# **Computer Vision HW4**

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## Part I

## **Theory**

## Q1.1

We know that

So,  $F_{33} = 0$ 

$$x_2^T F x_1 = 0$$

$$x_2^T \begin{bmatrix} f_{11} & f_{12} & f_{13} \\ f_{21} & f_{22} & f_{23} \\ f_{31} & f_{32} & f_{33} \end{bmatrix} x_1 = 0$$

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

$$\begin{bmatrix} f_{31} & f_{32} & f_{33} \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} = 0$$

$$\begin{bmatrix} f_{33} \end{bmatrix} = 0$$

## Q1.2

Let

$$t = \begin{bmatrix} t_1 \\ 0 \\ 0 \end{bmatrix}$$

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

$$E = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -t_1 \\ 0 & t_1 & 0 \end{bmatrix}$$

$$x_1 = \begin{bmatrix} x_{11} \\ x_{12} \\ 1 \end{bmatrix}$$

$$x_2 = \begin{bmatrix} x_{21} \\ x_{22} \\ 1 \end{bmatrix}$$

Then

$$l_1^T = \begin{bmatrix} x_{21} \\ x_{22} \\ 1 \end{bmatrix} E = \begin{bmatrix} 0 & t_1 & x_{22}t_1 \end{bmatrix}$$
$$l_2^T = \begin{bmatrix} x_{11} \\ x_{12} \\ 1 \end{bmatrix} E = \begin{bmatrix} 0 & -t_1 & x_{12}t_1 \end{bmatrix}$$

So, the epipolar lines are

$$t_1 y_1 - x_{22} t_1 = 0$$
$$-t_1 y_1 + x_{12} t_1 = 0$$

it is clear that the lines do not have an x component in it which means they are parallel to the x axis

Let P be the 3D coordinate and

$$x_1, x_2$$

the homogenous points on the image.

$$\begin{split} x_1 &= K(R_1P + t_1) \\ P &= R_1^{-1}(K^{-1}x_1 - t_1) \\ \end{split}$$
 
$$\begin{aligned} x_2 &= K(R_2P + t_2) = K(R_2(R_1^{-1}(K^{-1}x_1 - t_1)) + t_2) \\ &= K(R_2(R_1^{-1}K^{-1}x_1 - R_1^{-1}t_1) + t_2) \\ &= K(R_2R_1^{-1}K^{-1}x_1 - R_2R_1^{-1}t_1 + t_2) \\ &= KR_2R_1^{-1}K^{-1}x_1 - KR_2R_1^{-1}t_1 + Kt_2 \\ R_{rel} &= KR_2R_1^{-1}K^{-1} \\ t_{rel} &= -KR_2R_1^{-1}t_1 + Kt_2 \\ E &= t_{rel} \times R_{rel} \end{aligned}$$

 $F = K^{-T}EK^{-1} = K^{-T}t_{rel} \times R_{rel}K^{-1}$ 

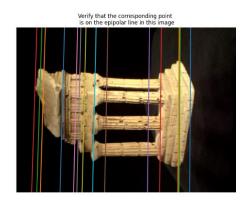
### Part II

## **Question 2**

## Q2.1

```
F = \begin{bmatrix} -2.19299581e - 07 & 2.95926445e - 05 & -2.51886343e - 01 \\ 1.28064547e - 05 & -6.64493709e - 07 & 2.63771740e - 03 \\ 2.42229086e - 01 & -6.82585550e - 03 & 1.00000000e + 00 \end{bmatrix}
```





```
def eightpoint(pts1, pts2, M):
    N = pts1.shape[0]

T = np.diag([1 / M, 1 / M, 1])

npts1 = pts1 / M
    npts2 = pts2 / M

x1 = npts1
    x2 = npts2

A = [
        [x2[i, 0] * x1[i, 0], x2[i, 0] * x1[i, 1], x2[i, 0], x2[i, 1] * x1[i, 0], x2[i, 1], x1[i, 0], x1[i, 1], 1]
        for i in range(N)
    ]

A = np.array(A).reshape(N, -1)
    u, s, vh = np.linalg.svd(A)
    F = vh[-1, :].reshape(3, 3)
```

```
F = _singularize(F)
F = refineF(F, npts1, npts2)

F = T.T @ F @ T
F = F / F[-1, -1]

np.savez('results/q2_1.npz', F=F, M=M)

return F
```

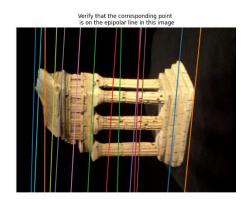
```
Final F:

[[-6.24506676e-07 -7.57931706e-06 -1.36008881e-01]

[ 3.23962377e-05 7.73246862e-06 -1.06791029e-02]

[ 1.30557801e-01 4.07163434e-03 1.00000000e+00]]
```





## Q3.1

```
def essentialMatrix(F, K1, K2):
    # Replace pass by your implementation
    E = K2.T @ F @ K1
    E = E / E[-1, -1]
    # save
    # np.savez('results/q3_1.npz', F=F, E=E)
    return E
```

$$A = egin{bmatrix} y_1c_{13} - c_{12} \ c_{11} - x_1c_{13} \ y_2c_{23} - c_{22} \ c_{21} - x_2c_{23} \end{bmatrix}$$

Where

$$C_1 = \begin{bmatrix} C_{11} \\ C_{12} \\ C_{13} \end{bmatrix}$$

$$C_2 = \begin{bmatrix} C_{21} \\ C_{22} \\ C_{23} \end{bmatrix}$$

and

 $(x_1, y_1)$ 

is the image projection to img1, and

 $(x_2, y_2)$ 

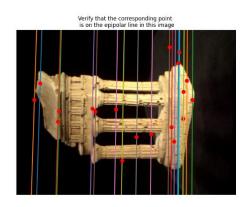
is the projection to img 2

```
pt3D = P
```

```
M2s = camera2(E)
C1 = K1.dot(M1)
        Pf = P
```

### Q4.1





```
def epipolarCorrespondence(im1, im2, F, x1, y1):
    x1, y1 = int(x1), int(y1)

# Replace pass by your implementation
A = list(F @ np.array([x1, y1, 1]).T)

[a, b, c] = [float(i) for i in A]

w_size = 10
search = 20

xs = np.array([i for i in range(w_size * 2, im2.shape[0] - w_size * 2)])
ys = -b / a * xs - c / a

xs = [int(i) for i in xs]
ys = [int(i) for i in ys]
zs = zip(xs, ys)

fzs = []
for (zx, zy) in zs:
    if y1 - search < zx < y1 + search:
        fzs.append([zx, zy])

img_g1 = ndimage.gaussian_filter(im1, sigma=2)
img_g2 = ndimage.gaussian_filter(im2, sigma=2)

# d1 = getDensity(img_g1, x1, y1, w_size)
d1 = img_g1[y1 - w_size: y1 + w_size, x1 - w_size: x1 + w_size]
min_d = 1000</pre>
```

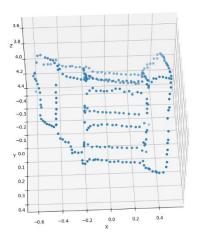
```
[x2, y2] = [0, 0]

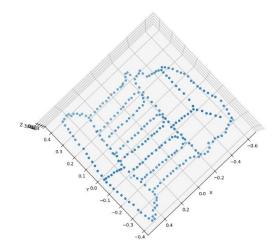
for (y, x) in fzs:
    if not possible(img_g2, w_size, x, y):
        continue
    d2 = img_g2[y - w_size: y + w_size, x - w_size: x + w_size]
    d = np.sqrt(np.sum((d1 - d2) ** 2))
    if d < min_d:
        min_d = d
        [x2, y2] = [x, y]

return x2, y2

def possible(img, w_size, x, y):
    xx = img.shape[1]
    yy = img.shape[0]

if not (0 <= x - w_size <= xx) or not (0 <= x + w_size <= xx):
        return False
    if not (0 <= y - w_size <= yy) or not (0 <= y + w_size <= yy):
        return False
    else:
        return True</pre>
```





#### Q5.1

When I run the ransac with the noisy points, I have to iterate more to get a good F where as to running the eight point algorithm will give me a good value right away. But overall with the right tuning (parameters niters/tolerance) the results are both good.

I used the error calculation matrix in helper function which calculates the error distances of the reprojection and returns the error.

I checked for every point and decided the inliers based on if the reprojection error for that set of points was below the tolerance.

Overall, when I increase the nIters, the F got closer to the F I got when I used the eightpoint algorithm. This is natural as the random sampling can be better as we sample more.

For the tolerance, I found that 5 was most optimal. If I decreased it down to 1, most of the points did not make it to the inlier category and my F generated a 3D point that was on a plane. When I increased it to 20, the they determined that most of the points were inliers and gave me the wrong F that made my 3D points not in the shape of the temple.

```
def ransacF(pts1, pts2, M, nIters=500, tol=5):
    # Replace pass by your implementation
    max_iters = nIters
    inlier_tol = tol

iters = 0
    max_right = 0

rand_len = pts1.shape[0]
    sampled = 8

M1 = np.hstack((np.identity(3), np.zeros(3)[:, np.newaxis]))

bestF = None

while iters < max_iters:
    iters += 1

    rand_points = np.random.choice(range(rand_len), sampled)

    pts1_c = pts1[rand_points, :]
    pts2_c = pts2[rand_points, :]

    F = eightpoint(pts1_c, pts2_c, M)

    right = np.zeros((rand_len, 1))</pre>
```

```
ptsl_homo, pts2_homo = toHomogenous(pts1), toHomogenous(pts2)
res = calc_epi_error(pts1_homo, pts2_homo, F)

for i in range(rand_len):
    err = res[i]
    if err < inlier_tol:
        right[i] = 1
    else:
        right[i] = 0

if np.sum(right) >= max_right:
    bestF = F
    max_right = np.sum(right)
    inliers = right

print(iters, "::", np.sum(max_right))

idx = np.where(inliers)[0]

pts1 = noisy_pts1[idx, :]
  pts2 = noisy_pts2[idx, :]

bestF = eightpoint(pts1, pts2, M)

np.savez('results/q5_1.npz', bestF=bestF, inliers=inliers)

return bestF, inliers
```

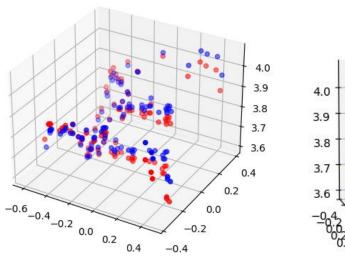
```
def invRodrigues(R):
    # Replace pass by your implementation
    c = (R[0, 0] + R[1, 1] + R[2, 2] - 1) / 2

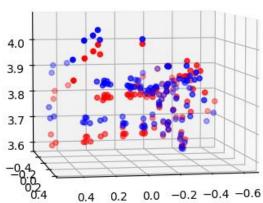
A = (R - R.T) / 2
    p = np.array([A[2, 1], A[0, 2], A[1, 0]]).T
    s = np.linalg.norm(p)
    if s == 0 and c == 1:
        return np.zeros((3, 1))
    elif s == 0 and c == -1:
        t = R + np.diag([1, 1, 1])
        for i in range(3):
            if np.sum(t[:, i]) != 0:
            v = t[:, i]
            break
        u = v / np.linalg.norm(v)
        up = u * math.pi

        if (np.linalg.norm(up) == math.pi and (u[0] == u[1] and u[2] < 0)) or ((u[0] == 0 and u[1] < 0) or u[0] < 0):
            up = -up
        r = up
        theta = np.arctan2(s, c)
    if math.sin(theta) != 0:
        u = p / s
        r = theta * u
    return r</pre>
```

```
init error: 491972.47419176035
after error 22.905571686573936
```

Blue: before; red: after Blue: before; red: after





```
def rodriguesResidual(K1, M1, p1, K2, p2, x):
    # Replace pass by your implementation
    P, r2, t2 = x[:-6], x[-6:-3], x[-3:]
    N = P.shape[0] // 3
    P = P.reshape((N, 3))
    r2 = r2.reshape((3, 1))
    t2 = t2.reshape((3, 1))
    R2 = rodrigues(r2)
    M2 = np.hstack((R2, t2))

P = np.vstack((P.T, np.ones((1, N))))
p1_hat = K1 @ M1 @ P
p1_hat /= p1_hat[2, :]

p2_hat /= p2_hat[2, :]

residuals = np.concatenate([(p1 - p1_hat[:2, :].T).reshape([-1]), (p2 - p2_hat[:2, :].T).reshape([-1])])

return residuals

def bundleAdjustment(K1, M1, pts1, K2, M2_init, pts2, P_init):
    # ----- TODO ------

R2_init, T2_init = M2_init[:, :3], M2_init[:, 3:]
    r2_init = invRodrigues(R2_init)
    x = np.concatenate([P_init[:, :3].reshape((-1, 1)), r2_init.reshape((-1, 1)), T2_init]).reshape((-1, 1))
    obj_start = np.linalg.norm(rodriguesResidual(K1, M1, pts1, K2, pts2, x))
** 2
```

```
def f(x):
    r = np.sum(rodriguesResidual(K1, M1, pts1, K2, pts2, x) ** 2)
    return r

t = scipy.optimize.minimize(f, x)
    f = t.x

P, r2, t2 = f[:-6], f[-6:-3], f[-3:]
    P, r2, t2 = P.reshape((-1, 3)), r2.reshape((3, 1)), t2.reshape((3, 1))
    R2 = rodrigues(r2).reshape((3, 3))
    M2 = np.hstack((R2, t2))

    obj_end = t.fun

    np.savez('results/q5.npz', f=f, M2=M2, P=P, obj_start=obj_start,
obj_end=obj_end)

return M2, P, obj_start, obj_end
```

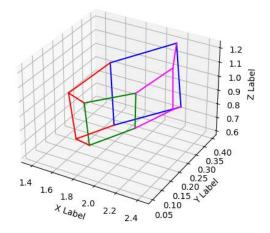
### Q6.1

Since I have 3 images instead of 2, for every point in P(world 3D space) I saw if the points were really valid (above threshold) and calculated the 3D points with only the confident values. For example if pts1, pts2's confidence was over the threshold and pts3's confidence was not, then I used triangulate on the two points. On the other hand, when all three points were confident, then I used all 3 points in triangulate. For that I needed to make a triangulate\_with\_three\_points function. In it, I just modified A to be

$$A = \begin{bmatrix} y_1c_{13} - c_{12} \\ c_{11} - x_1c_{13} \\ y_2c_{23} - c_{22} \\ c_{21} - x_2c_{23} \\ y_3c_{33} - c_{32} \\ c_{31} - x_3c_{33} \end{bmatrix}$$

Everything else is the same (using svd, taking the last col of v and so on).

The reprojection error for the first frame is 2429.7574300839638



Regarding the thresholds, if I gave it a value lower than 300, the reprojection error went up very high as all of the points (pts1, pts2, pts3) were always used to calculate P. If I set it too high, then there would be times when there would be only one good point and thus cannot run the triangulate algorithm. So, after some experiments, I choose 300 as it did not run into any errors, and gave me a small reprojection error.

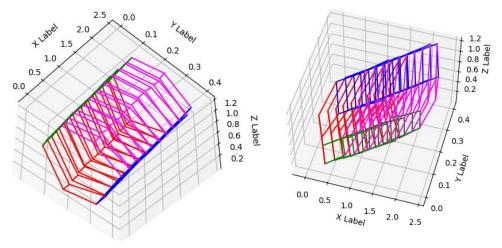
```
pts2[i, :2].reshape(1, 2), C3,
            X, error = triangulate(C1, pts1[i, :2].reshape(1, 2), C2,
pts2[i, :2].reshape(1, 2))
        P = P.reshape(4)
        Proj1 n = (Proj1 / Proj1[2])[:2] # 2xN
```

```
Proj1_n_list[i, :] = Proj1_n

Proj2 = C2 @ pt3D.T # 3xN
Proj2_n = (Proj2 / Proj2[2])[:2] # 2xN
Proj2_n_list[i, :] = Proj2_n

Proj3 = C3 @ pt3D.T # 3xN
Proj3_n = (Proj3 / Proj3[2])[:2] # 2xN
Proj3_n_list[i, :] = Proj3_n

e1 = (np.linalg.norm(Proj1_n - pts1[i, :])) ** 2
  e2 = (np.linalg.norm(Proj2_n - pts2[i, :])) ** 2
  e3 = (np.linalg.norm(Proj3_n - pts3[i, :])) ** 2
  error += (e1 + e2 + e3)
return X, error
```



```
def plot_3d_keypoint_video(pts_3d_video):
    # Replace pass by your implementation
    fig = plt.figure()
    num_points = len(pts_3d_video)
    ax = fig.add_subplot(111, projection='3d')
    for i in range(num_points):
        pts_3d = pts_3d_video[i]
        for j in range(len(connections_3d)):
            index0, index1 = connections_3d[j]
            xline = [pts_3d[index0, 0], pts_3d[index1, 0]]
            yline = [pts_3d[index0, 1], pts_3d[index1, 1]]
            zline = [pts_3d[index0, 2], pts_3d[index1, 2]]
            ax.plot(xline, yline, zline, color=colors[j])
    np.set_printoptions(threshold=le6, suppress=True)
    ax.set_xlabel('X Label')
    ax.set_zlabel('Y Label')
    plt.show()
```