

Computer Vision
Homework 2: Structure from Motion (SfM)
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3.1 Camera Pose from Essential Matrix

In the `estimate_initial_RT`, we can compute 4 initial guesses of the relative RT between the two cameras. E is the Essential Matrix between the two cameras. RT is a $4 \times 3 \times 4$ tensor in which the 3×4 matrix RT is one of the four possible transformations.

```
1 def estimate_initial_RT(E):
2     # TODO: Implement this method!
3     W = np.array([[0, -1, 0], [1, 0, 0], [0, 0, 1]])
4     U, S, V = np.linalg.svd(E)
5     Q1 = np.dot(U, np.dot(W, V))
6     Q2 = np.dot(U, np.dot(W.T, V))
7     R1 = np.linalg.det(Q1) * Q1
8     R2 = np.linalg.det(Q2) * Q2
9     t1 = U[:, 2]
10    t2 = -U[:, 2]
11    RT = np.zeros((4, 3, 4))
12    RT[0, :, :] = np.hstack((R1, t1.reshape(3, 1)))
13    RT[1, :, :] = np.hstack((R1, t2.reshape(3, 1)))
14    RT[2, :, :] = np.hstack((R2, t1.reshape(3, 1)))
15    RT[3, :, :] = np.hstack((R2, t2.reshape(3, 1)))
16
17    return RT
```

Output:

The third matrix matches the Example RT.

```
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Part A: Check your matrices against the example R,T
-----
Example RT:
[[ 0.9736 -0.0988 -0.2056  0.9994]
 [ 0.1019  0.9948  0.0045 -0.0089]
 [ 0.2041 -0.0254  0.9786  0.0331]]

Estimated RT:
[[[ 0.98305251 -0.11787055 -0.14040758  0.99941228]
  [-0.11925737 -0.99286228 -0.00147453 -0.00886961]
  [-0.13923158  0.01819418 -0.99009269  0.03311219]]

 [ 0.98305251 -0.11787055 -0.14040758 -0.99941228]
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 [ 0.97364135 -0.09878708 -0.20558119  0.99941228]
 [ 0.10189204  0.99478508  0.00454512 -0.00886961]
 [ 0.2040601  -0.02537241  0.97862951  0.03311219]]

 [ 0.97364135 -0.09878708 -0.20558119 -0.99941228]
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```

3.2 Linear 3D Points Estimation

In the `linear_estimate_3d_point` given corresponding points in different images, computing the 3D point is the best linear estimate. `Image_points` is the measured points in each of the `M` images.

`Camera_matrices` is the camera projective matrices. `Point_3d` is the 3D point

```
1 def linear_estimate_3d_point(image_points, camera_matrices):
2     # TODO: Implement this method!
3     M = image_points.shape[0]
4     A = np.zeros((2*M, 4))
5
6     for i in range(M):
7         A[2*i, :] = image_points[i, 1] * camera_matrices[i, 2, :] - camera_matrices[i, 1, :]
8         A[2*i+1, :] = camera_matrices[i, 0, :] - image_points[i, 0] * camera_matrices[i, 2, :]
9
10    U, S, V = np.linalg.svd(A)
11    point_3d = V[-1, :3] / V[-1, 3] # (x, y, z, w) -> (x/w, y/w, z/w)
12    return point_3d
```

Output:

```
-----
Part B: Check that the difference from expected point
is near zero
-----
```

```
Difference:  0.0029243053036643873
-----
```

3.3 Non-Linear 3D Points Estimation

Since the linear estimation from SVD is not robust to noise, we need to further apply non-linear optimization to our estimated points. In this question, you need to implement the Gauss-Newton approach.

In the `reprojection_error`, given a 3D point and its corresponding points in the image planes, computing the reprojection error vector and associated Jacobian.

```
1 def reprojection_error(point_3d, image_points, camera_matrices):
2     # TODO: Implement this method!
3     point_3d = np.hstack((point_3d, 1)) # (x, y, z) -> (x, y, z, 1)
4     error = []
5     for i in range(image_points.shape[0]):
6         pi = image_points[i, :]
7         P = camera_matrices[i, :, :]
8         y = np.dot(P, point_3d)
9         pi_prime = 1.0/y[2] * np.array([y[0], y[1]])
10        error_item = pi_prime - pi
11        error.append(error_item[0])
12        error.append(error_item[1])
13    error = np.array(error)
14    return error
```

```
1 def jacobian(point_3d, camera_matrices):
2     # TODO: Implement this method!
3     M = camera_matrices.shape[0]
4     P1, P2, P3 = point_3d[0], point_3d[1], point_3d[2]
5     jacobian = np.zeros((2*M, 3))
6
7     for i in range(M):
8         P = camera_matrices[i, :, :]
9         y1 = P[0, 0] * P1 + P[0, 1] * P2 + P[0, 2] * P3 + P[0, 3]
10        y2 = P[1, 0] * P1 + P[1, 1] * P2 + P[1, 2] * P3 + P[1, 3]
11        y3 = P[2, 0] * P1 + P[2, 1] * P2 + P[2, 2] * P3 + P[2, 3]
12        jacobian[2*i, 0] = (y3 * P[0, 0] - y1 * P[2, 0]) / y3**2
13        jacobian[2*i, 1] = (y3 * P[0, 1] - y1 * P[2, 1]) / y3**2
14        jacobian[2*i, 2] = (y3 * P[0, 2] - y1 * P[2, 2]) / y3**2
15        jacobian[2*i+1, 0] = (y3 * P[1, 0] - y2 * P[2, 0]) / y3**2
16        jacobian[2*i+1, 1] = (y3 * P[1, 1] - y2 * P[2, 1]) / y3**2
17        jacobian[2*i+1, 2] = (y3 * P[1, 2] - y2 * P[2, 2]) / y3**2
18
19    return jacobian
```

Output:

```
-----
Part C: Check that the difference from expected error/Jacobian
is near zero
-----
Error Difference:  8.301299988565727e-07
Jacobian Difference:  1.817115702351657e-08
-----
```

In the `nonlinear_estimate_3d_point`, given corresponding points in different images, computing the 3D point that iteratively updates the points.

```

1 def nonlinear_estimate_3d_point(image_points, camera_matrices):
2     # TODO: Implement this method!
3     point_3d = linear_estimate_3d_point(image_points, camera_matrices)
4     error = reprojection_error(point_3d, image_points, camera_matrices)
5     for i in range(10):
6         J = jacobian(point_3d, camera_matrices)
7         point_3d = point_3d - np.dot(np.linalg.inv(np.dot(J.T, J)), np.dot(J.T, error))
8         error = reprojection_error(point_3d, image_points, camera_matrices)
9     return point_3d

```

Output:

```

-----
Part D: Check that the reprojection error from nonlinear method
is lower than linear method
-----

```

```

Linear method error: 98.7354235689419

```

```

Nonlinear method error: 95.59481784846031
-----

```

3.4 Decide the Correct RT

In the `estimate_RT_from_E`, we can compute the relative RT between the two cameras from the Essential Matrix. K is the intrinsic camera matrix. E is the Essential Matrix between the two cameras. `image_points` are measured points in each of the M images.

```
1 def estimate_RT_from_E(E, image_points, K):
2     # TODO: Implement this method!
3     RT = estimate_initial_RT(E)
4     max_points = 0
5     for i in range(4):
6         positive_count = 0
7         RT_i = RT[i, :, :]
8         I = np.array([
9             [1.0, 0.0, 0.0, 0.0],
10            [0.0, 1.0, 0.0, 0.0],
11            [0.0, 0.0, 1.0, 0.0]
12        ])
13        c1 = np.dot(K, I)
14        c2 = np.dot(K, RT_i) # (3, 4)
15        camera_matrices = np.zeros((2, 3, 4))
16        camera_matrices[0, :, :] = c1
17        camera_matrices[1, :, :] = c2
18        for j in range(image_points.shape[0]):
19            point_3d = nonlinear_estimate_3d_point(image_points[j], camera_matrices)
20            point_3d_prime = camera1_to_camera2(point_3d, RT_i)
21            if point_3d[2] > 0 and point_3d_prime[2] > 0:
22                positive_count += 1
23        if positive_count > max_points:
24            max_points = positive_count
25            correct_RT = RT_i
26
27    return correct_RT
28
29 def camera1_to_camera2(P, RT):
30     temp = np.ones((4, 1))
31     temp[0:3, :] = P.reshape((3, 1))
32     temp1 = RT[:, :3].T
33     temp2 = -temp1.dot(RT[:, 3:])
34     A = np.concatenate((temp1, temp2), axis=1)
35     point_3d_prime = A.dot(temp)
36     return point_3d_prime
```

Output:

Part E: Check your matrix against the example R,T

Example RT:

```
[[ 0.9736 -0.0988 -0.2056  0.9994]
 [ 0.1019  0.9948  0.0045 -0.0089]
 [ 0.2041 -0.0254  0.9786  0.0331]]
```

Estimated RT:

```
[[ 0.97364135 -0.09878708 -0.20558119  0.99941228]
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-----
```

3.5 Result

