Technical Report - 3: Image Region Labelling

Scene Segmentation and Interpretation

Instructor
Olivier Laligant

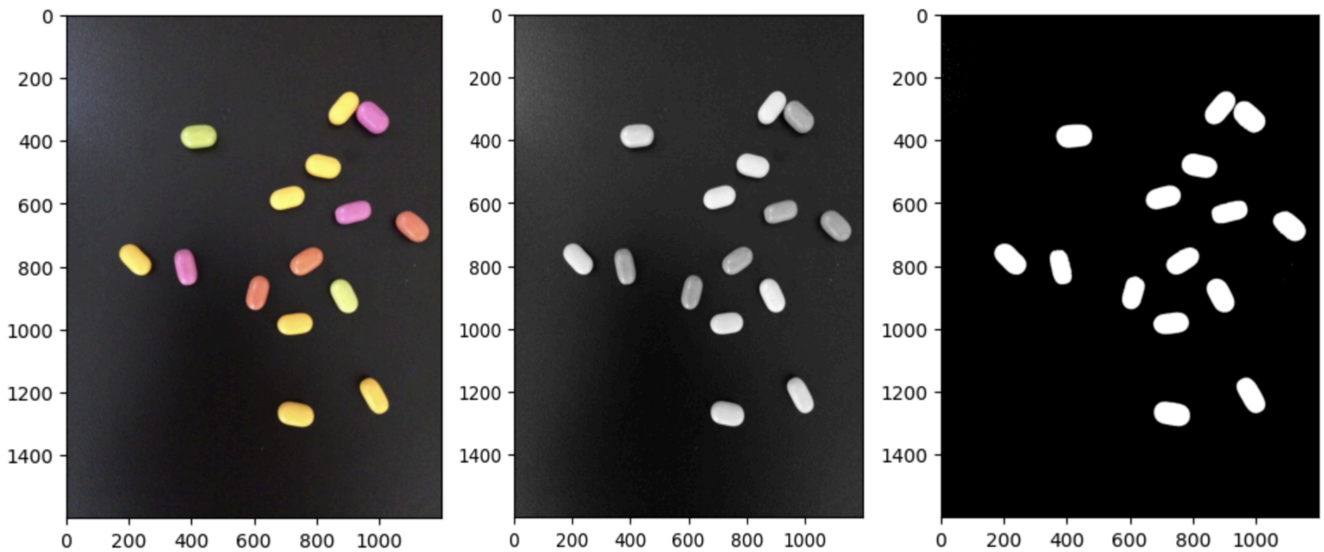
Mayank Kumar GUPTA

Objective:

The objective of this project is to develop an image processing algorithm for region labeling in a binary image. The algorithm aims to accurately label regions within the binary image, separating objects from the background. Additionally, the algorithm should refine the labeling process to handle multiple labels for the same region and merge them to define a single region.

Image Preprocessing:

The initial step is to convert the color image into a grayscale image, and then convert it to a binary image. This is achieved by applying a threshold value of 130, where pixel values above this threshold are set to 1 (representing objects), and those below are set to 0 (representing background).



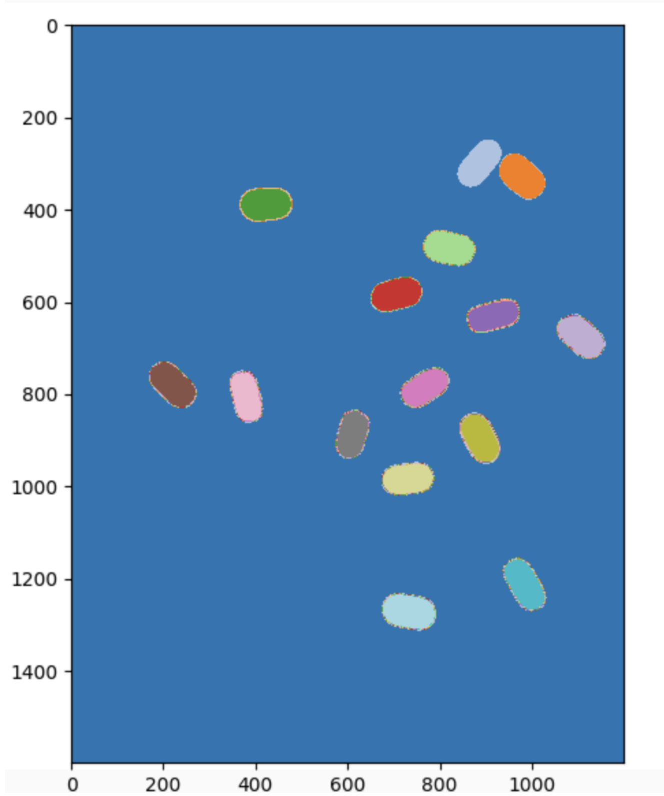
Original Image Grayscale Image Binary Image

Region Labeling Algorithm:

The algorithm iterates over each pixel in the binary image, and upon encountering a pixel with a value of 1, it assigns a new label to it.
As it progresses, it checks the neighboring pixels of each labeled pixel to determine connectivity. The labeling process is implemented using a recursive method, storing visited pixel indices in a list to track progress.

Refinement for Noise Reduction:

In the labeling process, it's common to encounter noisy regions that aren't actual objects.
To address this, a refinement step is introduced.
A threshold is set to the number of pixels associated with each label. If the total count falls below this threshold, indicating a noise region, the label is reset to 0. This effectively eliminates noise from the labeling results.



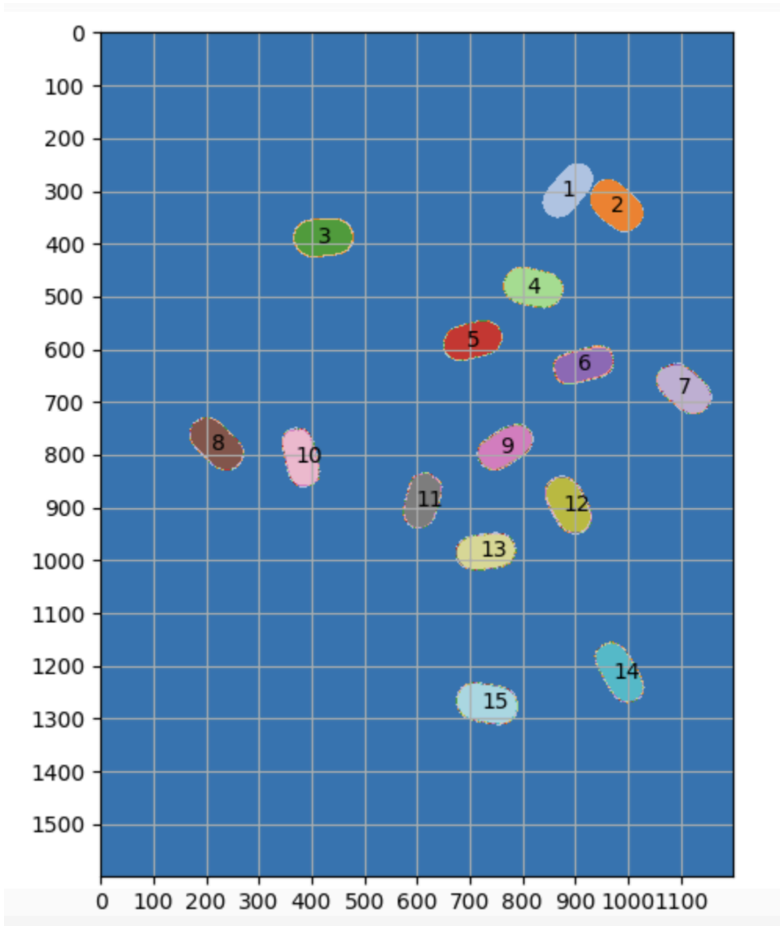
Processed image after Labeling and Refinement

Calculating Image moments:

In image processing, computer vision and related fields, an image moment is a certain particular weighted average (moment) of the image pixels' intensities, or a function of such moments, usually chosen to have some attractive property or interpretation.

Utilizing image moments, we derive essential parameters such as mean_x and mean_y, representing the center of each labeled region, alongside theta, denoting the orientation. These calculations serve as pivotal steps in analyzing and characterizing labeled regions within images.

By employing the coordinates of the center (x, y) and the orientation of a labeled region, we can efficiently determine its length and width. This involves iterating along the region's orientation from its center pixel to its edges to compute the length. Similarly, perpendicular iterations from the center facilitate width calculation in both directions.



Labelled image

Orientation and Dimensions:

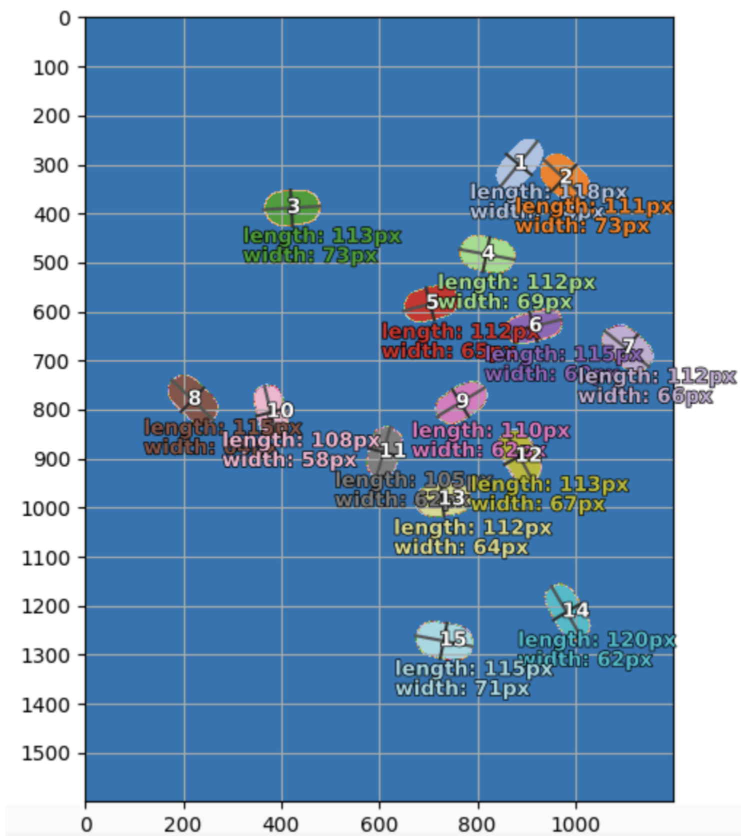
Below are the orientation and dimensions of each object, computed through our analysis.

Object 01 - theta in degree: -39.49 length: 118 width: 64
Object 02 - theta in degree: 46.92 length: 111 width: 73
Object 03 - theta in degree: -86.76 length: 113 width: 73
Object 04 - theta in degree: 79.36 length: 112 width: 69
Object 05 - theta in degree: -75.09 length: 112 width: 65
Object 06 - theta in degree: -75.78 length: 115 width: 60
Object 07 - theta in degree: 50.89 length: 112 width: 66

Object 08 - theta in degree: 46.34 length: 115   width: 64
Object 09 - theta in degree: -58.61 length: 110   width: 62
Object 10 - theta in degree: 14.01 length: 108   width: 58
Object 11 - theta in degree: -14.87 length: 105   width: 62
Object 12 - theta in degree: 28.76 length: 113   width: 67
Object 13 - theta in degree: -83.97 length: 112   width: 64
Object 14 - theta in degree: 30.50 length: 120   width: 62
Object 15 - theta in degree: 79.33 length: 115   width: 71

Additionally, the mean and standard deviation of both length and width is calculated:

Length Mean	:	112.73
Width Mean	:	65.33
Length Std	:	3.56
Width Std	:	4.37



Labelled image

Summary:

In summary, this report highlights the efficacy of employing neighboring pixel values for region labeling in images. Through analysis of these values, successful labeling was achieved across binary, grayscale, and color images, showcasing versatility for tasks like object recognition and segmentation. While effective, algorithm enhancements are warranted for improved region detection, particularly in noisy image environments.

Appendix

```
import numpy as np
import matplotlib.pyplot as plt
import cv2
import math
import sys
sys.setrecursionlimit(10000)

def find_neighbour(arr_np, i, j, size_row, size_col, label):
    if i < 0 or j < 0 or i >= size_row or j >= size_col or arr_np[i, j] != 1:
        return
    arr_np[i, j] = label
    explored_items.add((i, j))
    for k in range(-1, 2):
        for l in range(-1, 2):
            if k == 0 and l == 0:
                continue
            if (i + k, j + l) not in explored_items:
                find_neighbour(arr_np, i + k, j + l, size_row, size_col, label)

def connected_components(image):
    threshold = 130
    arr_np = np.where(image > threshold, 1, 0)
    size_row, size_col = arr_np.shape
    label = 2
    global explored_items
    explored_items = set()
```

```
    for i in range(size_row):
        for j in range(size_col):
            if arr_np[i, j] == 1 and (i, j) not in explored_items:
                find_neighbour(arr_np, i, j, size_row, size_col, label)
                label += 1
    return arr_np

def clean_image(image): # To remove extra pixel which is not actually a object
    clean_label = []
    unique, counts = np.unique(image, return_counts=True)
    for i in range(len(unique)):
        if counts[i]<50:
            image[image==unique[i]] = 0
        else:
            clean_label.append(unique[i])
    clean_label.pop(0)
    for i in range(1, len(clean_label)+1):
        image[image==clean_label[i-1]] = i
    return image


image = cv2.imread('tablets.jpeg', cv2.IMREAD_GRAYSCALE)
labeled_image = clean_image(connected_components(image))
img_shape = labeled_image.shape

plt.figure(figsize = (10,10))
plt.imshow(labeled_image, cmap='tab20')
plt.grid()
plt.xticks(np.arange(0, img_shape[1], 100))
plt.yticks(np.arange(0, img_shape[0], 50))
plt.show()


def generate_moments(image):
    li = ["m11", "m02", "m20", "m01", "m10", "m00", "mean_x", "mean_y", "mu20",
"mu02", "mu11", "theta", "theta_degree", "start_x", "start_y"]
    M_table_dict = { each: {i: 0 for i in range(1, np.max(image)+1)} for each in li}
    for i in range(img_shape[0]):
        for j in range(img_shape[1]):
```

```
            if labeled_image[i,j]:
                M_table_dict["m11"][image[i,j]] += (i * j)
                M_table_dict["m02"][image[i,j]] += (j**2)
                M_table_dict["m20"][image[i,j]] += (i**2)
                M_table_dict["m01"][image[i,j]] += j
                M_table_dict["m10"][image[i,j]] += i
                M_table_dict["m00"][image[i,j]] += 1
                if not M_table_dict["start_x"][image[i,j]]:
                    M_table_dict["start_x"][image[i,j]] = j
                if not M_table_dict["start_y"][image[i,j]]:
                    M_table_dict["start_y"][image[i,j]] = i

    plt.figure(figsize = (7,7))
    plt.imshow(image, cmap='tab20')

    for i, each in enumerate(M_table_dict['m11']):
        M_table_dict["mean_x"][each] =
M_table_dict["m10"][each]/M_table_dict["m00"][each]
        M_table_dict["mean_y"][each] =
M_table_dict["m01"][each]/M_table_dict["m00"][each]
        M_table_dict["mu20"][each] =
M_table_dict["m20"][each]/M_table_dict["m00"][each] -
M_table_dict["mean_x"][each]**2
        M_table_dict["mu02"][each] =
M_table_dict["m02"][each]/M_table_dict["m00"][each] -
M_table_dict["mean_y"][each]**2
        M_table_dict["mu11"][each] =
M_table_dict["m11"][each]/M_table_dict["m00"][each] -
M_table_dict["mean_x"][each]*M_table_dict["mean_y"][each]
        M_table_dict["theta"][each] = 1/2 * np.arctan2( 2 *
M_table_dict["mu11"][each], (M_table_dict["mu20"][each] -
M_table_dict["mu02"][each]) )
        M_table_dict["theta_degree"][each] =
np.degrees(M_table_dict["theta"][each])

        plt.text(M_table_dict["mean_y"][each] - 10, M_table_dict["mean_x"][each] +
10, str(i+1))

    plt.grid()
    plt.xticks(np.arange(0, img_shape[1], 100))
```

```
    plt.yticks(np.arange(0, img_shape[0], 100))
    plt.show()

    return M_table_dict

moments = generate_moments(labeled_image)
# for each in moments:
#     print(each, moments[each])
#     print()



dimensions = []
edge_locs = []
for i in range(1, np.max(labeled_image)+1):
    edge_points = [0 for i in range(4)]
    directions = [0, np.pi/2, np.pi, -np.pi/2] # left, bottom, right, top
    theta = moments['theta'][i]
    edge_pos = [0 for i in range(4)]
    k = 1
    while True:
        for l in range(4):
            if not edge_points[l]:
                val_x = int(moments['mean_x'][i] + k*np.cos(theta + directions[l]))
                val_y = int(moments['mean_y'][i] + k*np.sin(theta + directions[l]))
                if labeled_image[val_x, val_y] != i:
                    edge_points[l] = k - 1
                    edge_pos[l] = (int(moments['mean_x'][i] + k*np.cos(theta +
directions[l])),
                                   int(moments['mean_y'][i] + k*np.sin(theta + directions[l])))
        if all(edge_points):
            break
        k+=1
    print(i, "- theta in degree:", math.floor(moments['theta_degree'][i]*100)/100,
"length:", edge_points[0] + edge_points[2], "  width:", edge_points[1] +
edge_points[3])
    dimensions.append((edge_points[0] + edge_points[2], edge_points[1] +
edge_points[3]))
    edge_locs.append(edge_pos)
```

```
dimensions = np.array(dimensions)

r1 = np.mean(dimensions[:,0])
print("Length Mean: ", r1)

r2 = np.mean(dimensions[:,1])
print("Width Mean: ", r2)

r3 = np.std(dimensions[:,0])
print("Length Std: ", r3)

r4 = np.std(dimensions[:,1])
print("Width Std: ", r4)

plt.figure(figsize = (7,7))
plt.imshow(labeled_image, cmap='tab20')
import matplotlib.patheffects as PathEffects
for i in range(1, np.max(labeled_image)+1):
    txt_head = plt.text(moments["mean_y"][i] - 10, moments["mean_x"][i] + 10,
str(i), color = "white", weight='bold')
    txt_head.set_path_effects([PathEffects.withStroke(linewidth=1,
foreground='black')])
    txt1 = plt.text(moments["mean_y"][i] - 100, moments["mean_x"][i] + 70, "length:
"+str(dimensions[i-1][0])+"px", color =
plt.cm.tab20(int(i*20/np.max(labeled_image))), weight='bold')
    txt1.set_path_effects([PathEffects.withStroke(linewidth=1, foreground='black')])
    txt2 = plt.text(moments["mean_y"][i] - 100, moments["mean_x"][i] + 110, "width:
"+str(dimensions[i-1][1])+"px", color =
plt.cm.tab20(int(i*20/np.max(labeled_image))), weight='bold')
    txt2.set_path_effects([PathEffects.withStroke(linewidth=1, foreground='black')])
    #     if i == 1:
    #     print(edge_locs[i-1][0], edge_locs[i-1][2])
    plt.plot((edge_locs[i-1][0][1], edge_locs[i-1][2][1]), (edge_locs[i-1][0][0],
edge_locs[i-1][2][0]), color="#555555")
    plt.plot((edge_locs[i-1][1][1], edge_locs[i-1][3][1]), (edge_locs[i-1][1][0],
edge_locs[i-1][3][0]), color="#333333")

plt.grid()
plt.xticks(np.arange(0, img_shape[1], 200))
```

```
plt.yticks(np.arange(0, img_shape[0], 100))
plt.show()
```