

DEPARTMENT OF ELECTRONIC AND TELECOMMUNICATION  
UNIVERSITY OF MORATUWA  
EN3160 : Image processing and Machine Vision : Fitting and Alignment

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October 4, 2023

## 1 Question 01

In this question we are supposed to detect blobs in a given image. Blob detection is used to identify areas or objects that share characteristics like color, intensity, or texture. They distinguish out from their surroundings due to their homogenous characteristics.

The Laplacian of Gaussians (LoG), which uses a two-step procedure to improve features and find edges. The image is first smoothed using a Gaussian filter to reduces noise and highlights important structures. The Laplacian operator will draw attention to the areas where intensity changes have place. By changing the values of  $\sigma$  and threshold values we can detect blobs accurately. And generally blobs are the superpositioned ripple gained from LoG.

And the Laplacian of Gaussian (LoG) is defined as follows.

$$\nabla^2 G(x, y) = \frac{1}{2\pi\sigma^2} \left( \frac{x^2 + y^2 - 2\sigma^2}{\sigma^4} \right) e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (1)$$

And following is the code for the implementation of LoG.

```

1 def create_gaussian_kernel(size, sigma,
2     verbose=False):
3     kernel_1D = np.linspace(-(size // 2),
4         size // 2, size)
5     kernel_1D = np.exp(-(kernel_1D**2) / (2 *
6         * sigma**2)) / (sigma * np.sqrt(2 *
7             np.pi))
8     kernel_2D = np.outer(kernel_1D.T,
9         kernel_1D.T)
10    kernel_2D *= 1.0 / kernel_2D.max()
11    return kernel_2D
12 sigma = 0.6375
13 gaussian_kernel = create_gaussian_kernel(5,
14     sigma, verbose=False)
15 laplace_of_gaussian_kernel = cv.Laplacian(
16     gaussian_kernel, cv.CV_64F) * sigma**2
17 laplace_of_gaussian_img = cv.filter2D(img,
18     -1, laplace_of_gaussian_kernel)
19 threshold_value = 81 # Adjust as needed

```

```

12 _, binary_img = cv.threshold(np.abs(
13     laplace_of_gaussian_img),
14     threshold_value, 255, cv.THRESH_BINARY)
15 contours, _ = cv.findContours(binary_img,
16     astype(np.uint8), cv.RETR_EXTERNAL, cv.
17     CHAIN_APPROX_SIMPLE)
18 original_img = cv.cvtColor(img, cv.
19     COLOR_GRAY2BGR)
20 for contour in contours:
21     ((x, y), radius) = cv.
22         minEnclosingCircle(contour)
23     center = (int(x), int(y))
24     radius = int(radius)
25     cv.circle(original_img, center, radius,
26         (0, 255, 0), 2) # (0, 255, 0) is
27         color (green), 2 is thickness

```

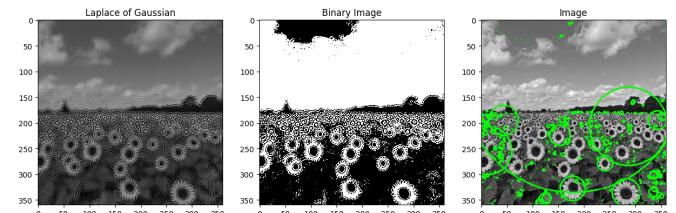


Figure 1: LoG, thresholded LoG and detected blobs

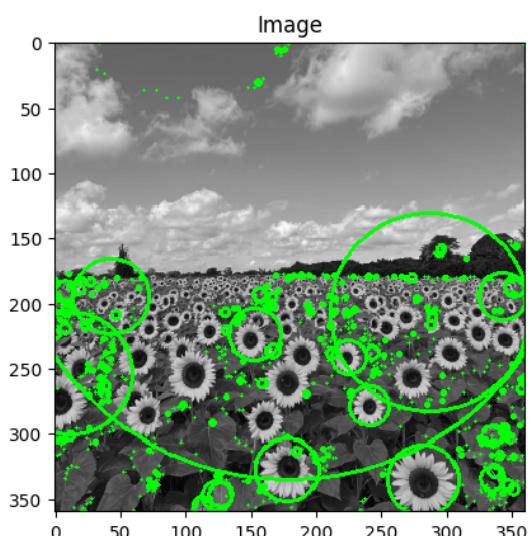


Figure 2: Detected blobs

- Maximum radius got : 76
- Range of  $\sigma$  values : 0.5, 0.6, 0.75, 1.0, 2.0, 3.0
- Selected  $\sigma$  value : 0.6375

## 2 Question 02

In this question we are supposed to estimate a line and a circle for a noisy dataset using RANSAC algorithm. RANSAC is an iterative method to estimate parameters of a mathematical model from a set of observed data that contains outliers.

Following will be the code for the implementation of RANSAC algorithm for predicting a line for a noisy dataset.

```

1 # create dataset
2 N = X.shape[0]
3 data = X
4 def calculate_distance(x1, y1, x2, y2):
5     distance_mag = math.sqrt((x2-x1)**2 +
6         (y2-y1)**2)
7     a = (x2-x1)/distance_mag
8     b = (y2-y1)/distance_mag
9     d = a*x1 + b*y1
10    return a, b, d
11 def calc_tls (x,indices):
12     a,b,d = x[0],x[1],x[2]
13     return np.sum(np.square(a*data[indices
14         ,0] + b*data[indices,1] - d))
15 def g(x):
16     return x[0]**2 + x[1]**2 - 1
17 constraints = ({'type': 'eq', 'fun': g})
18 def best_fit_line(X,x,t):
19     a,b,d = x[0],x[1],x[2]
20     e = np.absolute(a*X[:,0] + b*X[:,1] - d
21         )
22     return e < t
23 while iters < max_iters:
24     indices = np.random.randint(0, N, 2)
25     x0 = np.array([1,1,0])
26     res = minimize(fun = calc_tls, args =
27         indices, x0 = x0, tol= 1e-6,
28         constraints=constraints, options={
29             'disp': True})
30     line_inliers = best_fit_line(data,res.x
31         ,threshold_value)
32
33     if line_inliers.sum() > d :
34         x0 = res.x
35         res = minimize(fun = calc_tls, args
36             = line_inliers, x0 = x0, tol= 1
37             .e-6, constraints=constraints,
38             options={'disp': True})
39         if res.fun < best_error:
40             best_error = res.fun
41             best_line_model = res.x
42             best_sample_line = data[indices
43                 ,:]
44             best_inlier_line = line_inliers
45             res_only_with_sample = x0
46             iters += 1

```

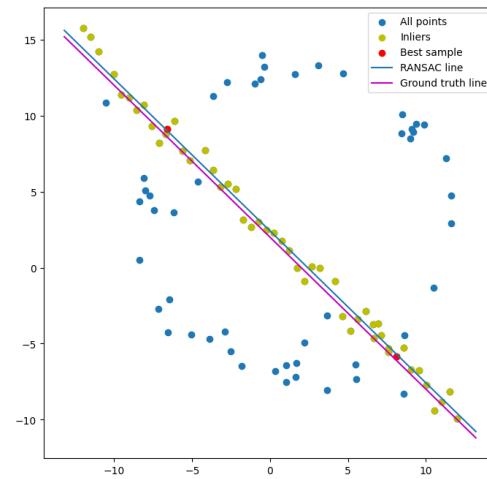


Figure 3: Best fit line for the noisy dataset

Code for estimating the circle

```

1 def fit_circle_ransac(points,
2     num_iterations, error_threshold,
3     min_consensus):
4     best_circle = None
5     best_inliers = []
6     for _ in range(num_iterations):
7         sample_indices = np.random.choice(
8             len(points), 3, replace=False)
9         sample_points = points[
10             sample_indices]
11         x, y, r =
12             calculate_circle_parameters(
13                 sample_points)
14         radial_errors = np.abs(np.sqrt((points[:, 0] - x)**2 + (points
15             [:, 1] - y)**2) - r)
16         inliers = np.where(radial_errors <
17             error_threshold)[0]
18         if len(inliers) >= min_consensus
19             and len(inliers) > len(
20                 best_inliers):
21                 best_inliers = inliers
22                 best_circle = (x, y, r)
23     return best_circle, best_inliers

```

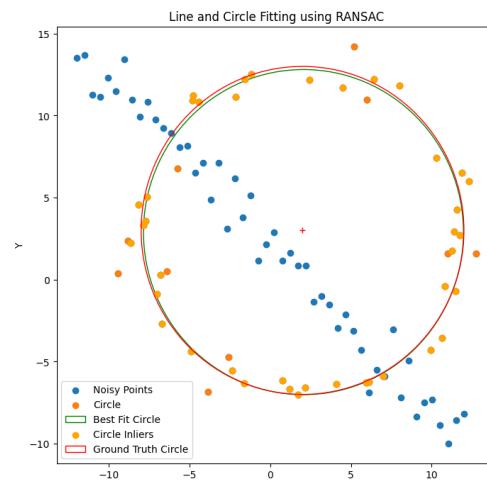


Figure 4: Best fit circle for the noisy dataset

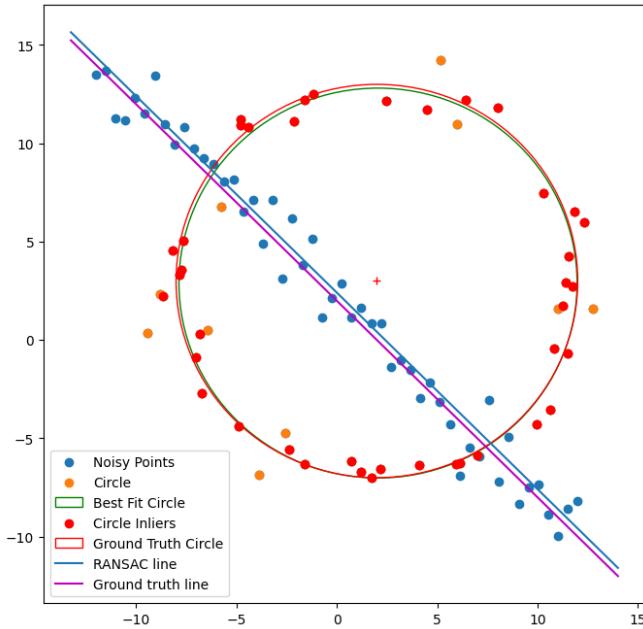


Figure 5: Best fit and Grown truth line and circle.

## 2.1 Answer for part (d)

In this case we are doing RANSAC fit for the line and subtract it from the noisy points and then we are proceeding with the fit for circle. Because of this RANSAC the circle inliers and creates a better fit for the circle by choosing random points.

But if we perform the ransac fit for the circle first, it will select some random points from the line inliers also. Because of this RANSAC can predict erroneous fits.

## 3 Question 03

This question is about wrapping one figure and superimposing it to another image.

```

1 def draw_circle(event,x,y,flags,param):
2     global n
3     architectural_points = param[0]
4     if event == cv.EVENT_LBUTTONDOWN:
5         cv.circle(param[1],(x,y)
6                 ,5,(255,0,0),-1)
7         architectural_points[n] = (x,y)
8         n += 1
9 cv.namedWindow('Image', cv.WINDOW_AUTOSIZE)
10 param = [architectural_points,
11           architectural_image]
12 cv.setMouseCallback('Image',draw_circle,
13                     param)
14 while(1):
15     cv.imshow('Image', architectural_image)
16     if n == number_of_points:
17         break
18     if cv.waitKey(20) & 0xFF == 27:
19         break
20 flag_points = np.array([[0, 0], [flag_image
21 .shape[1], 0], [flag_image.shape[1],
22 .shape[0], 0], [0, flag_image.shape[0]]])

```

```

23 flag_image.shape[0]], [0, flag_image.
24 shape[0]]], dtype=np.float32)
25 homography_matrix, _ = cv.findHomography(
26     flag_points, architectural_points)
27 flag_warped = cv.warpPerspective(flag_image
28     , homography_matrix,
29     architectural_image.shape[1],
30     architectural_image.shape[0]))
31 blended_image = cv.addWeighted(
32     architectural_image, 1, flag_warped,
33     0.7, 0)

```



Figure 6: Superposition Example 01



Figure 7: Superposition Example 02

## 4 Question 04

In this question we are supposed to stich to images together. For this we need to create keypoints and descriptors for both images and then match them using a matcher. Then we need to find the homography matrix and warp the image to the other image. We can SIFT for creating keypoints and descriptors. And we can use RANSAC for finding the best homography matrix along with BFmatcher for matching the descriptors.

Following will be the implementation for creating keypoints and descriptors.

```

1 sift = cv2.SIFT_create()
2 keypoints1, descriptors1 = sift.
3             detectAndCompute(img1, None)
4 keypoints5, descriptors5 = sift.
5             detectAndCompute(img5, None)
6 img1_with_keypoints = cv2.drawKeypoints(
7     img1, keypoints1, img1)
8 img5_with_keypoints = cv2.drawKeypoints(
9     img5, keypoints5, img5)

```

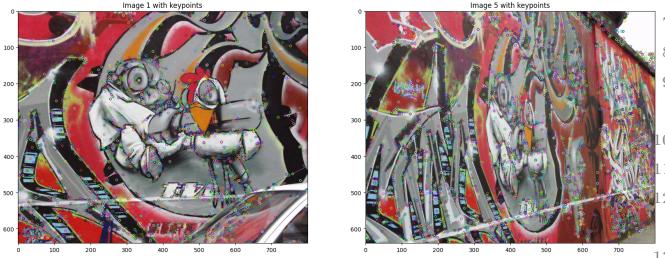


Figure 8: EDetected Keypoints

And the keypoints were matched using BFmatcher and the homography matrix was found using RANSAC. And the following is the code for that.

```

1 bf = cv2.BFMatcher()
2 matches = bf.knnMatch(descriptors1,
   descriptors5, k=2)
3 good_matches = []
4 for m, n in matches:
5     if m.distance < 0.85 * n.distance:
6         good_matches.append(m)
7 src_pts = np.float32([keypoints1[m.queryIdx]
   .pt for m in good_matches]).reshape(-1,
   1, 2)
8 dst_pts = np.float32([keypoints5[m.trainIdx]
   .pt for m in good_matches]).reshape(-1,
   1, 2)
9 homography_matrix, _ = cv2.findHomography(
   src_pts, dst_pts, cv2.RANSAC, 0.75)

```



Figure 9: Matched Keypoints

And I got the following matrix as my homography matrix. for the above code.

$$\begin{bmatrix} -3.99590 \times 10^{-1} & 1.98442 \times 10^{-1} & 1.73728 \times 10^2 \\ -9.24469 \times 10^{-1} & 4.81236 \times 10^{-1} & 3.95571 \times 10^2 \\ -2.32774 \times 10^{-3} & 1.19405 \times 10^{-3} & 1.00000 \end{bmatrix}$$

```

best_error = float('inf')
for _ in range(num_iterations):
    indices = np.random.choice(len(
        src_points), 4, replace=False)
    sampled_src = src_points[indices]
    sampled_dst = dst_points[indices]
    homography, _ = cv2.findHomography(
        sampled_src, sampled_dst)
    current_error = calculate_error(
        homography, src_points,
        dst_points)
    if current_error < best_error:
        best_error = current_error
        best_homography = homography
    if current_error < error_threshold:
        break
return best_homography

```



Figure 10: Matched Keypoints using RANSAC

And I tried to stich the matching keypoints but I could not able to accomplish it.



Figure 11: Stiched Image

```

1 def calculate_error(homography, src_points,
   dst_points):
2     transformed_points = cv2.
   perspectiveTransform(src_points,
   homography)
3     errors = np.sqrt(np.sum((
   transformed_points - dst_points)**2,
   axis=2))
4     return np.mean(errors)
5 def ransac_homography(src_points,
   dst_points, num_iterations=100,
   error_threshold=1.0):
   best_homography = None

```

## 5 References

- [Numpy Documentation](#)
- [OpenCV Documentation](#)

## 6 Github Repository

Following is the link to my Github repository for this assignment.

[Github/EN160\\_Assignment\\_02](#)