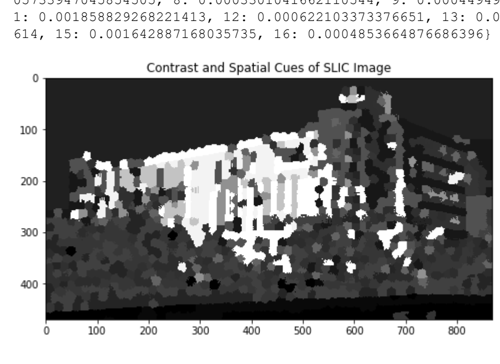
In [46]:
```python
def contrast_spatial_cue(slic_image, dict_pixels, label_slic, dict_centers):
    m,n = label_slic.shape

    data = np.zeros((len(list(dict_pixels.keys())), 3))
    l = sorted(list(dict_pixels.keys()))
    for i in range(len(l)):
        data[i] = dict_pixels[l[i]]

    data = np.float32(data)/255

    s_scores = []
    k = 5
    s_max = 0
    for k_i in tqdm(range(16,61), position = 0, desc = "Finding best k"):
        criteria = (cv2.TERM_CRITERIA_EPS + cv2.TERM_CRITERIA_MAX_ITER, 200, 0.2)
        _, labels, (centers) = cv2.kmeans(data, k_i, None, criteria, 200, cv2.KMEANS_RANDOM_CENTERS )
        ss = silhouette_score(data, np.squeeze(labels))
        s_scores.append(ss)
        if(ss > s_max):
            s_max = ss
            k = k_i

    plt.plot([i for i in range(16,61)], s_scores)
    plt.xlabel("Value of k")
    plt.ylabel("silhouette score")
    plt.show()

    print("\033[1mBest Value of k obtained is : \033[0m",k)
    criteria = (cv2.TERM_CRITERIA_EPS + cv2.TERM_CRITERIA_MAX_ITER, 200, 0.02)
    _, labels, (centers) = cv2.kmeans(data, k, None, criteria, 200, cv2.KMEANS_RANDOM_CENTERS )
    pred_matrix = np.squeeze(labels)
    cluster_dist = cdist(centers,centers, 'euclidean')
    clustered_img = pred_matrix[label_slic]

    n_i = {}
    for i in np.unique(clustered_img):
        n_i[i] = np.count_nonzero(clustered_img == i)
    print("\033[1mNumber of Image Pixels per cluster : \033[0m",n_i)

    contrast_cues = {}
    for i in range(k):
        val = 0
        for j in range(k):
            if(i!=j):
                val+=(n_i[j]/(clustered_img.shape[0]*clustered_img.shape[1]))*cluster_dist[i,j]
        contrast_cues[i] = val
    print("\033[1mContrast Cues : \033[0m",contrast_cues)


    center_data = np.zeros((len(list(dict_centers.keys())), 2))
    l = sorted(list(dict_centers.keys()))
    for i in range(len(l)):
        a,b = dict_centers[l[i]]
        center_data[i,0] = a
        center_data[i,1] = b
    slic_image_center = dict_centers[label_slic[m//2,n//2]].reshape((1,2))
    slic_image_center[0,0] = slic_image_center[0,0]
    slic_image_center[0,1] = slic_image_center[0,1]
    slic_center_dist = cdist(center_data,slic_image_center,'euclidean')
    slic_center_dist_var = np.std(slic_center_dist)

    spatail_cues = {}
    for c in range(k):
        val = 0
        for i in range(len(slic_center_dist)):
            if(pred_matrix[i] == c):
                val+=scipy.stats.norm(0, slic_center_dist_var).pdf(slic_center_dist[i,0])
        val = val/np.count_nonzero(pred_matrix == c)
        spatail_cues[c] = val


    print("\033[1mSpatial Cues : \033[0m",spatail_cues)

    final_image = np.zeros((m,n))
    for i in range(m):
        for j in range(n):
            idx = clustered_img[i,j]
            val = spatail_cues[idx]*contrast_cues[idx]

            final_image[i,j] = val
    plt.figure(figsize = (8,8))
    plt.imshow(final_image, cmap = 'gray')
    plt.title("Contrast and Spatial Cues of SLIC Image")
    return contrast_cues, spatail_cues,clustered_img, final_image
```

In [18]:
```python
contrast_cues, spatail_cues,clustered_img, final_image = contrast_spatial_cue(slic_image, dict_pixels, label_slic, dict_centers)
```

```
Finding best k: 100%|██████████████████████████████| 45/45 [00:13<00:00,  3.45it/s]
```




```
Best Value of k obtained is :  17
Number of Image Pixels per cluster :  {0: 15514, 1: 31062, 2: 26788, 3: 10953, 4: 19745, 5: 31740, 6: 7982, 7: 9879, 8: 103649, 9: 21198, 10: 18604, 11: 17659, 12: 5484, 13: 13022, 14: 28326, 15: 9541, 16: 37754}
Contrast Cues :  {0: 0.4944047952686209, 1: 0.4722449659073934, 2: 0.5567290925962213, 3: 0.4578088282387095, 4: 0.7533045836957364, 5: 0.5203890119232772, 6: 0.4431900045142752, 7: 0.439256346432681, 8: 0.6014940160675262, 9: 0.5728682666790024, 10: 0.5203539672048046, 11: 0.5159432385154153, 12: 0.4429462354277046, 13: 0.485510440183346, 14: 0.4447145079227963, 15: 0.4753008723938985, 16: 0.6441795611688751}
Spatial Cues :  {0: 0.0004912521934934001, 1: 0.0007906799423250554, 2: 0.000501836910440256, 3: 0.0009578881369992587, 4: 0.0002894904905817073, 5: 0.001918743501893 43, 6: 0.001361914302093526, 7: 0.0005733947045854505, 8: 0.0003301041662110544, 9: 0.0004494953247607 1366, 10: 0.00016044733428914552, 11: 0.001858829268221413, 12: 0.0006221033733376651, 13: 0.0002388766933571 7187, 14: 0.0003753585627477614, 15: 0.001642887168035735, 16: 0.0004853664876686396}
```



Question 3

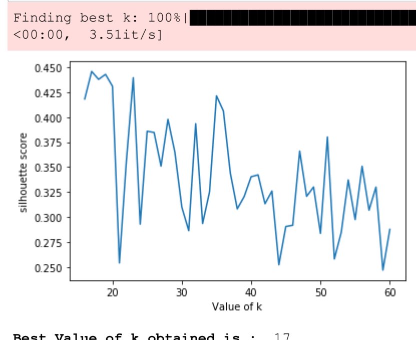
Implement the separation measure discussed in Sec III.B.1 of the following paper to obtain quality scores for the two cues obtained in Q2. Use these quality scores as weights while performing the weighted sum of the two cues for getting the final saliency cue. [4 marks]

In [47]:
```python
def otsu(img):

    min_cost = float('inf')
    threshold = 0

    for i in range(1,256):
        v0 = np.var(img[img < i], ddof = 1)
        w0 = len(img[img < i])
        v1 = np.var(img[img >= i], ddof = 1)
        w1 = len(img[img >= i])

        cost = w0*v0 + w1*v1
        if(cost < min_cost):
            min_cost = cost
            threshold = i
    return threshold
```

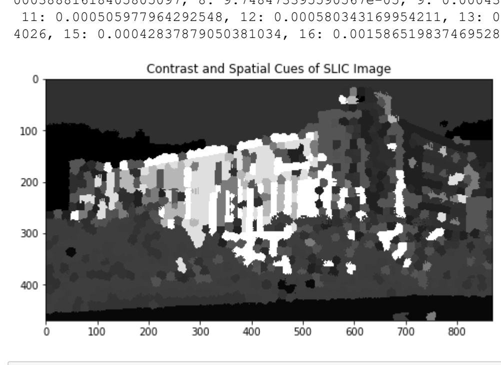
In [48]:
```python
def select_foreground(img):
    m,n = img.shape

    m0 = int(0.15*m)
    n0 = int(0.15*n)
    c0 = 0
    c1 = 0
    for i in range(m//2 - m0, m//2 + m0):
        for j in range(n//2 - n0, n//2 + n0):
            if(img[i,j] == 0):
                c0 = c0 + 1
            else:
                c1 = c1 + 1
    if(c0 > c1):
        return 0
    else :
        return 1
```

In [21]:
```python
contrast_cues, spatail_cues,clustered_img, final_image = contrast_spatial_cue(slic_image, dict_pixels, label_slic, dict_centers)
```

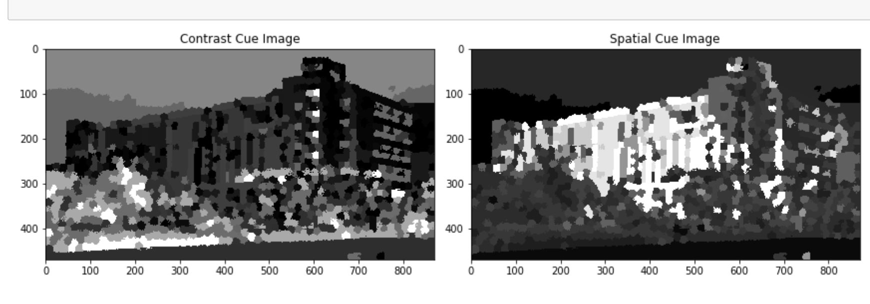
```
Finding best k: 100%|██████████████████████████████| 45/45 [00:12<00:00,  3.51it/s]
```




```
Best Value of k obtained is :  17
Number of Image Pixels per cluster :  {0: 21746, 1: 12302, 2: 7951, 3: 10295, 4: 30620, 5: 30614, 6: 12047, 7: 81847, 8: 22193, 9: 36819, 10: 29734, 11: 26885, 12: 23393, 13: 18743, 14: 13641, 15: 20000, 16: 10070}
Contrast Cues :  {0: 0.44900704399293695, 1: 0.44071208348229013, 2: 0.4416887414384442, 3: 0.44084309610782096, 4: 0.5010092398974022, 5: 0.5219705522610326, 6: 0.45601065910553085, 7: 0.6156837742270231, 8: 0.5749335066113366, 9: 0.6616597372635812, 10: 0.47426619913257073, 11: 0.5822774630455001, 12: 0.5050601072503417, 13: 0.5112179844250152, 14: 0.774821601451449, 15: 0.5722444196596066, 16: 0.4724174329813396}
Spatial Cues :  {0: 0.0003967969932272541, 1: 0.0005271478958266999, 2: 0.0004921561035972357, 3: 0.0011920831613975824, 4: 0.000177053747804512, 5: 0.001969898748356991, 6: 0.0008115445512653653, 7: 0.0003888161840580509 7, 8: 9.748473395590567e-05, 9: 0.0004337763529412004, 10: 0.0007989662132898918, 11: 0.000505977964292548, 12: 0.000580343169954211, 13: 0.0017735019190148447, 14: 0.0003235213528164026, 15: 0.00042837879050381034, 16: 0.0015865198374695288}
```



In [54]:
```python
m,n = clustered_img.shape
contrast_cue_image = np.zeros((m,n))
spatial_cue_image = np.zeros((m,n))
for i in range(m):
    for j in range(n):
        contrast_cue_image[i,j] = contrast_cues[clustered_img[i,j]]
contrast_cue_image = (contrast_cue_image - np.min(contrast_cue_image))/(np.max(contrast_cue_image) - np.min(contrast_cue_image))
for i in range(m):
    for j in range(n):
        spatial_cue_image[i,j] = spatail_cues[clustered_img[i,j]]

spatial_cue_image = (spatial_cue_image - np.min(spatial_cue_image))/(np.max(spatial_cue_image) - np.min(spatial_cue_image))
columns = 2
rows = 1
fig=plt.figure(figsize=(12, 12))
fig.add_subplot(rows, columns, 1)
plt.imshow(contrast_cue_image, cmap = 'gray')
plt.title("Contrast Cue Image")
fig.add_subplot(rows, columns, 2)
plt.imshow(spatial_cue_image, cmap = 'gray')
plt.title("Spatial Cue Image")
fig.tight_layout()
plt.show()
```



Separation Measure

A high-quality saliency mapshould have well-separated foreground and background likelihoods like a ground-truth binary mask. Assuming distributions of these likelihoods to be of Gaussian in nature, we attempt to measure the separation between the two. Let $\mu_f(S)$,$\mu_b(S)$, $\sigma_f(S)$, and $\sigma_b(S)$ denote foreground mean, background mean,foreground standard deviation, and background standard deviation, respectively, computed based on the two likelihood distributions (obtained by Otsu thresholding). Let us denote $D_f(z;S)$ and $D_b(z;S)$as foreground and background Gaussian distributions, respectively, whereztakes saliency value ranging between 0 and 1. Specifically,

$$D_f(z;S) = \frac{e^{-(\frac{z-\mu_f(S)}{\sigma_f(S)})^2}}{\sigma_f(S)\sqrt(2\pi)} \text{ and } D_b(z;S) = \frac{e^{-(\frac{z-\mu_b(S)}{\sigma_b(S)})^2}}{\sigma_b(S)\sqrt(2\pi)},$$

It is clear that the less the two distributions overlap with each other, the better the saliency map is, i.e., the foreground and background are more likely to be separable. In order to calculate such overlap,it is needed to figure out the intersecting point z^*. It can be obtained by equating the two functions, i.e. $D_f(z;S) = D_b(z;S)$, which finally leads to

$$z^2(\frac{1}{\sigma_b^2} - \frac{1}{\sigma_f^2}) - 2z(\frac{\mu_b}{\sigma_b^2} - \frac{\mu_f}{\sigma_f^2}) + \frac{\mu_b^2}{\sigma_b^2} - \frac{\mu_f^2}{\sigma_f^2} + 2log(\frac{\sigma_b}{\sigma_f}) = 0$$

When we solve the above quadratic equation, we get

$$z^* = \frac{\mu_b\sigma_f^2 - \mu_f\sigma_b^2}{\sigma_f^2 - \sigma_b^2} \pm \frac{\sigma_f\sigma_b}{\sigma_f^2 - \sigma_b^2} \times ((\mu_f - \mu_b)^2 - 2(\sigma_f^2 - \sigma_b^2)(log(\sigma_b) - log(\sigma_f)))^{\frac{1}{2}}$$

Having obtained z^*, overlap $L(S)$ can now be computed as

$$L(s) = \int_{z=0}^{z=z^*} D_f(z;S)dz + \int_{z=z^*}^{z=1} D_b(z;S)dz$$

And finally, separation measure ϕ for saliency map S is calculated as

$$\phi(S) = \frac{1}{1 + log_{10}(1 + \gamma L(S))}$$

where γ is set as number of bins used for representing the two distributions.

Reference : Quality-Guided Fusion-Based Co-Saliency Estimation for Image Co-Segmentation and Colocalization

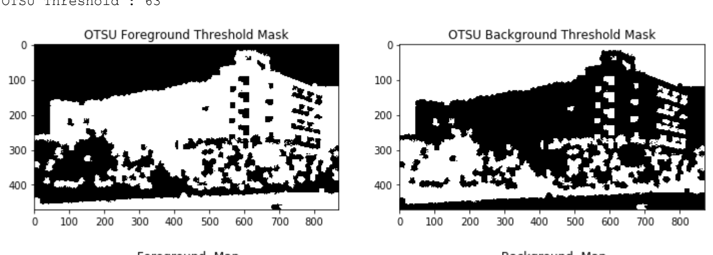
In [56]:
```python
def gaussian_distribution(x, mu, sigma):
    return (1/(sigma*math.sqrt(2*math.pi)))*np.exp(-(x/sigma - mu/sigma)**2)
```

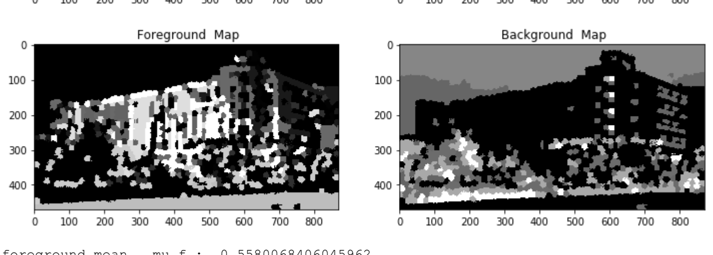
In [57]:
```python
def separation_Measure(saliency_map):
    saliency_map = (saliency_map/np.max(saliency_map))*255
    thres = otsu(saliency_map.astype(int))
    print("OTSU Threshold :", thres)
    mask = copy.deepcopy(saliency_map)
    mask[mask < thres] = 0
    mask[mask >= thres] = 1
    fg = select_foreground(mask)
    if(fg == 1):
        foreground_mask = mask
        background_mask = 1 - foreground_mask
    else:
        foreground_mask = 1- mask
        background_mask = 1 - foreground_mask

    fig=plt.figure(figsize=(12, 12))
    columns = 2
    rows = 1
    fig.add_subplot(rows, columns, 1)
    plt.imshow(foreground_mask, cmap = 'gray')
    plt.title("OTSU Foreground Threshold Mask")
    fig.add_subplot(rows, columns, 2)
    plt.imshow(background_mask, cmap = 'gray')
    plt.title("OTSU Background Threshold Mask")
    plt.show()

    foreground_map = saliency_map*foreground_mask
    background_map = saliency_map*background_mask
    foreground_map = foreground_map/np.max(foreground_map)
    background_map = background_map/np.max(background_map)


    fig=plt.figure(figsize=(12, 12))
    columns = 2
    rows = 1
    fig.add_subplot(rows, columns, 1)
    plt.imshow(foreground_map, cmap = 'gray')
    plt.title(" Foreground  Map")
    fig.add_subplot(rows, columns, 2)
    plt.imshow(background_map, cmap = 'gray')
    plt.title(" Background  Map")
    plt.show()

    mu_f = np.mean(foreground_map[foreground_map > 0])
    sigma_f = np.std(foreground_map[foreground_map > 0])
    mu_b = np.mean(background_map[background_map > 0])
    sigma_b = np.std(background_map[background_map > 0])
    print("foreground mean , mu_f : ", mu_f)
    print("background mean , mu_b : ", mu_b)
    print("foreground  standard  deviation , sigma_f : ", sigma_f)
    print("background standard  deviation , sigma_b : ", sigma_b)

    fg_vals = foreground_map[foreground_map > 0].flatten()
    bg_vals = background_map[background_map > 0].flatten()
    fg_dist = scipy.stats.norm(mu_f, sigma_f**2).pdf(fg_vals)
    bg_dist = scipy.stats.norm(mu_b, sigma_b**2).pdf(bg_vals)

    z_star = (mu_b*sigma_f**2 - mu_f*sigma_b**2)/(sigma_f**2 - sigma_b**2)  +  (sigma_f*sigma_b/(sigma_f**2 - sigma_b**2))*((mu_f - mu_b)**2 - 2*(sigma_f**2 - sigma_b**2)*(math.log(sigma_b) - math.log(sigma_f)))**0.5
    print("z_star : ", z_star)
    L_s = quad(gaussian_distribution, 0, z_star, args=(mu_f,sigma_f))[0] + quad(gaussian_distribution, z_star, 1, args=(mu_b,sigma_b))[0]
    print("L_s : ", L_s)
#     gamma = np.count_nonzero([foreground_map > 0]) + np.count_nonzero([background_map > 0])
    gamma = 255
    phi_s = 1/(1 + math.log(1 + gamma*L_s,10))
    print("phi_s : ", phi_s)
    return phi_s
```

In [58]:
```python
print('\033[1mFor Contrast Cue \n  \033[0m')
sm_1 = separation_Measure(contrast_cue_image)
print('\n')
print('\033[1mFor Spatial Cue \n  \033[0m')
sm_2 = separation_Measure(spatial_cue_image)
```

For Contrast Cue

```
OTSU Threshold : 63
```

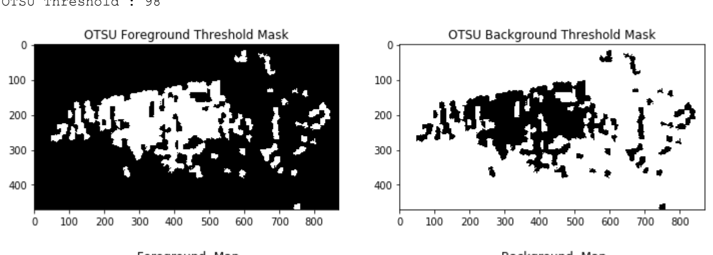


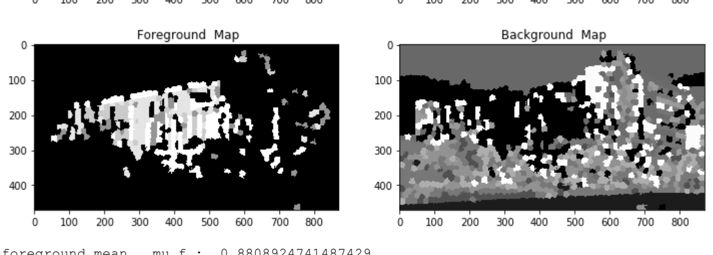



```
foreground mean , mu_f :  0.5580068406045962
background mean , mu_b :  0.5414158820133714
foreground  standard  deviation , sigma_f :  0.3412185993067307
background standard  deviation , sigma_b :  0.1522095105418457
z_star :  0.7535866969716658
L_s :  0.5693383449421361
phi_s :  0.31596657251943905
```

For Spatial Cue

```
OTSU Threshold : 98
```






```
foreground mean , mu_f :  0.8808924741487429
background mean , mu_b :  0.5082246560220149
foreground  standard  deviation , sigma_f :  0.14250026441919153
background standard  deviation , sigma_b :  0.2308980359587217
z_star :  0.6982573963272953
L_s :  0.11022622960350613
phi_s :  0.4058428843995639
```

In [59]:
```python
final_saliency_image = np.zeros((m,n))
for i in range(m):
    for j in range(n):
        final_saliency_image[i,j] = sm_1*contrast_cues[clustered_img[i,j]] + sm_2*spatail_cues[clustered_img[i,j]]

final_saliency_image = (final_saliency_image - np.min(final_saliency_image))/(np.max(final_saliency_image) - np.min(final_saliency_image))

plt.figure(figsize = (8,8))
plt.imshow(final_saliency_image, cmap = 'gray')
plt.title("Final Saliency Image")
```

Out[59]:
```
Text(0.5, 1.0, 'Final Saliency Image')
```

$---------------- END ----------------$