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Part 1

Q1.1

We know that the projected points of P in each plane are $\mathbf{x}_1 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$ and $\mathbf{x}_2 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$.

Also, from the Epipolar Geometry, we know that

$$\mathbf{x_2^T} \mathbf{F} \mathbf{x_1} = 0 \tag{1}$$

$$\begin{bmatrix} 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} F_{11} & F_{12} & F_{13} \\ F_{21} & F_{22} & F_{23} \\ F_{31} & F_{32} & F_{33} \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} = 0$$
 (2)

$$\begin{bmatrix} F_{31} & F_{32} & F_{33} \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} = 0 \tag{3}$$

$$F_{33} = 0 \tag{4}$$

We can thus prove that the F_{33} element of the Fundamental Matrix is zero.

Q1.2

We know that the second camera differs from the first by a pure translation that is parallel to the x-axis. So, we can assume the translation vector \mathbf{t} and the rotation matrix \mathbf{R} and compute the Essential matrix \mathbf{E} .

$$\mathbf{t} = \begin{bmatrix} a \\ 0 \\ 0 \end{bmatrix}, \hat{\mathbf{t}} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -a \\ 0 & a & 0 \end{bmatrix}$$
 (5)

$$\mathbf{R} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{6}$$

$$\mathbf{E} = \hat{\mathbf{t}}\mathbf{R} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -a \\ 0 & a & 0 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -a \\ 0 & a & 0 \end{bmatrix}$$
(7)

Compute the epipolar lines in the two cameras:

$$\boldsymbol{x} \boldsymbol{1}^{T} \mathbf{E} \boldsymbol{x} \boldsymbol{2} = \begin{bmatrix} x_{1} & y_{1} & 1 \end{bmatrix} \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -a \\ 0 & a & 0 \end{bmatrix} \begin{bmatrix} x_{2} \\ y_{2} \\ 1 \end{bmatrix}$$
(8)

$$= \begin{bmatrix} x_1 & y_1 & 1 \end{bmatrix} \begin{bmatrix} 0 \\ -a \\ ay_2 \end{bmatrix} = 0 \tag{9}$$

$$\boldsymbol{x2^T}\mathbf{E}\boldsymbol{x1} = \begin{bmatrix} x_2 & y_2 & 1 \end{bmatrix} \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -a \\ 0 & a & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ y_1 \\ 1 \end{bmatrix}$$
 (10)

$$= \begin{bmatrix} x_2 & y_2 & 1 \end{bmatrix} \begin{bmatrix} 0 \\ -a \\ ay_1 \end{bmatrix} = 0 \tag{11}$$

From equation (9) and (11), we know that the equation of the first epipolar line is (-a) $y_1 + (ay_2) = 0$, and the equation of the first epipolar line is (-a) $y_2 + (ay_1) = 0$. Both of the lines are parallel to the x-axis.

Q1.3

Assume the point in the world frame \mathbf{P} , and the points in the camera frame at time i and j are \mathbf{p}_i and \mathbf{p}_j . Then, we know that

$$\mathbf{p_i} = \mathbf{R_i} \mathbf{P} + \mathbf{t_i} \tag{12}$$

$$\mathbf{p_j} = \mathbf{R_j} \mathbf{P} + \mathbf{t_j} \tag{13}$$

From equation 12, we can derive \mathbf{P}

$$\mathbf{P} = \mathbf{R}_{\mathbf{i}}^{-1}(\mathbf{p}_{\mathbf{i}} - \mathbf{t}_{\mathbf{i}}) \tag{14}$$

Combine equation 13 and 14, we can get

$$\mathbf{p_j} = \mathbf{R_j} \mathbf{P} + \mathbf{t_j} = \mathbf{R_j} [\mathbf{R_i}^{-1} (\mathbf{p_i} - \mathbf{t_i})] + \mathbf{t_j}$$
(15)

$$\mathbf{p_j} = (\mathbf{R_j}\mathbf{R_i^{-1}})\mathbf{p_i} + (-\mathbf{R_j}\mathbf{R_i^{-1}}\mathbf{t_i} + \mathbf{t_j}) = \mathbf{R_{rel}}\mathbf{p_i} + \mathbf{t_{rel}}$$
(16)

$$\mathbf{R_{rel}} = \mathbf{R_j} \mathbf{R_i^{-1}} \tag{17}$$

$$\mathbf{t_{rel}} = -\mathbf{R_j}\mathbf{R_i^{-1}}\mathbf{t_i} + \mathbf{t_j} \tag{18}$$

Equation 17 and 18 show the effective rotation and translation between frame at time i and frame at time j.

Based on the definition, the essential matrix \mathbf{E} and fundamental matrix \mathbf{F} are

$$\mathbf{E} = \mathbf{t_{rel}} \times \mathbf{R_{rel}} = \hat{\mathbf{t}_{rel}} \mathbf{R_{rel}} \tag{19}$$

$$\mathbf{F} = \mathbf{K}^{-T} \mathbf{E} \mathbf{K}^{-1} = \mathbf{K}^{-T} (\hat{\mathbf{t}}_{rel} \mathbf{R}_{rel}) \mathbf{K}^{-1}$$
(20)

Q1.4

Assume that the object is flat, meaning that all the points of the object are of equal distance to the mirror. This means that the transformation between the object and its reflection is a pure translation. Therefore, the effective rotation matrix \mathbf{R} and translation vector \mathbf{t} are:

$$\mathbf{R} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} = \mathbf{I} \tag{21}$$

$$\mathbf{t} = \begin{bmatrix} x \\ y \\ z \end{bmatrix} \tag{22}$$

From equation 19, we can compute the Essential Matrix **E**:

$$\mathbf{E} = \hat{\mathbf{t}}\mathbf{R} = \mathbf{t} \times \mathbf{R} = \begin{bmatrix} 0 & z & -y \\ -z & 0 & x \\ y & -x & 0 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 0 & z & -y \\ -z & 0 & x \\ y & -x & 0 \end{bmatrix}$$
(23)

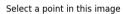
From equation 23, we know that the Essential Matrix is a "skew-symmetric matrix." Based on the relationship between the Essential Matrix $\bf E$ and the Fundamental Matrix $\bf F$ (equation 20), we can also prove that the Fundamental Matrix $\bf F$ is also a skew-symmetric matrix.

Part 2

Q2.1

Fundamental Matrix \mathbf{F} :

$$\mathbf{F} = \begin{bmatrix} 9.78833285e - 10 & -1.32135929e - 07 & 1.12585666e - 03 \\ -5.73843315e - 08 & 2.96800276e - 09 & -1.17611996e - 05 \\ -1.08269003e - 03 & 3.04846703e - 05 & -4.47032655e - 03 \end{bmatrix}$$
(24)





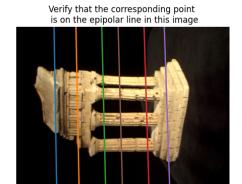


Figure 1: Visualization of the Epipolar Lines

Q3.1

Essential Matrix E:

$$\mathbf{E} = \begin{bmatrix} 2.26268684e - 03 & -3.06552495e - 01 & 1.66260633e + 00 \\ -1.33130407e - 01 & 6.91061098e - 03 & -4.33003420e - 02 \\ -1.66721070e + 00 & -1.33210350e - 02 & -6.72186431e - 04 \end{bmatrix}$$
(25)

Q3.2.1

Assume the 3D points $\mathbf{W}_i = \begin{bmatrix} X_i \\ Y_i \\ Z_i \end{bmatrix}$, we can use \mathbf{C}_1 and \mathbf{C}_2 to project it back to the 2D images.

$$\mathbf{p_1} = \begin{bmatrix} x_1 \\ y_1 \\ 1 \end{bmatrix} = \mathbf{C_1} \tilde{\mathbf{W}}_{\mathbf{i}} = \begin{bmatrix} C_{11}^{(1)} & C_{12}^{(1)} & C_{13}^{(1)} & C_{14}^{(1)} \\ C_{21}^{(1)} & C_{22}^{(1)} & C_{23}^{(1)} & C_{24}^{(1)} \\ C_{31}^{(1)} & C_{32}^{(1)} & C_{33}^{(1)} & C_{34}^{(1)} \end{bmatrix} \begin{bmatrix} X_i \\ Y_i \\ Z_i \\ 1 \end{bmatrix} = \begin{bmatrix} -C_1^{(1)} - \\ -C_2^{(1)} - \\ -C_3^{(1)} - \end{bmatrix} \begin{bmatrix} X_i \\ Y_i \\ Z_i \\ 1 \end{bmatrix}$$
(26)

$$\mathbf{p_2} = \begin{bmatrix} x_2 \\ y_2 \\ 1 \end{bmatrix} = \mathbf{C_2} \tilde{\mathbf{W}}_{\mathbf{i}} = \begin{bmatrix} C_{11}^{(2)} & C_{12}^{(2)} & C_{13}^{(2)} & C_{14}^{(2)} \\ C_{21}^{(2)} & C_{22}^{(2)} & C_{23}^{(2)} & C_{24}^{(2)} \\ C_{31}^{(2)} & C_{32}^{(2)} & C_{33}^{(2)} & C_{34}^{(2)} \end{bmatrix} \begin{bmatrix} X_i \\ Y_i \\ Z_i \\ 1 \end{bmatrix} = \begin{bmatrix} -C_1^{(2)} - \\ -C_2^{(2)} - \\ -C_3^{(2)} - \end{bmatrix} \begin{bmatrix} X_i \\ Y_i \\ Z_i \\ 1 \end{bmatrix}$$
(27)

From equation 26 and 27, we can derive that

$$\begin{bmatrix} x_1 C_3^{(1)} - C_1^{(1)} \\ y_1 C_3^{(1)} - C_2^{(1)} \end{bmatrix} \begin{bmatrix} X_i \\ Y_i \\ Z_i \\ 1 \end{bmatrix} = 0$$
 (28)

$$\begin{bmatrix} x_2 C_3^{(2)} - C_1^{(2)} \\ y_2 C_3^{(2)} - C_2^{(2)} \end{bmatrix} \begin{bmatrix} X_i \\ Y_i \\ Z_i \\ 1 \end{bmatrix} = 0$$
 (29)

Combine equation 28 and 29 to get

$$\begin{bmatrix} x_1 C_3^{(1)} - C_1^{(1)} \\ y_1 C_3^{(1)} - C_2^{(1)} \\ x_2 C_3^{(2)} - C_1^{(2)} \\ y_2 C_3^{(2)} - C_2^{(2)} \end{bmatrix} \begin{bmatrix} X_i \\ Y_i \\ Z_i \\ 1 \end{bmatrix} = \mathbf{A_i \tilde{W}_i} = 0$$
(30)

$$\mathbf{A_{i}} = \begin{bmatrix} x_{1}C_{3}^{(1)} - C_{1}^{(1)} \\ y_{1}C_{3}^{(1)} - C_{2}^{(1)} \\ x_{2}C_{3}^{(2)} - C_{1}^{(2)} \\ y_{2}C_{3}^{(2)} - C_{2}^{(2)} \end{bmatrix}$$
(31)

Q3.2.2

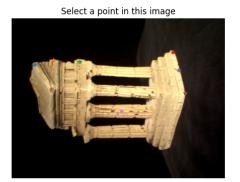
The scalar reprojection error = 352.2302235117389

Q3.3

Projective Camera Matrix M_2 :

$$\mathbf{M2} = \begin{bmatrix} 0.99942701 & 0.03331428 & 0.0059843 & -0.02601138 \\ -0.03372743 & 0.96531375 & 0.25890503 & -1. \\ 0.00284851 & -0.25895852 & 0.96588424 & 0.07981688 \end{bmatrix}$$
(32)

Q4.1



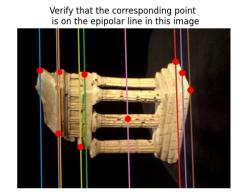


Figure 2: Visualization of the Epipolar Lines and the Corresponding Points

Q4.2

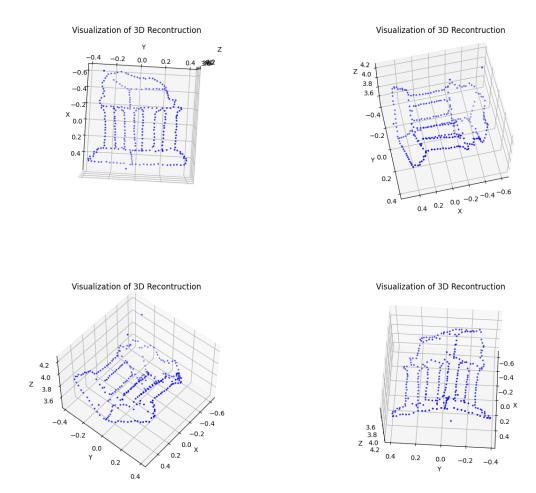


Figure 3: Visualization of the 3D Reconstruction

Q5.1

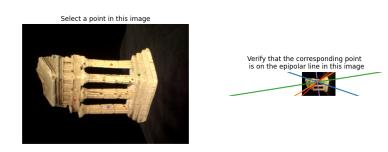


Figure 4: Visualization of the Epipolar Lines and the Corresponding Points using Eight Point Algorithm

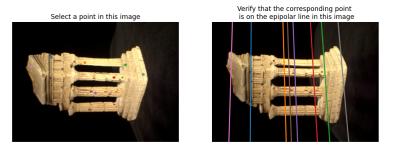


Figure 5: Visualization of the Epipolar Lines and the Corresponding Points using RANSAC

The Fundamental Matrix **F** obtained from the RANSAC algorithm:

$$\mathbf{F} = \begin{bmatrix} -8.77851454e - 09 & 7.87966154e - 08 & 1.06704280e - 03 \\ -2.85381105e - 07 & -2.94550521e - 09 & 5.16841948e - 05 \\ -1.01621163e - 03 & -2.45719616e - 05 & -6.16797059e - 03 \end{bmatrix}$$
(33)

The error metrics I used is the euclidean distance between the epipolar line and the real point (pts2) on frame2.

$$error = \mathbf{X_2^T} \mathbf{F} \mathbf{X_1} \tag{34}$$

where $\mathbf{F}\mathbf{X}_1$ solves the coefficients of the epipolar lines.

If the euclidean disatance between the epipolar line and the real point (pts2) on frame2 is smaller than the tolerance, then the points are the inliers.

Q5.3

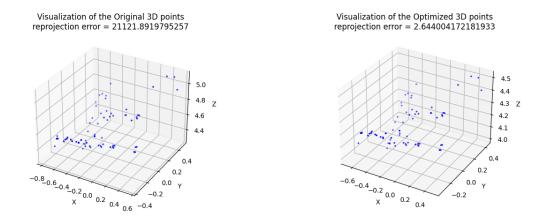


Figure 6: Visualization of the Original 3D Points and the Optimized 3D Points

Reprojection Error with initial M_2 and w = 21121.8919795257Reprojection Error with optimized matrices = 2.644004172181933

Bundle Adjustment minimize the reprojection error.

Code Appendix

0.1 submission.py

```
Homework4.
2
    Replace 'pass' by your implementation.
3
4
    import numpy as np
6
    import scipy.ndimage
    import util
8
    import scipy
9
10
    111
11
    Q2.1: Eight Point Algorithm
12
        Input: pts1, Nx2 Matrix
13
                 pts2, Nx2 Matrix
14
                 M, a scalar parameter computed as max (inwidth, imheight)
15
        Output: F, the fundamental matrix
16
17
    def eightpoint(pts1, pts2, M):
18
        # Scale the data
19
        pts1 = pts1 / M
20
        pts2 = pts2 / M
21
22
        # Form matrix A
23
        x1, y1 = pts1[:, 0].reshape(-1, 1), pts1[:, 1].reshape(-1, 1)
24
        x2, y2 = pts2[:, 0].reshape(-1, 1), pts2[:, 1].reshape(-1, 1)
25
        one = np.ones((x1.shape[0], 1))
26
        A = np.concatenate((x2*x1, x2*y1, x2, y2*x1, y2*y1, y2, x1, y1, one),
27
                                                                                 axis = 1)
28
29
        # Singular Value Decomposition
30
        u, s, vh = np.linalg.svd(A)
31
        F = vh.T[:, -1].reshape(3, 3)
32
33
        # Refine and Singularize F
34
        F = util.refineF(F, pts1, pts2)
35
36
        # Unscale the Fundamental Matrix
37
        T = np.array([[1/M, 0, 0], [0, 1/M, 0], [0, 0, 1]])
38
        F = T.T @ F @ T
39
40
        return F
41
42
43
    Q3.1: Compute the essential matrix E.
44
```

```
Input: F, fundamental matrix
45
                 K1, internal camera calibration matrix of camera 1
46
                 K2, internal camera calibration matrix of camera 2
47
        Output: E, the essential matrix
48
49
    def essentialMatrix(F, K1, K2):
50
        # Form the Essential Matrix
51
        E = K2.T @ F @ K1
52
        return E
53
54
    111
55
    Q3.2: Triangulate a set of 2D coordinates in the image to a set of 3D points.
56
        Input: C1, the 3x4 camera matrix
57
                pts1, the Nx2 matrix with the 2D image coordinates per row
58
                 C2, the 3x4 camera matrix
59
                pts2, the Nx2 matrix with the 2D image coordinates per row
60
        Output: P, the Nx3 matrix with the corresponding 3D points per row
61
                 err, the reprojection error.
62
    111
63
    def triangulate(C1, pts1, C2, pts2):
64
        # Initialize P and error
65
        N = pts1.shape[0]
66
        P = np.zeros((N, 3))
67
        err = 0
68
69
        # Extract 2D values
70
        x1, y1 = pts1[:, 0], pts1[:, 1]
71
        x2, y2 = pts2[:, 0], pts2[:, 1]
72
73
        # Triangulation
74
        for i in range(N):
75
            # Form matrix A
76
            A = np.asarray([x1[i] * C1[2, :] - C1[0, :],
77
                             y1[i] * C1[2, :] - C1[1, :],
78
                             x2[i] * C2[2, :] - C2[0, :],
79
                             y2[i] * C2[2, :] - C2[1, :]])
80
81
            # Singular Value Decomposition
82
            u, s, vh = np.linalg.svd(A)
83
            p = vh.T[:, -1]
84
            # Normalization
85
            p = p / p[-1]
86
            # Update P
87
            P[i, :] = p[0:3]
88
89
            # Reprojection
90
            91
```

```
p2 = C2 \ 0 \ p
92
             # Normailization
93
94
             p1 = p1 / p1[-1]
             p2 = p2 / p2[-1]
95
             # Compute and Update reprojection error
96
             error = np.sum((p1[0:2] - pts1[i, :])**2) +
97
                                                       np.sum((p2[0:2] - pts2[i, :])**2)
98
             err = err + error
99
100
         return P, err
101
102
103
     Q4.1: 3D visualization of the temple images.
104
         Input: im1, the first image
105
                  im2, the second image
106
                 F, the fundamental matrix
107
                 x1, x-coordinates of a pixel on im1
108
                  y1, y-coordinates of a pixel on im1
109
         Output: x2, x-coordinates of the pixel on im2
110
                  y2, y-coordinates of the pixel on im2
111
     111
112
     def epipolarCorrespondence(im1, im2, F, x1, y1):
113
         # Apply Gaussian Filter to both images
114
         img1_filter = scipy.ndimage.gaussian_filter(im1, sigma = 1)
115
         img2_filter = scipy.ndimage.gaussian_filter(im2, sigma = 1)
117
         # Find the epipolar line on image2
118
         p1 = np.array([x1, y1, 1]).reshape(-1, 1)
119
         epi_line = F @ p1
120
         # Get the coefficients : ax + by + c = 0
121
         a, b, c = epi_line
122
123
         # Find the possible matches along the epi_line
124
         search = 40
125
         poss_y = np.arange(y1 - search, y1 + search)
126
         poss_x = (-c - b * poss_y) / a
127
         poss_x = poss_x.astype(int)
128
         # Check the validity (depend on window size)
129
         H, W, D = im2.shape
130
         window = 10
131
         half_w = window//2
132
         valid = (poss_x >= half_w) & (poss_x < W-half_w) & (poss_y >= half_w) &
133
                                                                       (poss_y < H-half_w)
134
         poss_x, poss_y = poss_x[valid], poss_y[valid]
135
136
         # Correspondence Matching
137
         error = np.inf
138
```

```
for i in range(poss_x.shape[0]):
139
             # Possible corresponding points on image2
140
             p2_x, p2_y = poss_x[i], poss_y[i]
141
142
             # Compute the window similarity
143
             window1 = img1_filter[y1-half_w:y1+half_w+1, x1-half_w:x1+half_w+1, :]
144
             window2 = img2_filter[p2_y-half_w:p2_y+half_w+1,
145
                                                         p2_x-half_w:p2_x+half_w+1, :]
146
             dis = np.sum((window1 - window2) ** 2)
147
148
             # Find the closest correspondences
149
             if dis < error:
150
                  error = dis
151
                 x2, y2 = p2_x, p2_y
152
153
         return x2, y2
154
155
     111
156
     Q5.1: Extra Credit RANSAC method.
157
         Input: pts1, Nx2 Matrix
158
                 pts2, Nx2 Matrix
159
                 M, a scaler parameter
160
         Output: F, the fundamental matrix
161
                  inliers, Nx1 bool vector set to true for inliers
162
163
     def ransacF(pts1, pts2, M, nIters=1000, tol=0.42):
164
         # Initialize max inliers
165
         N = pts1.shape[0]
166
         max_inliers = 0
167
168
         # RANSAC Algorithm
169
         for iter in range(nIters):
170
             # Print out iteration index
171
             print(f"iteration = {iter+1}")
173
             # Initialize inliers
174
             current_inliers = np.zeros(N, dtype = np.bool)
175
176
             # Randomly select 8 points to compute F
177
             # np.random.seed()
178
             # sample = np.random.choice(N, size = 8, replace = False)
179
             sample = np.random.choice(N, size = 8)
180
             pts1_sample = pts1[sample, :]
181
             pts2_sample = pts2[sample, :]
182
183
             # Compute the Fundamental Matrix using Eight Point Algorithm
184
             current_F = eightpoint(pts1_sample, pts2_sample, M)
185
186
```

```
# Compute the epipolar line
187
             p1_homo = np.concatenate((pts1, np.ones((N, 1))), axis = 1)
188
             p2_pred = (current_F @ p1_homo.T).T
189
190
             # Compute the euclidean distance between epipolar line and pts2
191
             p2_homo = np.concatenate((pts2, np.ones((N, 1))), axis = 1)
192
             factor = np.sqrt(np.sum(p2\_pred[:, 0:2] ** 2, axis = 1))
193
             dis = abs(np.sum(p2_pred * p2_homo, axis = 1)) / factor
194
             # Update current inliers
196
             current_inliers[sample] = True
197
             current_inliers[dis < tol] = True</pre>
198
             # Compute the number of inliers
199
             num_inliers = np.sum(current_inliers)
200
201
             # Update F and inliers if needed
202
             if (num_inliers > max_inliers):
203
                  max_inliers = num_inliers
204
                  F = current_F
205
                  inliers = current_inliers
206
207
             # Print max_inliers to check
208
             print(f"max_inliers = {max_inliers}")
209
210
         return F, inliers
211
212
     111
213
     Q5.2:Extra Credit Rodrigues formula.
214
         Input: r, a 3x1 vector
215
         Output: R, a rotation matrix
^{216}
217
     def rodrigues(r):
218
         # Compute the rotation angle theta
219
         theta = np.sqrt(np.sum(r ** 2))
220
221
         # Deal with corner case : no rotation
222
         if theta == 0:
223
             k = r
224
         else:
225
             k = r / theta
226
227
         # Compute the cross-product matrix K
228
         k1, k2, k3 = k[:, 0]
229
         K = np.array([[0, -k3, k2]],
230
                         [k3, 0, -k1],
231
                         [-k2, k1, 0]])
232
233
```

```
# Apply Rodrigues Rotation Formula
234
         \# R = I + sin(theta) * K + (1-cos(theta)) * K^2
235
         R = np.eye(3) + np.sin(theta) * K + (1 - np.cos(theta)) * (K 0 K)
236
237
         return R
238
239
     111
240
     Q5.2:Extra Credit Inverse Rodrigues formula.
^{241}
         Input: R, a rotation matrix
242
         Output: r, a 3x1 vector
243
244
     def invRodrigues(R):
245
          111
246
         Reference:
247
         https://www2.cs.duke.edu/courses/compsci527/fall13/notes/rodriques.pdf
^{248}
          # Define A, rho, s, and c
250
         A = (R - R.T) / 2
251
         rho = np.array([A[2, 1], A[0, 2], A[1, 0]]).reshape(-1, 1)
252
         s = np.sqrt(np.sum(rho ** 2))
253
         c = (np.sum(np.diag(R)) - 1) / 2
254
255
         \# s = 0 \text{ and } c = 1
256
         if s == 0 and c == 1:
257
              r = np.zeros((3, 1))
258
259
          \# s = 0 \text{ and } c = -1
260
         elif s ==0 and c ==-1:
261
              # Compute v
262
              R_plus_I = R + np.eye(3)
263
              for col in range(3):
264
                   if np.sum(R_plus_I[:, col]) != 0:
^{265}
                       v = R_plus_I[:, col]
266
                       break
267
              \# Compute u and r
268
              u = v / np.sqrt(np.sum(v ** 2))
269
              r = u * np.pi
270
271
              # Distinguish r or -r
272
              r1, r2, r3 = r[:, 0]
273
              if np.sqrt(np.sum(r ** 2)) == np.pi
274
                                             and ((r1 == 0 \text{ and } r2 == 0 \text{ and } r3 < 0))
275
                                             or (r1 == 0 \text{ and } r2 < 0) \text{ or } (r1 < 0)):
276
                   r = -r
277
              else:
278
                   r = r
279
280
```

```
# remaining cases
281
         else:
282
             u = rho / s
283
             theta = np.arctan2(s, c)
284
             r = u * theta
285
286
         return r
287
288
     111
289
     Q5.3: Extra Credit Rodrigues residual.
290
         Input: K1, the intrinsics of camera 1
291
                 M1, the extrinsics of camera 1
292
                 p1, the 2D coordinates of points in image 1
293
                 K2, the intrinsics of camera 2
294
                 p2, the 2D coordinates of points in image 2
295
                 x, the flattened concatenationg of P, r2, and t2.
296
         Output: residuals, 4N x 1 vector, the difference between original and
297
                             estimated projections
298
     111
299
     def rodriguesResidual(K1, M1, p1, K2, p2, x):
300
         # Extract w, r, and t
301
         N = p1.shape[0]
302
         w = x[0: -6].reshape(N, 3)
303
         w_homo = np.concatenate((w, np.ones((N, 1))), axis = 1)
304
         r2 = x[-6: -3].reshape(3, 1)
305
         t2 = x[-3:].reshape(3, 1)
306
307
         # Compute C1 and C2
308
         309
         M2 = np.concatenate((rodrigues(r2), t2), axis = 1)
310
         C2 = K2 @ M2
311
312
         # Compute estimated projections
313
         p1_est = C1 @ w_homo.T
314
         p2_est = C2 @ w_homo.T
315
         p1_hat = p1_est.T / p1_est.T[:, -1].reshape(-1, 1)
316
         p2_hat = p2_est.T / p2_est.T[:, -1].reshape(-1, 1)
317
318
         # Compute Residuals
319
         residuals = np.concatenate([(p1-p1_hat[:, :2]).reshape([-1]),
320
                                       (p2-p2_hat[:, :2]).reshape([-1])])
321
322
         return residuals
323
324
325
     Q5.3 Extra Credit Bundle adjustment.
326
         Input: K1, the intrinsics of camera 1
327
```

```
M1, the extrinsics of camera 1
328
                 p1, the 2D coordinates of points in image 1
329
                 K2, the intrinsics of camera 2
330
                 M2_init, the initial extrinsics of camera 1
331
                 p2, the 2D coordinates of points in image 2
332
                 P_init, the initial 3D coordinates of points
333
         Output: M2, the optimized extrinsics of camera 1
334
                 w, the optimized 3D coordinates of points
335
336
     def bundleAdjustment(K1, M1, p1, K2, M2_init, p2, P_init):
337
         # Set up the x for rodriquesResidual
338
         r2_init = invRodrigues(M2_init[:, 0:3]).reshape(-1, 1)
339
         t2_{init} = M2_{init}[:, 3].reshape(-1, 1)
340
         w_init = P_init.reshape(-1, 1)
341
         x_init = np.concatenate((w_init, r2_init, t2_init), axis = 0).reshape([-1])
342
343
         # Define the residual function
344
         def residual_func(x):
345
             return rodriguesResidual(K1, M1, p1, K2, p2, x)
346
347
         # Apply Least Square Optimizer to solve for x
348
         x = scipy.optimize.leastsq(residual_func, x_init)
349
         x = x[0]
350
351
         # Extract w, r2, and t2
352
         N = p1.shape[0]
353
         w = x[0: -6].reshape(N, 3)
354
         r2 = x[-6: -3].reshape(3, 1)
355
         t2 = x[-3:].reshape(3, 1)
356
357
         # Build M2 using r2 and t2
358
         R2 = rodrigues(r2)
359
         M2 = np.concatenate((R2, t2), axis = 1)
360
361
         return M2, w
362
```

$0.2 \quad \text{findM2.py}$

```
,,,
    Q3.3:
2
        1. Load point correspondences
3
        2. Obtain the correct M2
4
        3. Save the correct M2, C2, and P to q3_3.npz
5
6
7
    # Import necessary package
    import numpy as np
9
    import matplotlib.pyplot as plt
10
    import helper
11
    import submission
12
    import os
13
14
    # Load the image and M
15
    data_dir = '../data/'
16
    img1 = plt.imread(data_dir + 'im1.png')
17
    M = np.max(img1.shape)
18
19
    # Load the correspondences
20
    corresp = np.load(data_dir + 'some_corresp.npz')
21
    pts1 = corresp['pts1']
22
    pts2 = corresp['pts2']
23
24
    # Compute the Fundamental Matrix
25
    F = submission.eightpoint(pts1, pts2, M)
26
27
    # Load the Intrinsic Matrices
28
    intrinsics = np.load(data_dir + 'intrinsics.npz')
29
    K1 = intrinsics['K1']
30
    K2 = intrinsics['K2']
31
32
    # Compute the Essential Matrix
33
    E = submission.essentialMatrix(F, K1, K2)
34
35
    # Compute M1, C1, and M2s
36
    M1 = np.concatenate((np.eye(3), np.zeros((3, 1))), axis = 1)
37
    38
    M2s = helper.camera2(E)
39
40
    # Find the correct M2
41
    for i in range(4):
42
        # Check each M2
43
        M2 = M2s[:, :, i]
44
        C2 = K2 @ M2
45
        P, err = submission.triangulate(C1, pts1, C2, pts2)
46
```

```
47
        # Check the validity (z is positive)
48
        if np.min(P[:, 2]) > 0:
^{49}
            # Print the reprojection error
50
            print(f"reprojection error = {err}")
51
            break
52
53
    # Save M2, C2, and P
54
    results_dir = '../results/'
55
    if not os.path.exists(results_dir):
56
        os.makedirs(results_dir)
57
   np.savez(results_dir+ 'q3_3.npz', M2 = M2, C2 = C2, P = P)
58
```

0.3 visualize.py

```
,,,
    Q4.2:
2
        1. Integrating everything together.
3
        2. Loads necessary files from ../data/ and visualizes 3D reconstruction
4
        using scatter
5
6
7
    # Import necessary package
    import numpy as np
9
    import matplotlib.pyplot as plt
10
    import helper
11
    import submission
12
    import os
13
14
    # Load the image and M
15
    data_dir = '../data/'
16
    img1 = plt.imread(data_dir + 'im1.png')
17
    img2 = plt.imread(data_dir + 'im2.png')
18
    M = np.max(img1.shape)
19
20
    # Load the correspondences
21
    corresp = np.load(data_dir + 'some_corresp.npz')
22
    pts1 = corresp['pts1']
23
    pts2 = corresp['pts2']
24
25
    # Compute the Fundamental Matrix
26
    F = submission.eightpoint(pts1, pts2, M)
27
28
    # Load the Intrinsic Matrices
29
    intrinsics = np.load(data_dir + 'intrinsics.npz')
30
    K1 = intrinsics['K1']
    K2 = intrinsics['K2']
32
33
    # Compute the Essential Matrix
34
    E = submission.essentialMatrix(F, K1, K2)
35
36
    # Compute M1, C1, and M2s
37
    M1 = np.concatenate((np.eye(3), np.zeros((3, 1))), axis = 1)
    C1 = K1 @ M1
39
    M2s = helper.camera2(E)
40
41
    # Load the Temple Coordinates on image1
42
    templeCoords = np.load(data_dir + 'templeCoords.npz')
43
   x1s = templeCoords['x1']
44
   y1s = templeCoords['y1']
45
   p1 = np.concatenate((x1s, y1s), axis = 1)
```

```
47
    # Find the epipolar correspondence
48
    p2 = np.zeros_like(p1)
49
    for i in range(p2.shape[0]):
50
        x1, y1 = p1[i, 0], p1[i, 1]
51
        p2[i, 0], p2[i, 1] = submission.epipolarCorrespondence(img1, img2, F, x1, y1)
52
53
    # Find the correct M2
54
    for i in range(4):
55
        # Check each M2
56
        M2 = M2s[:, :, i]
57
        58
        P, err = submission.triangulate(C1, p1, C2, p2)
59
60
        # Check the validity (z is positive)
61
        if np.min(P[:, 2]) > 0:
62
            # Print the reprojection error
63
            print(f"reprojection error = {err}")
64
            break
65
66
    # Plot the 3D reconstruction
67
    fig = plt.figure()
68
    ax = fig.add_subplot(1, 1, 1, projection = '3d')
69
    ax.scatter(P[:, 0], P[:, 1], P[:, 2], c = 'b', s = 3)
70
    ax.set_title('Visualization of 3D Recontruction')
71
    plt.setp(ax, xlabel = 'X', ylabel = 'Y', zlabel = 'Z')
72
    plt.show()
73
74
    # Save F, M1, M2, C1, and C2
75
    results_dir = '../results/'
76
    if not os.path.exists(results_dir):
77
        os.makedirs(results_dir)
78
    np.savez(results\_dir+ 'q4\_2.npz', F = F, M1 = M1, M2 = M2, C1 = C1, C2 = C2)
79
```

0.4 util.py

```
import numpy as np
    import scipy.optimize
2
3
    def _singularize(F):
4
        U, S, V = np.linalg.svd(F)
5
        S[-1] = 0
6
        F = U.dot(np.diag(S).dot(V))
7
        return F
9
    def _objective_F(f, pts1, pts2):
10
        F = _singularize(f.reshape([3, 3]))
11
        num_points = pts1.shape[0]
12
        hpts1 = np.concatenate([pts1, np.ones([num_points, 1])], axis=1)
13
        hpts2 = np.concatenate([pts2, np.ones([num_points, 1])], axis=1)
14
        Fp1 = F.dot(hpts1.T)
15
        FTp2 = F.T.dot(hpts2.T)
16
17
        r = 0
18
        for fp1, fp2, hp2 in zip(Fp1.T, FTp2.T, hpts2):
19
            r += (hp2.dot(fp1))**2 * (1/(fp1[0]**2 + fp1[1]**2)
20
                                          + 1/(fp2[0]**2 + fp2[1]**2))
^{21}
        return r
22
23
    def refineF(F, pts1, pts2):
24
        f = scipy.optimize.fmin_powell(
25
            lambda x: _objective_F(x, pts1, pts2), F.reshape([-1]),
26
            maxiter=100000,
27
            maxfun=10000
28
29
        return _singularize(f.reshape([3, 3]))
30
```

0.5 helper.py

```
11 11 11
    Homework4.
2
    Helper functions.
3
4
    Written by Dinesh Reddy, 2020.
5
6
    import numpy as np
7
    import matplotlib.pyplot as plt
    import scipy.optimize
    import submission as sub
10
    from mpl_toolkits.mplot3d import Axes3D
11
    import os
12
13
14
    connections_3d = [[0,1], [1,3], [2,3], [2,0], [4,5], [6,7], [8,9], [9,11],
15
                       [10,11], [10,8], [0,4], [4,8], [1,5], [5,9], [2,6], [6,10],
16
                       [3,7], [7,11]]
17
    color_links = [(255,0,0),(255,0,0),(255,0,0),(255,0,0),(0,0,255),(255,0,255),
18
                    (0,255,0),(0,255,0),(0,255,0),(0,255,0),(0,0,255),(0,0,255),
19
                    (0,0,255),(0,0,255),(255,0,255),(255,0,255),(255,0,255),
20
                    (255,0,255)
21
    colors = ['blue','blue','blue','blue','red','magenta','green','green','green',
22
               'green', 'red', 'red', 'red', 'magenta', 'magenta', 'magenta',
23
               'magenta']
24
25
26
    def visualize_keypoints(image, pts, Threshold=None):
27
        111
28
        plot 2d keypoint
29
        :param image: image
30
        :param car_points: np.array points * 3
31
        I I I
32
        import cv2
33
        image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
34
        for i in range(12):
35
            cx, cy = pts[i][0:2]
36
            if pts[i][2]>Threshold:
37
                 cv2.circle(image,(int(cx),int(cy)),5,(0,255,255),5)
38
39
        for i in range(len(connections_3d)):
40
            idx0, idx1 = connections_3d[i]
41
            if pts[idx0][2]>Threshold and pts[idx1][2]>Threshold:
42
                 x0, y0 = pts[idx0][0:2]
43
                 x1, y1 = pts[idx1][0:2]
44
                 cv2.line(image, (int(x0), int(y0)), (int(x1), int(y1)),
45
                          color_links[i], 2)
46
```

```
while True:
47
             cv2.imshow("sample", image)
48
             if cv2.waitKey(0) == 27:
49
                 break
50
        cv2.destroyAllWindows()
51
        return (image)
52
53
    def plot_3d_keypoint(pts_3d):
54
55
        plot 3d keypoint
56
         :param car_points: np.array points * 3
57
58
        fig = plt.figure()
59
        num_points = pts_3d.shape[0]
60
        ax = fig.add_subplot(111, projection='3d')
61
        for j in range(len(connections_3d)):
62
             index0, index1 = connections_3d[j]
63
             xline = [pts_3d[index0,0], pts_3d[index1,0]]
64
             yline = [pts_3d[index0,1], pts_3d[index1,1]]
65
             zline = [pts_3d[index0,2], pts_3d[index1,2]]
66
             ax.plot(xline, yline, zline, color=colors[j])
67
        np.set_printoptions(threshold=1e6, suppress=True)
68
        ax.set_xlabel('X Label')
69
        ax.set_ylabel('Y Label')
70
        ax.set_zlabel('Z Label')
71
        plt.show()
72
73
74
    def _epipoles(E):
75
        U, S, V = np.linalg.svd(E)
76
        e1 = V[-1, :]
77
        U, S, V = np.linalg.svd(E.T)
78
        e2 = V[-1, :]
79
        return e1, e2
80
81
    def displayEpipolarF(I1, I2, F):
82
        e1, e2 = _epipoles(F)
83
84
        sy, sx, _{-} = I2.shape
85
86
        f, [ax1, ax2] = plt.subplots(1, 2, figsize=(12, 9))
        ax1.imshow(I1)
88
        ax1.set_title('Select a point in this image')
89
        ax1.set_axis_off()
90
        ax2.imshow(I2)
91
        ax2.set_title('Verify that the corresponding point \n is on the epipolar
92
                         line in this image')
93
        ax2.set_axis_off()
94
```

```
95
         while True:
96
              plt.sca(ax1)
97
              x, y = plt.ginput(1, timeout=3600, mouse_stop=2)[0]
98
99
              xc = x
100
              yc = y
101
              v = np.array([xc, yc, 1])
102
              1 = F.dot(v)
103
              s = np.sqrt(1[0]**2+1[1]**2)
104
105
              if s==0:
106
                  print('Zero line vector in displayEpipolar')
107
108
              1 = 1/s
109
110
              if 1[0] != 0:
111
                  ye = sy-1
112
                  ys = 0
113
                  xe = -(1[1] * ye + 1[2])/1[0]
114
                  xs = -(1[1] * ys + 1[2])/1[0]
115
              else:
116
                  xe = sx-1
117
                  xs = 0
118
                  ye = -(1[0] * xe + 1[2])/1[1]
119
                  ys = -(1[0] * xs + 1[2])/1[1]
120
121
              \# plt.plot(x,y, '*', 'MarkerSize', 6, 'LineWidth', 2);
122
              ax1.plot(x, y, '*', MarkerSize=6, linewidth=2)
123
              ax2.plot([xs, xe], [ys, ye], linewidth=2)
124
              plt.draw()
125
126
127
128
129
     def camera2(E):
130
         U,S,V = np.linalg.svd(E)
131
         m = S[:2].mean()
132
         E = U.dot(np.array([[m,0,0], [0,m,0], [0,0,0]])).dot(V)
133
         U,S,V = np.linalg.svd(E)
134
         W = np.array([[0,-1,0], [1,0,0], [0,0,1]])
135
136
         if np.linalg.det(U.dot(W).dot(V))<0:</pre>
137
              W = -W
138
139
         M2s = np.zeros([3,4,4])
140
         M2s[:,:,0] = np.concatenate([U.dot(W).dot(V), U[:,2].reshape([-1, 1]))
141
                                         /abs(U[:,2]).max()], axis=1)
142
```

```
M2s[:,:,1] = np.concatenate([U.dot(W).dot(V), -U[:,2].reshape([-1, 1]))
143
                                         /abs(U[:,2]).max()], axis=1)
144
         M2s[:,:,2] = np.concatenate([U.dot(W.T).dot(V), U[:,2].reshape([-1, 1]))
145
                                         /abs(U[:,2]).max()], axis=1)
146
         M2s[:,:,3] = np.concatenate([U.dot(W.T).dot(V), -U[:,2].reshape([-1, 1]))
147
                                         /abs(U[:,2]).max()], axis=1)
148
         return M2s
149
150
     def epipolarMatchGUI(I1, I2, F):
151
         e1, e2 = _epipoles(F)
152
153
         sy, sx, _ = I2.shape
154
155
         f, [ax1, ax2] = plt.subplots(1, 2, figsize=(12, 9))
156
         ax1.imshow(I1)
157
         ax1.set_title('Select a point in this image')
158
         ax1.set_axis_off()
159
         ax2.imshow(I2)
160
         ax2.set_title('Verify that the corresponding point \n is on the epipolar
161
                          line in this image')
162
         ax2.set_axis_off()
163
164
         # Create p1s and p2s to store the corresponding points
165
         p1s = []
166
         p2s = []
167
168
         while True:
169
             plt.sca(ax1)
170
             # Get the input point on image1
171
             p1 = plt.ginput(1, mouse_stop=2)
172
             # Check p1
173
             if not p1:
174
                  break
175
             # Extract x1 and y1
176
             x1, y1 = p1[0]
177
178
             xc = int(x1)
179
             yc = int(y1)
180
             v = np.array([xc, yc, 1])
181
             1 = F.dot(v)
182
             s = np.sqrt(1[0]**2+1[1]**2)
184
             if s==0:
185
                  print('Zero line vector in displayEpipolar')
186
187
             1 = 1/s;
188
189
             if 1[0] != 0:
190
```

```
ye = sy-1
191
                 ys = 0
192
                 xe = -(1[1] * ye + 1[2])/1[0]
193
                 xs = -(1[1] * ys + 1[2])/1[0]
194
             else:
195
                 xe = sx-1
196
                 xs = 0
197
                 ye = -(1[0] * xe + 1[2])/1[1]
198
                 ys = -(1[0] * xs + 1[2])/1[1]
199
200
             # plt.plot(x,y, '*', 'MarkerSize', 6, 'LineWidth', 2);
201
             ax1.plot(x1, y1, '*', MarkerSize=6, linewidth=2)
202
             ax2.plot([xs, xe], [ys, ye], linewidth=2)
203
204
             # draw points
205
             x2, y2 = sub.epipolarCorrespondence(I1, I2, F, xc, yc)
206
             ax2.plot(x2, y2, 'ro', MarkerSize=8, linewidth=2)
207
             plt.draw()
208
209
             # Append p1 and p2 to p1s and p2s
210
             p1 = [x1, y1]
211
             p2 = [x2, y2]
212
             p1s.append(p1)
213
             p2s.append(p2)
214
215
         # Save F, p1s, and p2s
216
         results_dir = '../results/'
217
         if not os.path.exists(results_dir):
218
             os.makedirs(results_dir)
219
         np.savez(results_dir+ 'q4_1.npz', F = F, pts1 = p1s, pts2 = p2s)
220
```