20171056_Assignment3_up

March 17, 2020

```
In [1]: import cv2
        import sklearn.mixture
        import matplotlib.pyplot as plt
        import numpy as np
        import igraph
```

1 Grabcut assignment

1.1 Grabcut class defined here

1.1.1 Implementation details

- The code has classes
  - class 0 - background
  - class 1 - probably background
  - class 2 - probably foreground
  - class 3 - foreground
- First select the bounding box which becomes the probable foreground class.
- Learn two GMM models
  - Foreground (class 2 and class 3)
  - Background (class 0 and class 1)
- Depending on the class labels edges from source, sink and neighboring nodes are weighted.
- We first construct the graph with number of image pixels + 2 nodes (source and sink).
- We know the probable foreground nodes and background nodes in the first iteration.
- Edge weights assigned given class
  - class 0
    * Sink - pixel - K
    * Source - pixel - 0
    * pixel - pixel - 0 (if class 0 or 1)
    * pixel - pixel - neigboring penalty

- class 1
  - Sink - pixel - negative log likelihood (foreground)
  - Source - pixel - negative log likelihood (background)
  - pixel - pixel - 0 (if class 0 or 1)
  - pixel - pixel - neigboring penalty
- class 2
  - Sink - pixel - negative log likelihood (foreground)
  - Source - pixel - negative log likelihood (background)
  - pixel - pixel - 0 (if class 3 or 2)
  - pixel - pixel - neigboring penalty
- class 3
  - Sink - pixel - 0
  - Source - pixel - K
  - pixel - pixel - 0 (if class 2 or 3)
  - pixel - pixel - neigboring penalty

- Once the graph is constructed with edge weights we perform source terminal mincut. This partitions the graph into 2 parts.
- The above is repeated until convergence.

```
In [5]: class GrabCut:
            def __init__(self, image, gamma = 50, option = 0, num_components = 5, conv_threshold

                '''
                Class constructor
                Input:
                    image - H x W x 3 - input image
                    conv_threshold - scalar - convergence threshold for grabcut
                    bbox - list - bounding box coordinates
                    gamma - scalar - gamma value for grabcut
                    option - scalar
                        0 - 4 neighborhood
                        1 - 8 neighborhood
                    num_components - scalar - number of gaussian components
                    disp_output - scalar - 1) shows intermediate outputs
                                           0) does not show intermediate results
                Returns:
                    None
                '''
                self.threshold = conv_threshold
                self.disp = disp_output
                self.image = image
                if bbox is None:
                    r = cv2.selectROI(self.image)
                    bbox = [r[0], r[1], r[0] + r[2], r[1] + r[3]]
                    self.bbox = bbox
```

```python
        else:
            self.bbox = bbox

        self.option = option
        self.x1 = int(bbox[0])
        self.x2 = int(bbox[2])
        self.y1 = int(bbox[1])
        self.y2 = int(bbox[3])

        self.gamma = gamma
        self.mask = None
        self.graph = None
        self.num_components = num_components

        self.bg_gmm = None
        self.fg_gmm = None

        self.create_mask_init()
        self.create_graph_image()
        cv2.destroyAllWindows()

    def create_mask_init(self):
        '''
        Creates initial mask
            0 - bg
            1 - probably bg
            2 - probably fg
            3 - fg
        '''

        mask = np.zeros((self.image.shape[0], self.image.shape[1]))
        mask[ self.y1:self.y2, self.x1:self.x2] = 2
        self.mask = mask


    def GMMPrediction(self):
        '''
        Function to cluster images sections using gaussian mixture models
        '''
        image = self.image
        mask = self.mask

        bg_mask = np.logical_or(mask == 0 , mask == 1)
        fg_mask = np.logical_or(mask == 2 , mask == 3)


        image_mask_vector_bg = image[bg_mask, :]
        image_mask_vector_fg = image[fg_mask, :]
```

```python
        gmm_model_bg = sklearn.mixture.GaussianMixture(n_components = self.num_component
        gmm_model_fg = sklearn.mixture.GaussianMixture(n_components = self.num_component

        image_vector = image.reshape((-1, 3))

        neg_log_likelihood_bg = -gmm_model_bg.score_samples(image_vector)
        neg_log_likelihood_fg = -gmm_model_fg.score_samples(image_vector)

        self.bg_gmm = neg_log_likelihood_bg.reshape((image.shape[0], image.shape[1]))
        self.fg_gmm = neg_log_likelihood_fg.reshape((image.shape[0], image.shape[1]))



    def create_graph_image(self):
        '''
        Function to create graph of image
        '''

        self.graph = igraph.Graph()
        self.graph.add_vertices(self.image.shape[0] * self.image.shape[1] + 2)

    def calc_beta_value(self):
        '''
        Function to calculate beta value used in neighboring edge weight
        '''

        image = self.image
        height = image.shape[0]
        width = image.shape[1]

        diff_up = np.sum(np.sum(np.square(image[1:height - 1, :] - image[:height - 2, :]
        diff_side = np.sum(np.sum(np.square(image[:, 1:width - 1] - image[:, :width - 2]
        diff_diag = np.sum(np.sum(np.square(image[1:height - 1, 1:width - 1] - image[:he
        diff_lower_diag = np.sum(np.sum(np.square(image[:height - 2, 1:width - 1] - imag

        # 2 * (h - 1)(w - 1) + (h - 1)w + (w - 1)h = 4hw - 3h - 3w + 2
        beta = (1 / 2) * (2 * (height - 1) * (width - 1) + height * (width - 1) + (heigh

        return beta

    def add_graph_edges(self):
        '''
        Function to add edges and their respective weights to th graph
        '''

        beta = self.calc_beta_value()
        image = self.image
```

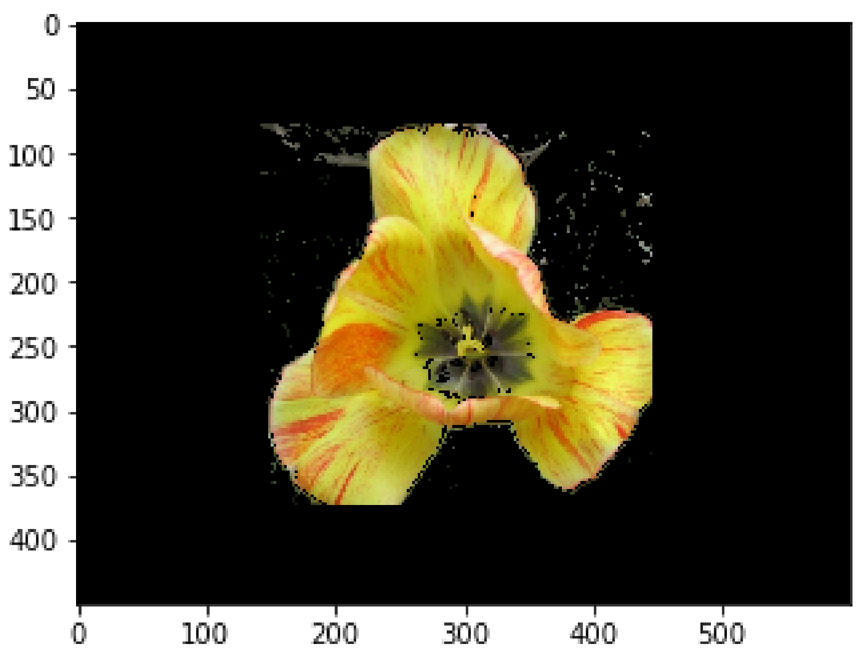
```
height = image.shape[0]
width = image.shape[1]

sink_node = int(image.shape[0]*image.shape[1] + 1)
source_node = int(0)

gamma = self.gamma
edges = []
weights = []
mask = self.mask

for row in range(height):
    for column in range(width):

        # bottom pixel weight

        if (row + 1) < height:
            edges.append((row*width + column + 1, (row + 1)*width + column + 1))

            if mask[row + 1, column] == mask[row, column] or (mask[row + 1, colu
                weights.append(0)
            else:
                weights.append(gamma*np.exp(-beta * np.sum(np.square(image[row +

        #right pixel

        if (column + 1) < width:
            edges.append((row*width + column + 1, (row)*width + column + 2))

            if mask[row, column + 1] == mask[row, column] or (mask[row, column +
                weights.append(0)
            else:
                weights.append(gamma*np.exp(-beta * np.sum(np.square(image[row,

        # diagonal pixel

        if (column + 1) < width and (row + 1) < height and self.option == 1:
            edges.append(((row + 1)*width + column + 2, (row)*width + column + 1

            if mask[row + 1, column + 1] == mask[row, column] or (mask[row + 1,
                weights.append(0)
            else:
                weights.append(gamma*np.exp(-beta * np.sum(np.square(image[row +

K = 1 + max(weights)


for row in range(height):
```

```python
            for column in range(width):

                if mask[row, column] == 1 or mask[row, column] == 2:
                    edges.append((source_node, int(row*width + column + 1)))
                    weights.append(self.bg_gmm[ row, column])

                    edges.append((sink_node, int(row*width + column + 1)))
                    weights.append(self.fg_gmm[ row, column])

                elif mask[row, column] == 0:
                    edges.append((source_node, int(row*width + column + 1)))
                    weights.append(0)

                    edges.append((sink_node, int(row*width + column + 1)))
                    weights.append(K)
                else:
                    edges.append((source_node, int(row*width + column + 1)))
                    weights.append(K)

                    edges.append((sink_node, int(row*width + column + 1)))
                    weights.append(0)



        self.graph.add_edges(edges)
        self.graph.es['weight'] = weights

    def update_mask(self, partition_source):
        '''
        Update mask after st mincut
        '''
        init_mask = self.mask
        mask = np.zeros((self.image.shape[0], self.image.shape[1]))
        mask[ self.y1:self.y2, self.x1:self.x2] = 1
        mask2 = mask.copy()
        mask2[self.y1:self.y2, self.x1:self.x2] = 1
        bbox_width = image.shape[1]

        # removing source node from partition
        partition_source = np.array(partition_source, dtype = int)


        partition_source = partition_source - 1
        mask_partition = partition_source >= 0

        partition_source = partition_source[mask_partition]
```

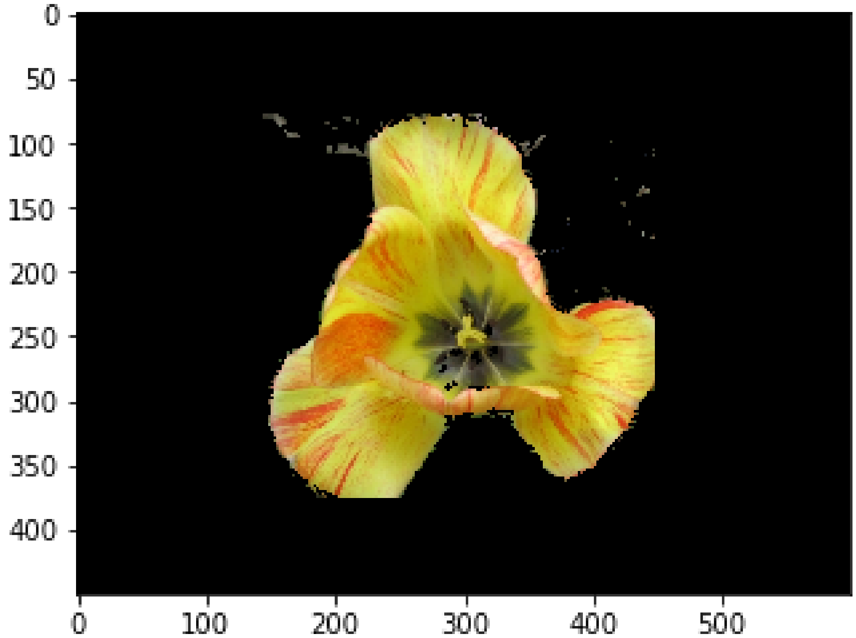
```
        fg_row = partition_source // bbox_width
        fg_col = partition_source % bbox_width

        mask[fg_row, fg_col] = 2
        mask[np.where(init_mask) == 3] = 3
        self.mask = mask * mask2

    def generate_image_mask(self):
        '''
        Generate segmented image
        '''

        masked_image = np.zeros(self.image.shape)
        mask = np.logical_or(self.mask == 2, self.mask == 3) * 1
        for i in range(3):
            masked_image[:, :, i] = self.image[:, :, i] * mask
        masked_image = masked_image.astype('uint8')

        return masked_image

    def grabCut(self):

        '''
        Function performs grabcut
        Input:
            Class object
        Returns:
            masked_image - H x W x 3 - image containing foreground only

        '''
        running = True
        i = 0
        while running:
            self.GMMPrediction()
            self.add_graph_edges()
            mc = self.graph.st_mincut( int(0), image.shape[0]*image.shape[1] + 1, self.g

            if i != 0:
                threshold = (mc.value - E_init) / mc.value
                print(threshold)
                if threshold < self.threshold:
                    running = False

            E_init = mc.value
            partition_source, partition_terminal = mc.partition
            self.update_mask(partition_source)
            i = i + 1
            masked_image = self.generate_image_mask()
```

```
                masked_image = cv2.cvtColor(masked_image, cv2.COLOR_BGR2RGB)
                if self.disp == 1:
                    plt.imshow(masked_image)
                    plt.show()

            return masked_image
```

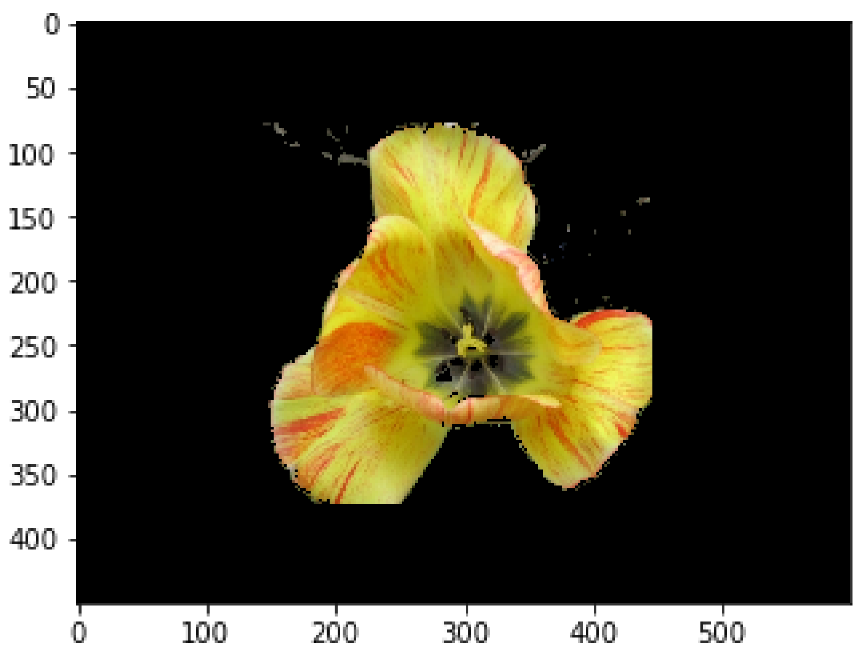
```
In [6]: if __name__ == "__main__":

            name = 'flower'
            image_name = './data/images/%s.jpg' % (name)
            bbox_name = './data/bboxes/%s.txt' % (name)
            bbox = np.loadtxt(bbox_name, delimiter = ' ')
            image = cv2.imread(image_name)
            gamma = 50
            option = 0
            num_components = 5
            convergence_threshold = 0.1
            print_output = 1
            grabcut_object = GrabCut(image, gamma, option, num_components, convergence_threshold
            image_output = grabcut_object.grabCut()
```



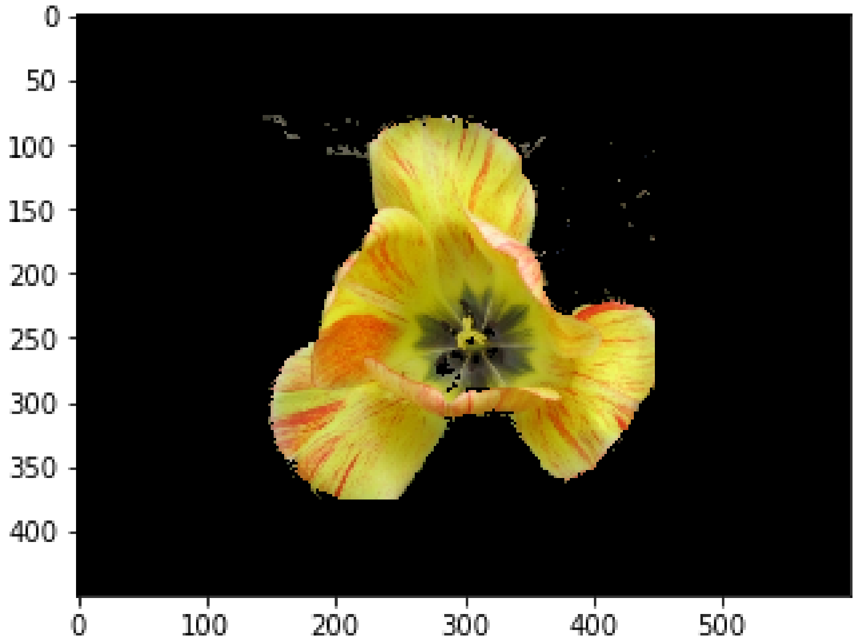

```
0.4846690730081838
```



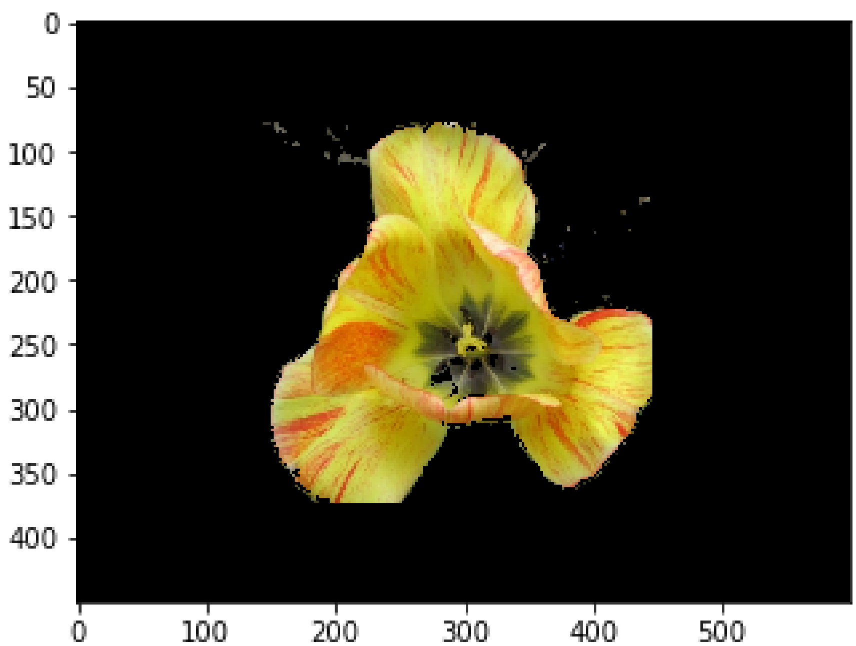
0.3314579455319971



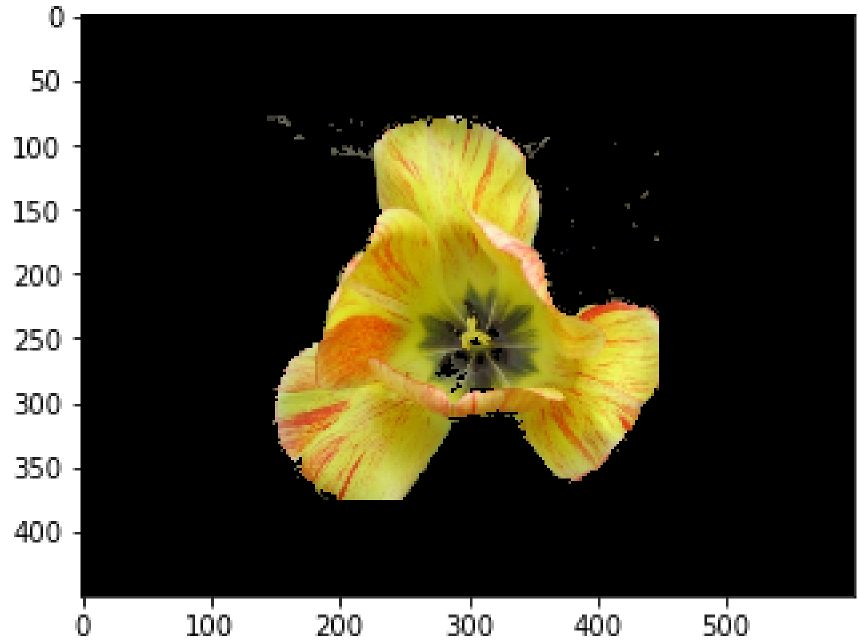
0.25023953165851426



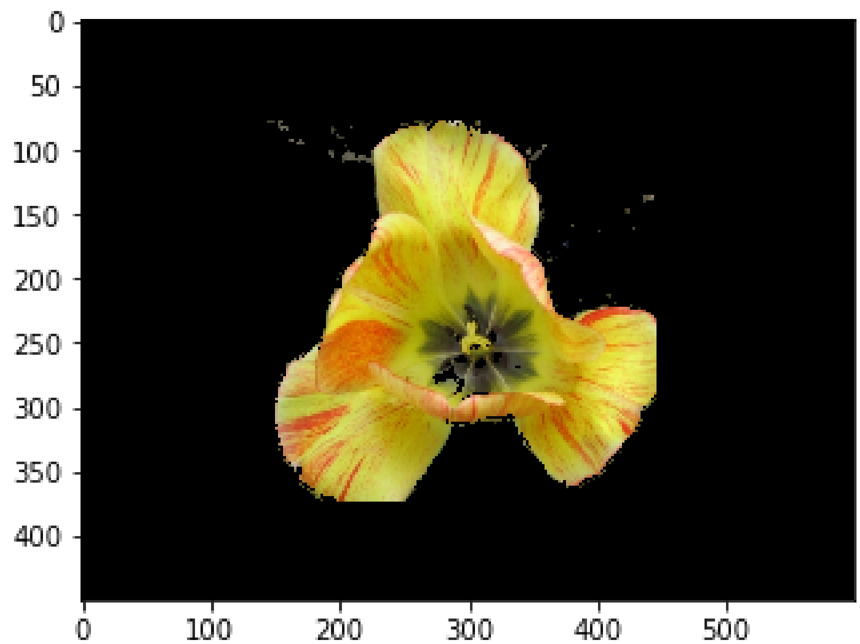
0.19948358511151848



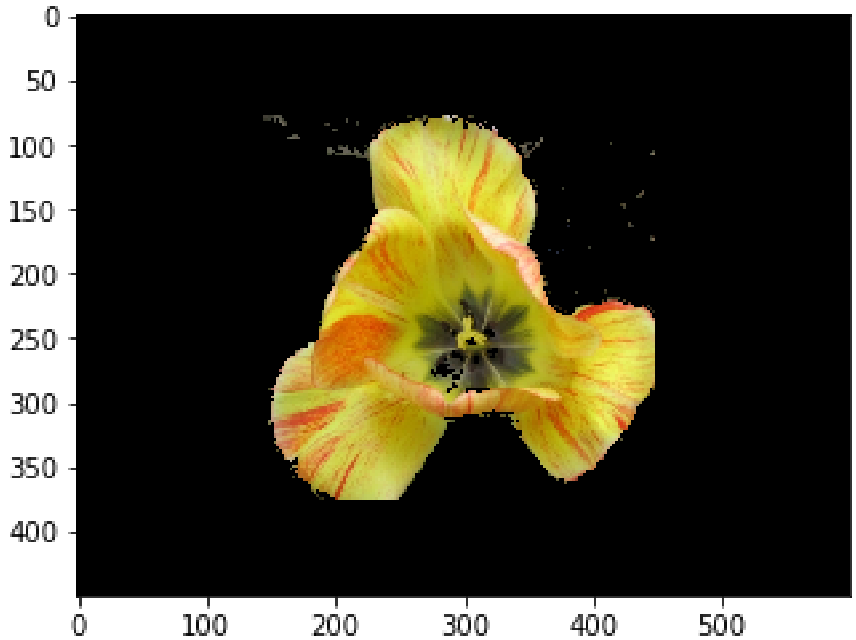
0.16660283583520244



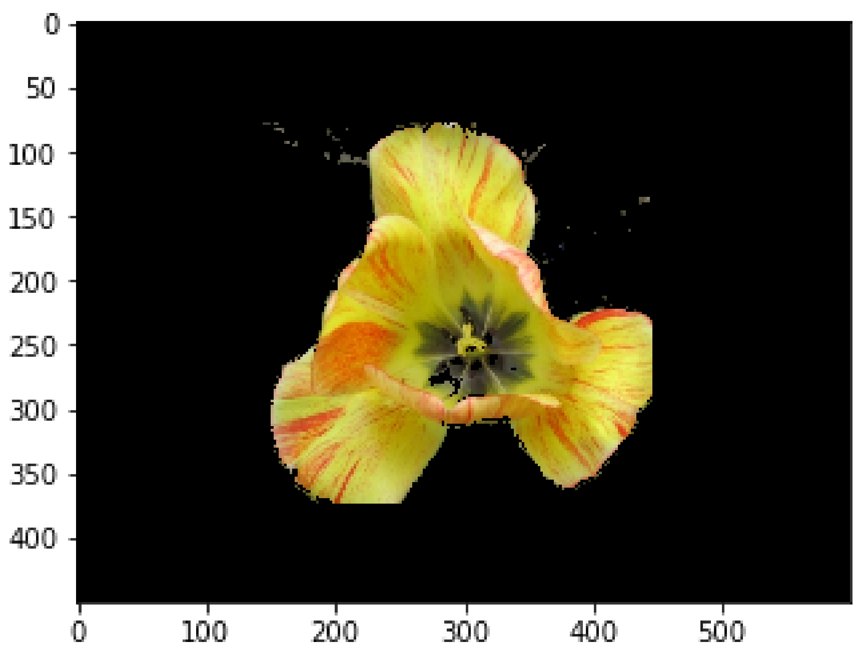
0.14276839702053631



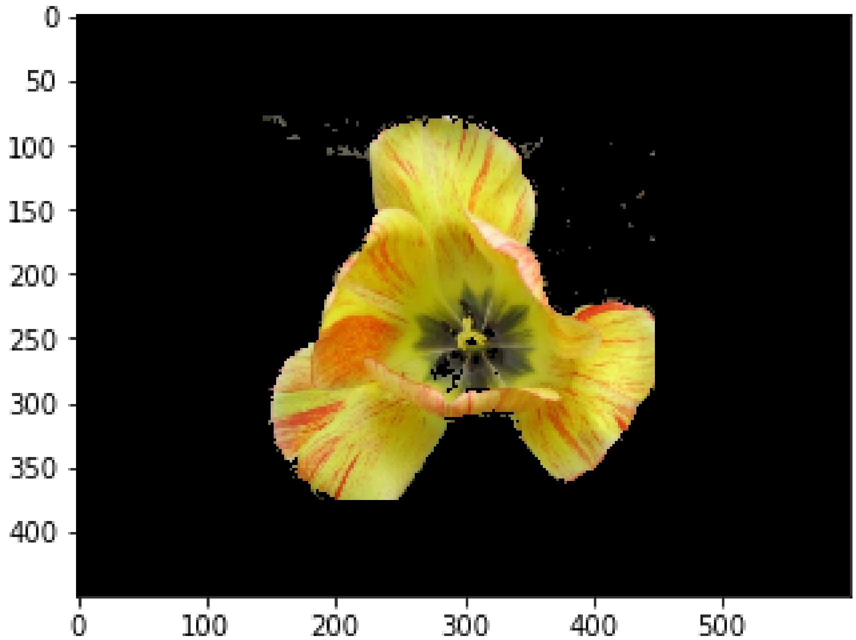
0.12502269705973068



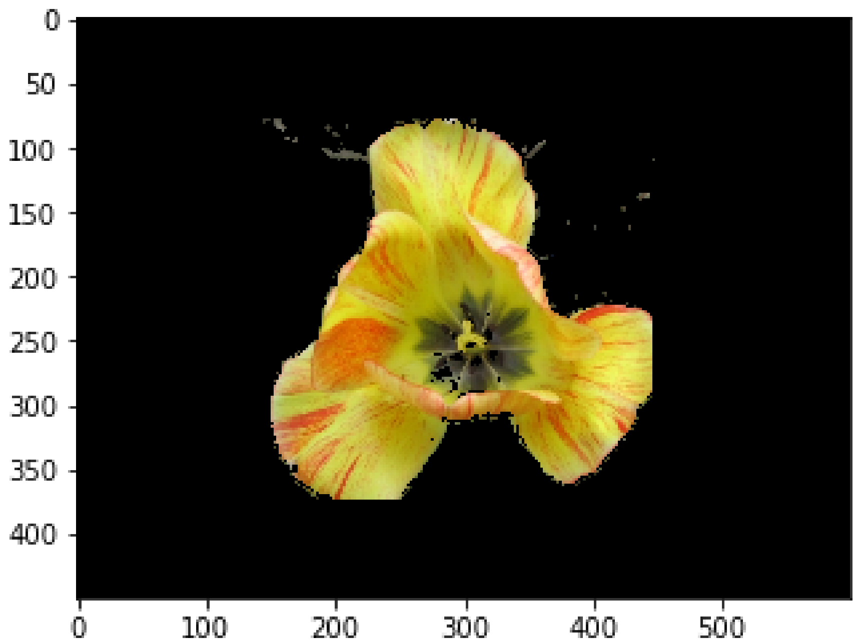
0.11104850966726496



```
0.10003330856192441
```




```
0.0898919100540024
```

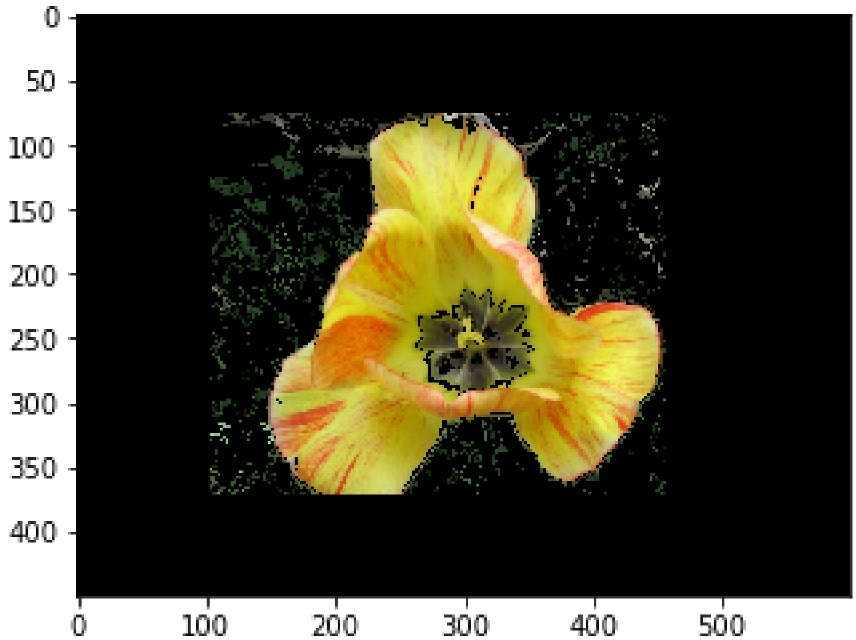


1.1.2 Testing with 8 neighbors

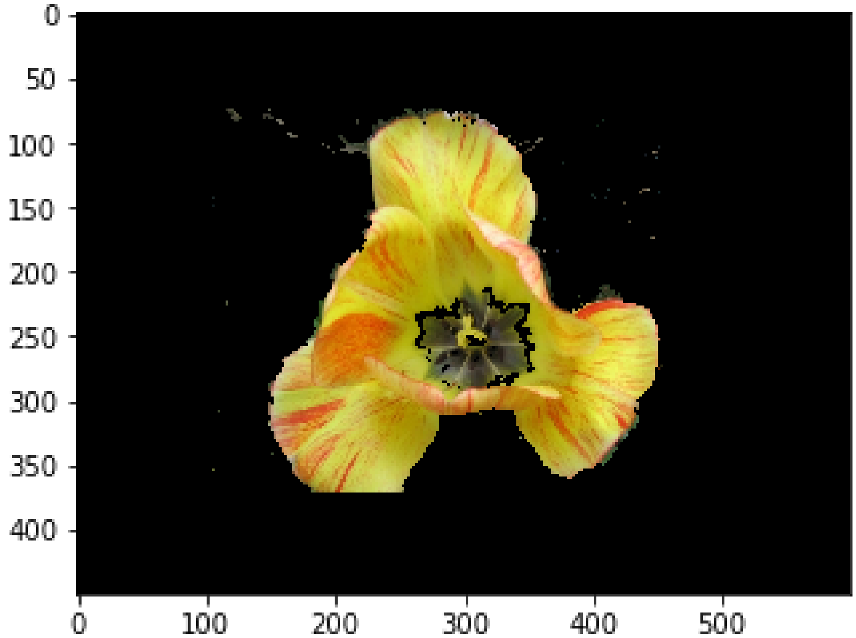
Inference

```
- With 8 neighbors the foreground segmentation is more uniform diagonally
```

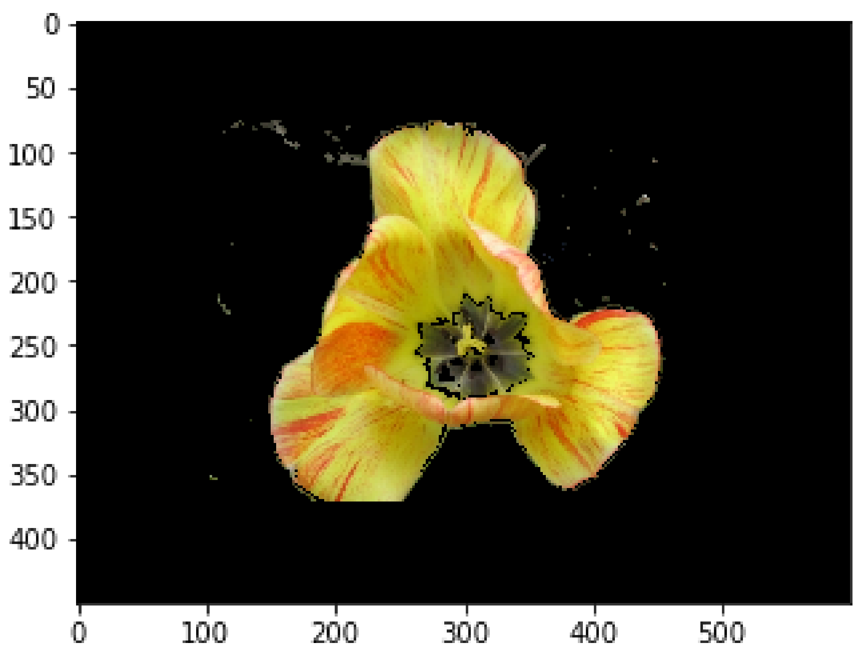
In [7]:
```
name = 'flower'
image_name = './data/images/%s.jpg' % (name)
bbox_name = './data/bboxes/%s.txt' % (name)
bbox = np.loadtxt(bbox_name, delimiter = ' ')
image = cv2.imread(image_name)
gamma = 50
option = 1
num_components = 5
convergence_threshold = 0.1
print_output = 1
grabcut_object = GrabCut(image, gamma, option, num_components, convergence_threshold
image_output = grabcut_object.grabCut()
```



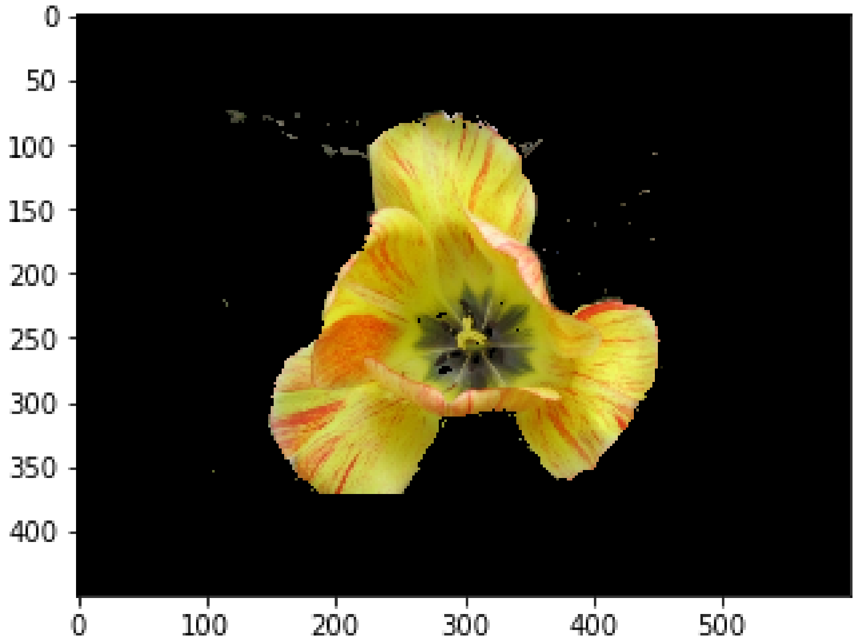

```
0.48784311639911937
```



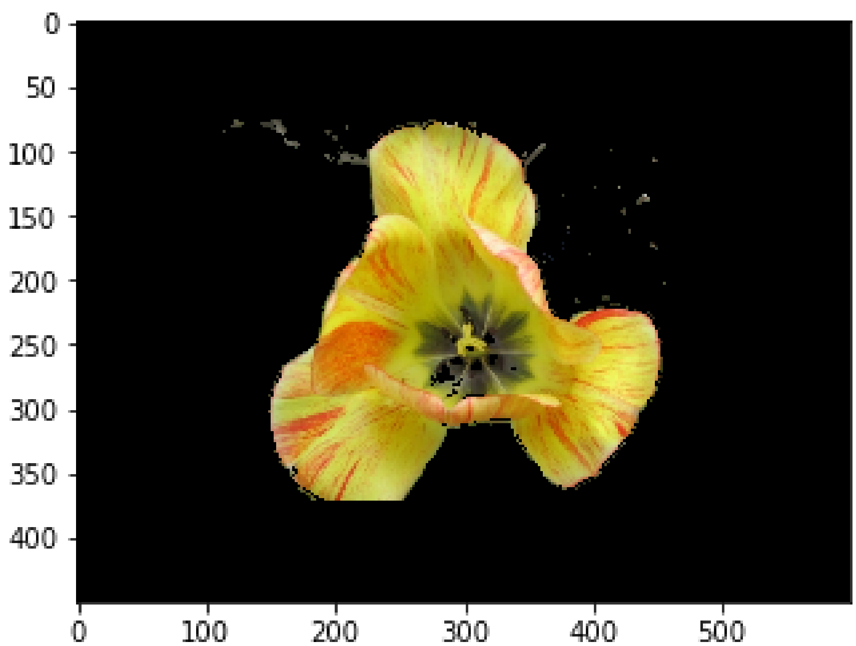
0.3276402273521335



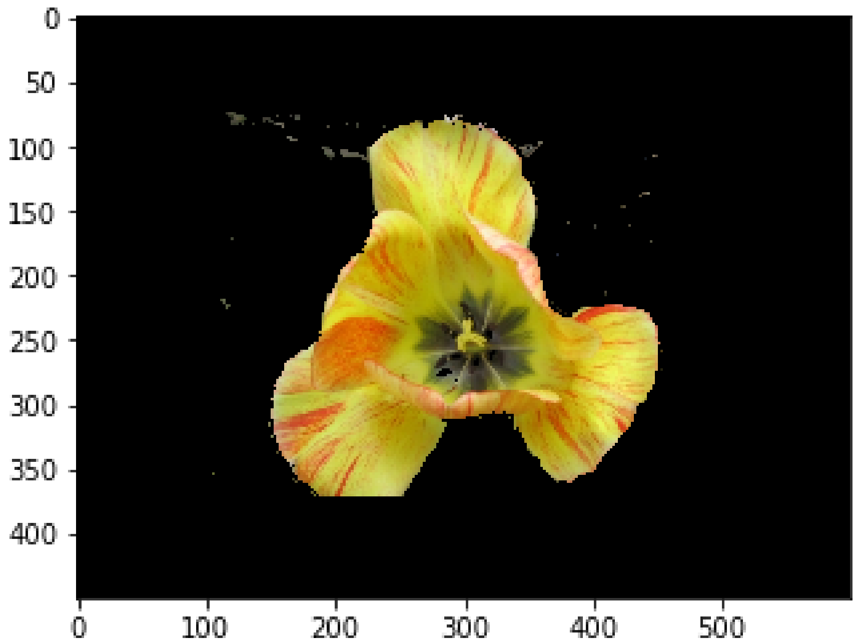
```
0.25019220244636836
```



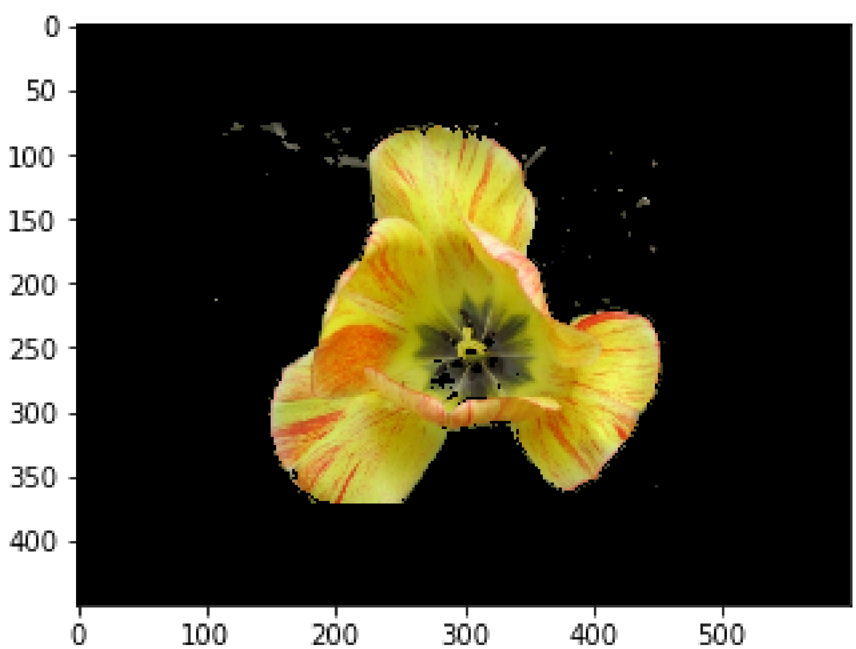

```
0.19809750603803203
```



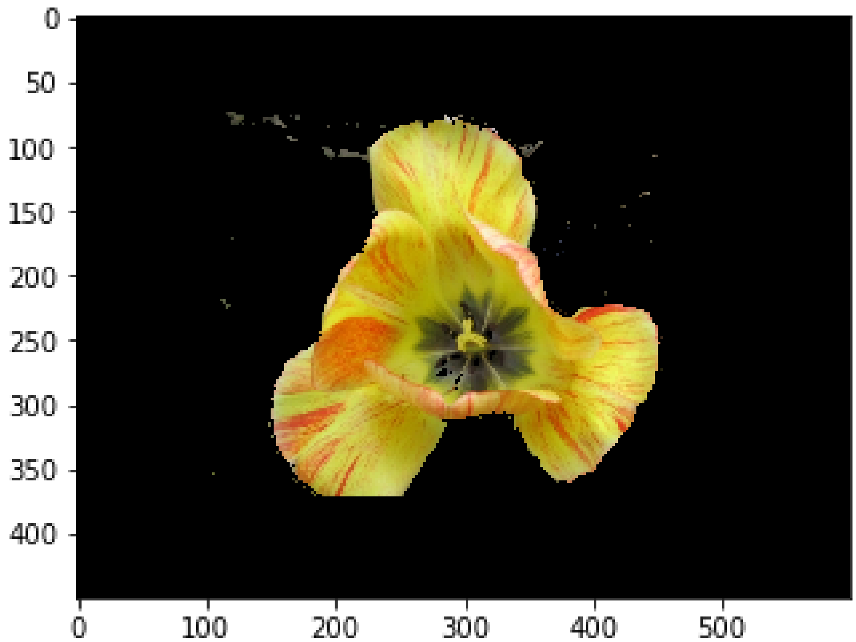
0.1682033655744191



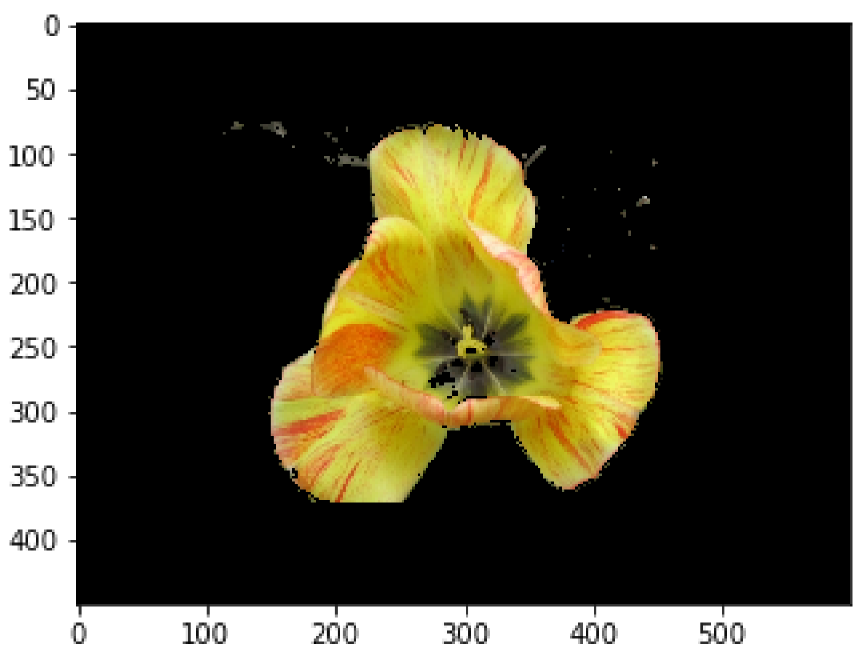
0.14034618541618352



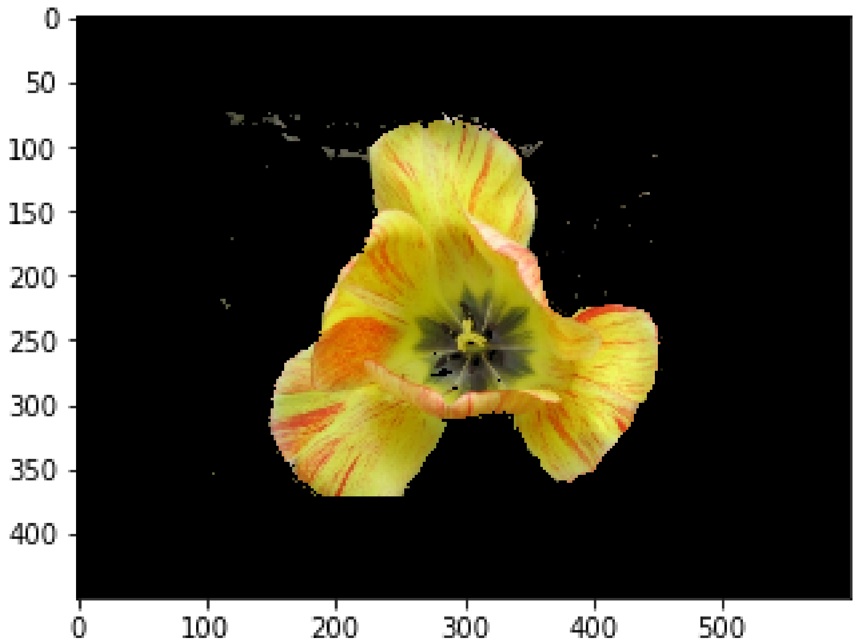
0.12733181461437545



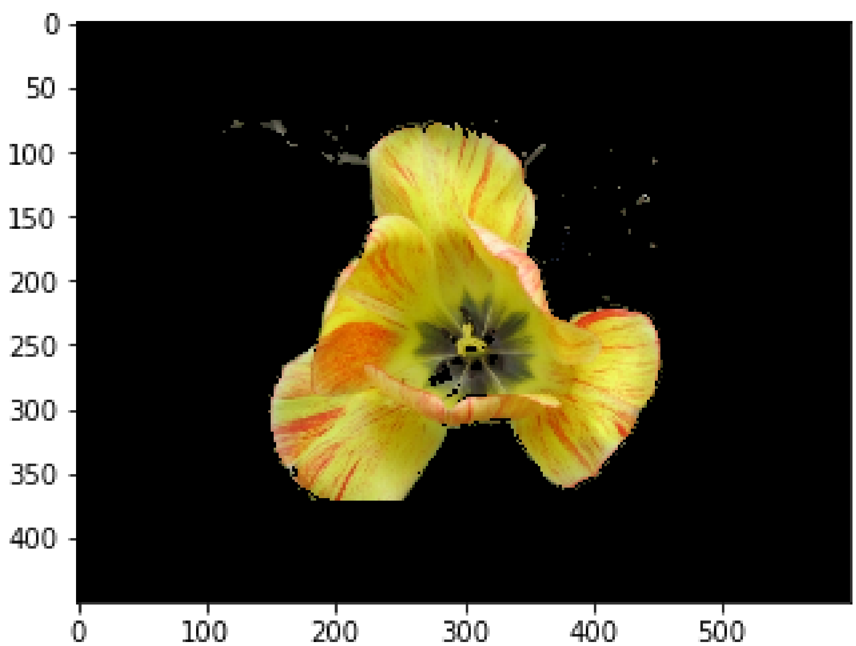
0.10982823742887424



0.10051433427503613



0.09031618583009131



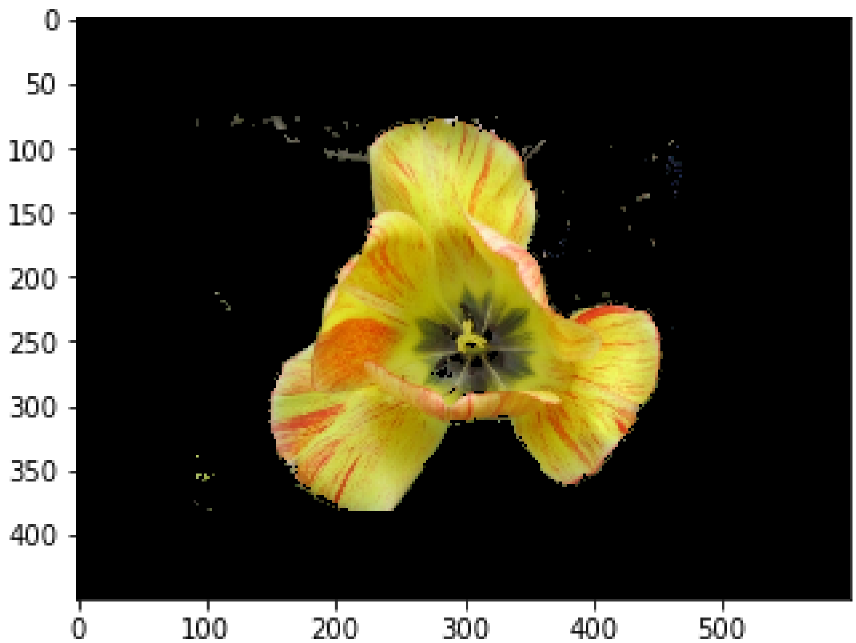
1.1.3 Testing with higher value of gamma

Inference

```
- Giving high gamma value means we are stressing over the neighbors to belong to same class this
```

In [8]:
```
name = 'flower'
image_name = './data/images/%s.jpg' % (name)
bbox_name = './data/bboxes/%s.txt' % (name)
bbox = np.loadtxt(bbox_name, delimiter = ' ')
image = cv2.imread(image_name)
gamma = 100
option = 0
num_components = 5
convergence_threshold = 0.1
print_output = 0
grabcut_object = GrabCut(image, gamma, option, num_components, convergence_threshold
image_output = grabcut_object.grabCut()
plt.imshow(image_output)
plt.show()
```

```
0.48722826367366456
0.3291582149590456
0.25005990914366905
0.19816484687373787
0.16708732594467054
0.14145399023205224
0.12576589261663812
0.11056142690712724
0.10080799818767916
0.09000614041396057
```



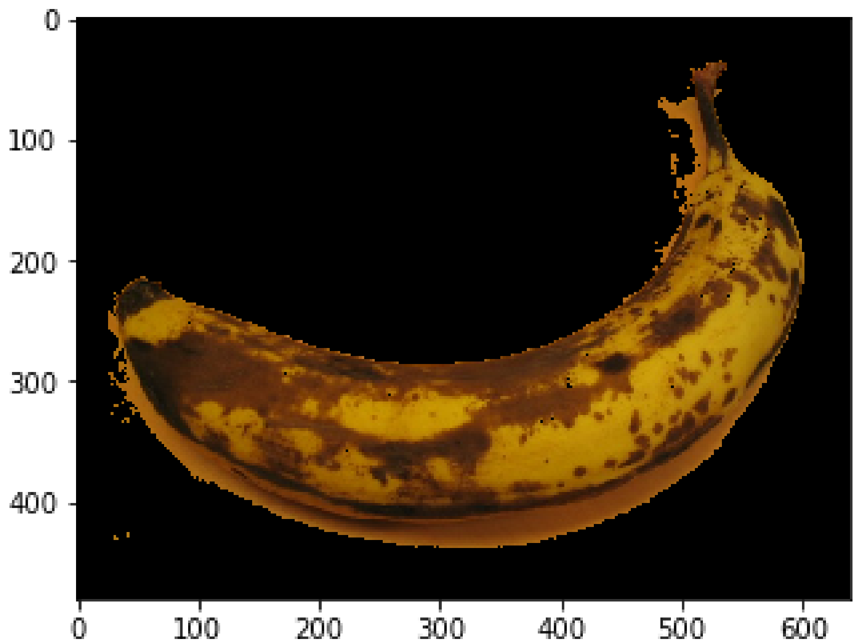
1.1.4 Varying GMM components

GMM component = 1

In [9]:
```
name = 'banana1'
image_name = './data/images/%s.jpg' % (name)
bbox_name = './data/bboxes/%s.txt' % (name)
bbox = np.loadtxt(bbox_name, delimiter = ' ')
image = cv2.imread(image_name)
gamma = 50
option = 0
num_components = 1
convergence_threshold = 0.1
print_output = 0
grabcut_object = GrabCut(image, gamma, option, num_components, convergence_threshold
image_output = grabcut_object.grabCut()
plt.imshow(image_output)
plt.show()
```

```
0.48004695255834995
0.2984890645589716
0.24272279553262927
0.20011467122571516
0.16666146315652355
0.1429198643140213
0.12496023499405283
```

```
0.11115309569354133
0.0999602300614365
```

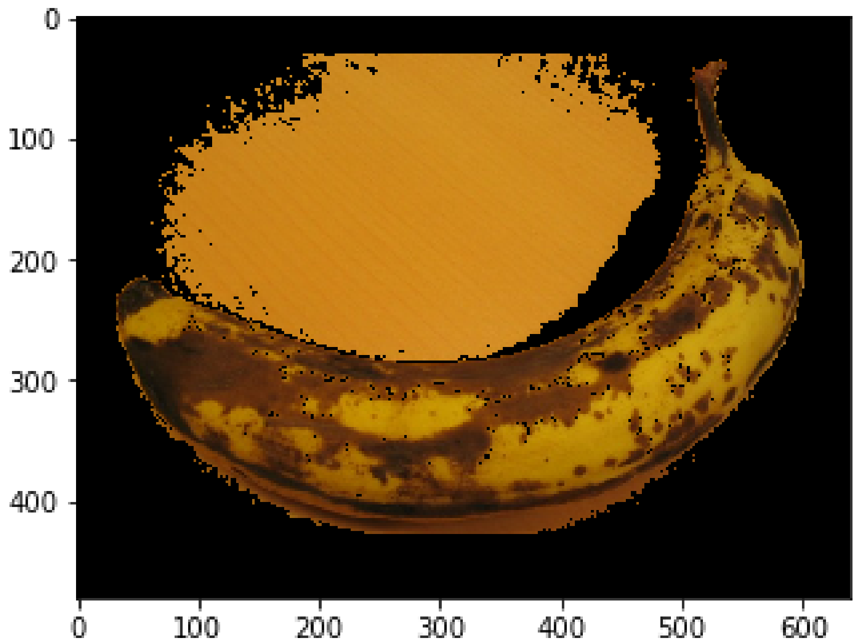


GMM components = 5

In [10]:
```
name = 'banana1'
image_name = './data/images/%s.jpg' % (name)
bbox_name = './data/bboxes/%s.txt' % (name)
bbox = np.loadtxt(bbox_name, delimiter = ' ')
image = cv2.imread(image_name)
gamma = 50
option = 0
num_components = 5
convergence_threshold = 0.1
print_output = 0
grabcut_object = GrabCut(image, gamma, option, num_components, convergence_threshol
image_output = grabcut_object.grabCut()
plt.imshow(image_output)
plt.show()
```

```
0.4835244309625366
0.32738216641414775
0.24934476851369308
0.19871776637329905
0.1666412551857611
```

```
0.14235503031675814
0.1254341325165165
0.11065429747657508
0.10010883892281666
0.09066831940429741
```



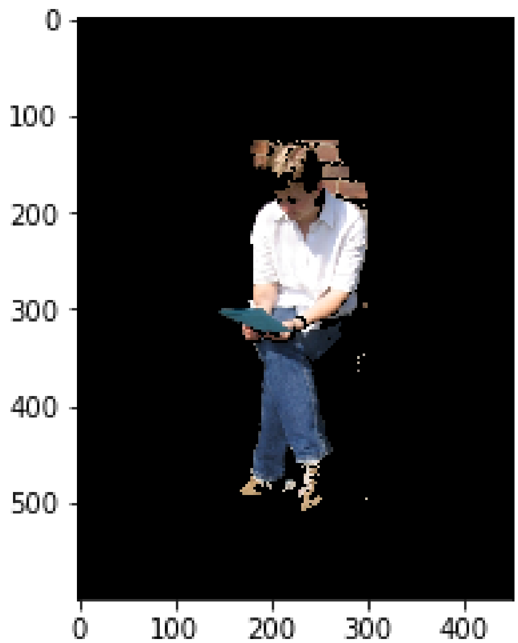
1.1.5 Tight bounding box

```
- Tighter bounding box gives higher accuracy
- With loose bounding box we have more pixels that are not in the foreground as probable foregro
```

In [11]:

```python
name = 'person6'
image_name = './data/images/%s.jpg' % (name)
bbox_name = './data/bboxes/%s.txt' % (name)
bbox = np.loadtxt(bbox_name, delimiter = ' ')
image = cv2.imread(image_name)
gamma = 50
option = 1
num_components = 1
convergence_threshold = 0.1
print_output = 0
grabcut_object = GrabCut(image, gamma, option, num_components, convergence_threshol
image_output = grabcut_object.grabCut()
plt.imshow(image_output)
plt.show()
```

```
0.49041299122697846
0.33180842954919404
0.2508846387920136
0.19893331409627926
0.16772006350435364
0.14175244450743651
0.12612353287380462
0.10996793516867336
0.10115597896841295
0.08973993369523252
```

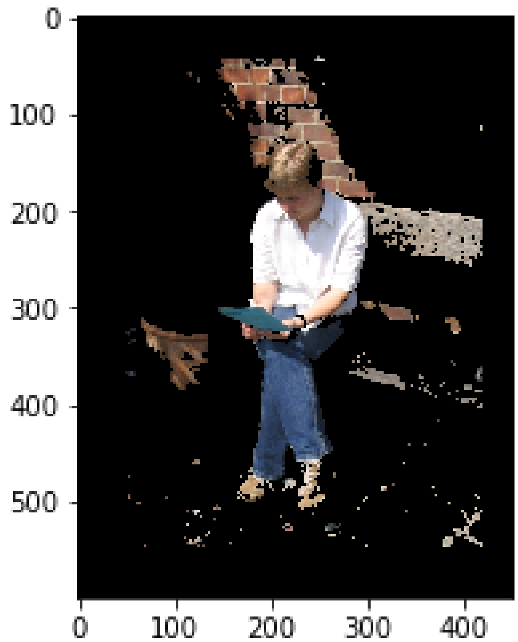


1.1.6 Loose bounding box

In [12]:
```
name = 'person6'
image_name = './data/images/%s.jpg' % (name)
bbox_name = './data/bboxes/%s.txt' % (name)
bbox = np.loadtxt(bbox_name, delimiter = ' ')
image = cv2.imread(image_name)
gamma = 50
option = 1
num_components = 1
convergence_threshold = 0.1
print_output = 0
grabcut_object = GrabCut(image, gamma, option, num_components, convergence_threshol
image_output = grabcut_object.grabCut()
```

```
    plt.imshow(image_output)
    plt.show()
```

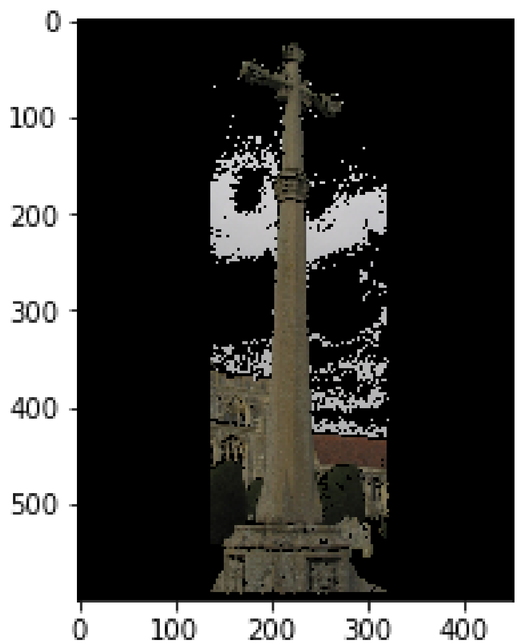
```
0.47755721295967557
0.33198249241625827
0.2503626144980008
0.1995347047184657
0.16710279546992302
0.14240116942188277
0.12546287591716515
0.11063996167209182
0.10047678609044333
0.09042723352747796
```



In [13]:
```
name = 'cross'
image_name = './data/images/%s.jpg' % (name)
bbox_name = './data/bboxes/%s.txt' % (name)
bbox = np.loadtxt(bbox_name, delimiter = ' ')
image = cv2.imread(image_name)
gamma = 50
option = 0
num_components = 3
convergence_threshold = 0.1
print_output = 0
grabcut_object = GrabCut(image, gamma, option, num_components, convergence_threshol
```

```
image_output = grabcut_object.grabCut()
plt.imshow(image_output)
plt.show()
```

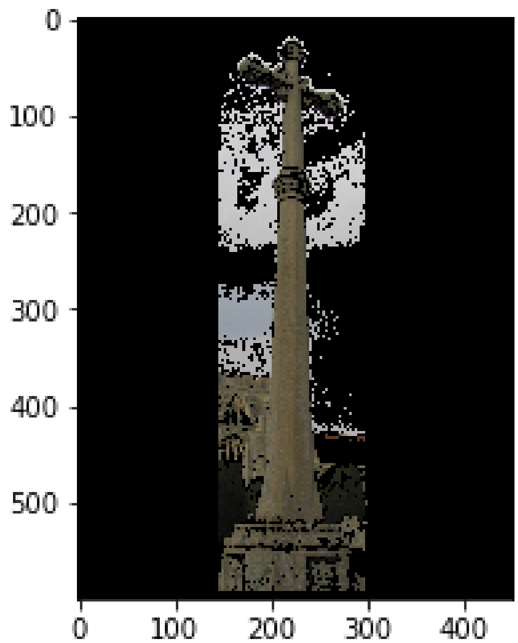
```
0.4848829345713043
0.33051042938323094
0.24910948967922233
0.19954943994714694
0.16666297824197926
0.14254639411659045
0.12506033325816562
0.11079659538476527
0.10007594768028226
0.09047683591795898
```




```
In [14]:    name = 'cross'
            image_name = './data/images/%s.jpg' % (name)
            bbox_name = './data/bboxes/%s.txt' % (name)
            bbox = np.loadtxt(bbox_name, delimiter = ' ')
            image = cv2.imread(image_name)
            gamma = 50
            option = 0
            num_components = 5
            convergence_threshold = 0.1
            print_output = 0
```

```
            grabcut_object = GrabCut(image, gamma, option, num_components, convergence_threshol
            image_output = grabcut_object.grabCut()
            plt.imshow(image_output)
            plt.show()
```

```
0.4939997990455215
0.3283214037183475
0.2508581012445524
0.19707577983056299
0.16832506790367133
0.14089995889715876
0.12613626422670798
0.10967879541946883
0.10091810145696103
0.08960723419817657
```

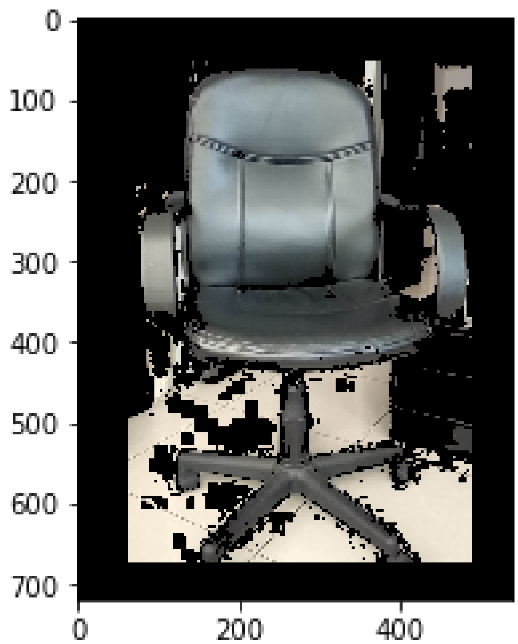


1.1.7 testing with my own image

In [15]:
```
name = 'chair_image'
image_name = './data/images/%s.jpg' % (name)
#bbox_name = './data/bboxes/%s.txt' % (name)
bbox = np.loadtxt(bbox_name, delimiter = ' ')
image = cv2.imread(image_name)
gamma = 50
option = 0
```

```
num_components = 3
convergence_threshold = 0.1
print_output = 0
grabcut_object = GrabCut(image, gamma, option, num_components, convergence_threshol
image_output = grabcut_object.grabCut()
plt.imshow(image_output)
plt.show()
```

```
0.48405088351616776
0.3295249214759268
0.2503350275430667
0.19816026844742068
0.16771554486540816
0.14128109328902294
0.12618119616672308
0.10963334795923246
0.10123894504915058
0.08944276242329999
```




```
In [ ]:
```