$$x^{T}Fx' = 0$$

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

$$x^{*}F = \begin{bmatrix} 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} F_{11} & F_{12} & F_{13} \\ F_{21} & F_{22} & F_{23} \\ F_{31} & F_{32} & F_{33} \end{bmatrix} = \begin{bmatrix} F_{31} & F_{32} & F_{33} \end{bmatrix}$$

$$(xF)^{*}x' = \begin{bmatrix} F_{31} & F_{32} & F_{33} \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} = F_{33} = 0$$

$$x_2^T E x_1$$

 $R = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}; R is the identity matrix since it is pure translation$ 

As such lines are parallel to x-axis.

At time 1:  $w_t1 = R_1w + t_1$ , at time 2:  $w_t2 = R_2w + t_2$ 

Solve for w in equation 1 for time 1:

$$w = R_1^{-1}(w_{t1} - t_1)$$
  
$$w_{t2} = R_2 R_1^{-1}(w_{t1} - t_1) + t_2$$

Simplify to get  $R_{rel}$  and  $t_{rel}$ 

$$w_{t2} = R_2 R_1^{-1} (w_{t1} - t_1) + t_2$$

$$w_{t2} = R_2 R_1^{-1} w_{t1} - R_2 R_1^{-1} t_1 + t_2$$

$$R_{rel} = R_2 R_1^{-1}$$

$$t_{rel} = -R_2 R_1^{-1} t_1 + t_2$$

Plug into equation:  $E = t_{rel}R_{rel}$  and F equation

$$F = KE = K * t_{rel}R_{rel}$$

Assume a 3D point p on an object which are all equidistance to the mirror, there is **no rotation** (R is the identity matrix) and **only translation** between the point p and its reflection in the mirror (p').

$$M_2 = TM_1; T^TT = I$$

$$x_1 = KM_1p$$

$$x_2 = KTM_1p$$

$$x_2^TFx_1 + x_1^TFx_2 = 0$$

Substitute the equations for  $x_1$  and  $x_2$  into transposed equation of  $x_2^T F x_1$ , respectively.

$$(KTM_1p)^TF(KM_1p) + (KM_1p)^TF(KTM_1p) = 0$$

Solve for  $F = -F^T$ 

$$K^{T}T^{T}M_{1}^{T}p^{T} * F * K^{T}M_{1}^{T}p^{T} + K^{T}M_{1}^{T}p^{T} * F * K^{T}T^{T}M_{1}^{T}p^{T} = 0$$

Rearrange terms to get

$$K^{T}(F + F^{T})K = 0$$
$$F = -F^{T}$$

return F

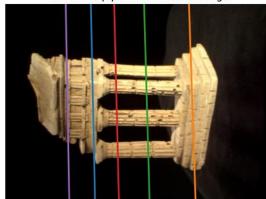
```
def eightpoint(pts1, pts2, M):
    # Get the diagonal matrix T
    T = np.diag((1Mn,1M,1))
    #How normalize the points using T Xnorm = TX
    x1,y1 = pts1[:,0]*T[0,0],pts1[:,1]*T[1,1]
    x1_prime.y1_prime = pts2[:,0]*T[0,0],pts2[:,1]*T[1,1]

A = np.zeros((pts1.shape[0],9))
    for i in range(0,pts1.shape[0]):
        A[i] = np.array([xi[i]*x1_prime[i],xi[i]*y1_prime[i],x1[i],y1[i]*x1_prime[i],y1[i]*y1_prime[i],y1[i],x1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i
```

Select a point in this image



Verify that the corresponding point is on the epipolar line in this image



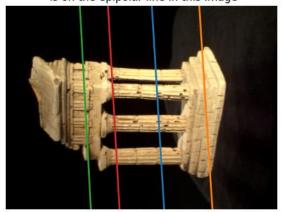
```
[[-8.33149236e-09 1.29538462e-07 -1.17187851e-03]
[ 6.51358336e-08 5.70670059e-09 -4.13435037e-05]
[ 1.13078765e-03 1.91823637e-05 4.16862080e-03]]
```

```
sevenpoint(pts1, pts2, M):
         x1,y1 = pts1[:,0]/M,pts1[:,1]/M
         x1_prime,y1_prime = pts2[:,0]/M,pts2[:,1]/M
         A = np.zeros((7,9))
         T = np.diag([1/M, 1/M, 1])
         for i in range(0,7):
                   A[i] = np.array([x1[i]*y1[i],x1[i]*y1_prime[i],x1[i],x1[i],x1[i],x1_prime[i],y1[i],x1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prime[i],y1_prim
         u,s,vT = np.linalg.svd(A)
         F1 = np.reshape((vT[-1,:]),(3,3))
         F2 = np.reshape((vT[-2,:]),(3,3))
         # det(F1+lambda*F2) = a3*lambda**3+a2*lambda**2+a1*lambda+a0 = 0
     poly = lambda x: np.linalg.det(x*F1+(1-x)*F2)
     coeff = extract_coefficients(poly,3)
     import pdb; pdb.set_trace()
     Y = np.roots(coeff)
               if np.isreal(s):
                        Farray.append(F)
ef extract_coefficients(p, degree):
   n = degree + 1
    sample_x = [ x for x in range(n) ]
sample_y = [ p(x) for x in sample_x ]
           A = [ [ 0 for _ in range(n) ] for _ in range(n) ]
           for line in range(n):
                               for column in range(n):
                                                 A[line][column] = sample_x[line] ** column
           c = np.linalg.solve(A, sample y)
           return c[::-1]
```

Select a point in this image



Verify that the corresponding point is on the epipolar line in this image



## **Farray returned:**

```
Q3.1: Compute the essential matrix E.

Input: F, fundamental matrix

K1, internal camera calibration matrix of camera 1

K2, internal camera calibration matrix of camera 2

Output: E, the essential matrix

def essentialMatrix(F, K1, K2):

# Replace pass by your implementation

E = np.dot(np.dot(K2.T,F),K1)

return E
```

```
def triangulate(C1, pts1, C2, pts2):
                x1,y1 = pts1[:,0],pts1[:,1]
                x1_prime,y1_prime = pts2[:,0],pts2[:,1]
               p1 = C1[0,:].T
               p2 = C1[1,:].T
               p3 = C1[2,:].T
               p1_prime = C2[0,:].T
               p2_prime = C2[1,:].T
               p3_prime = C2[2,:].T
               non_homo = np.zeros((pts1.shape[0],4))
               homogenous = np.zeros((pts1.shape[0],3))
               repr_error = 0
               proj_norm = np.zeros((3,pts1.shape[0]))
                for i in range(0,pts1.shape[0]):
                           row1 = np.array([y1[i]*p3-p2])
                            row2 = np.array([x1[i]*p3-p1])
                            row3 = np.array([y1_prime[i]*p3_prime-p2_prime])
                           row4 = np.array([x1_prime[i]*p3_prime-p1_prime])
                           A = np.vstack((row1,row2,row3,row4)) #4x4
                # import pdb; pdb.set_trace()
          # (3) Solve for the least square solution using SVD.
                  u,s,vT = np.linalg.svd(A)
                   F = vT[-1,:]
                  homogenous[i] = F[0:3]/F[-1]
                   non\_homo[i,:] = np.array([homogenous[i][0],homogenous[i][1],homogenous[i][2],np.ones(1)], \\ dtype=object) \# Non-homogenous matrix is a simple of the property of the propert
         proj_matrix_1 = np.dot(C1,non_homo.T).T
         proj_matrix_2 = np.dot(C2,non_homo.T).T
         for i in range (0, pts1.shape[0]):
                   proj_norm = proj_matrix_1[i]/proj_matrix_1[i][-1] #3XN
                   proj_norm2 = proj_matrix_2[i]/proj_matrix_2[i][-1]
                  repr_error += np.sum((pts1[i]- proj_norm.T[0:2].T)**2)+np.sum((pts2[i]-proj_norm2.T[0:2].T)**2)
 \begin{aligned} y_1 * C_{13}^T & -C_{12}^T \\ \text{Ai} &= C_{11}^T & -x_1 C_{13}^T \\ y_{2*} C_{23}^T & -x_2 C_{22}^T \end{aligned}
```

$$y_{1} * C_{13}^{T} - C_{12}^{T}$$

$$Ai = C_{11}^{T} - x_{1}C_{13}^{T}$$

$$y_{2}*C_{23}^{T} - x_{2}C_{22}^{T}$$

$$C_{21}^{T} - x_{2}C_{11}^{T}$$

$$\begin{bmatrix} y \boldsymbol{p}_3^\top - \boldsymbol{p}_2^\top \\ \boldsymbol{p}_1^\top - x \boldsymbol{p}_3^\top \\ y' \boldsymbol{p}_3'^\top - \boldsymbol{p}_2'^\top \\ \boldsymbol{p}_1'^\top - x' \boldsymbol{p}_3'^\top \end{bmatrix}$$

The reprojection error varied between 99-352, as I changed my implementation of the Ai matrix, with 352 being the last value achieved. Note equation may differ from what was implemented as using the original Ai matrix resulted in a lot of errors

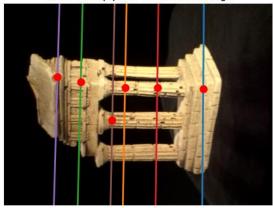
```
def epipolarCorrespondence(imi, imi, rx, rx, rx);

# Replace pass by your implementation
x = np.arrey(day,1,1)
qp_line = np.dot(fx,x) #fipiolar line on image 1
# epiline = np.dot(fx,x) #fipiolar line on image 1
# epiline = np.dot(fx,x) #fipiolar line on image 1
# epiline = np.dot(fx,x) #fipiolar line on image 1
# epiline = np.dot(fx,x) #fipiolar line on image 1
# indow_def = imi[y1.window//2:y1.window//2:x1.window//2:x1.window//2:x1] #fihis is a fixed window for image 1
# y2.search_array = np.armay(range(y1.50.y1x50))
# x2.search_array = np.armay(range(y1.50.y1x50))
# x3.search_array = np.armay(range(y1.50.y1x50))
# x4.cv_asearch_array = np.armay(range(y1.50.y1x50))
# x4.cv_asearch_array = np.armay(range(y1.50.y1x50))
# x3.search_array = np.armay(range(y1.50.y1x50)
# x3.search_array = np.armay(range(y1.50.y1x50))
# x3.search_array = np.armay(range(y1.50.y1x50))
# x3.search_array = np.armay(range(y1.50.y1x50))
# x3.search_array = np.armay(range(y1.50.y1x5
```

## Select a point in this image



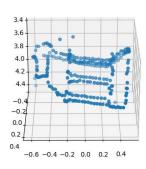
Verify that the corresponding point is on the epipolar line in this image

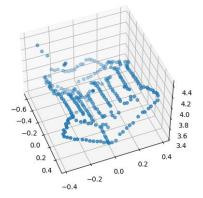


```
def compute3D_pts(temple_pts1, intrinsics, F, im1, im2):
     #Get x2, y2; x1 and y1 passed in to epipolar will be at a single index
x2 = np.zeros(shape = (1,temple_pts1['x1'].shape[0]))
y2 = np.zeros(shape = (1,temple_pts1['y1'].shape[0]))
     for i in range(0,temple_pts1['x1'].shape[0]):
    x2_, y2_ = epipolarCorrespondence(im1, im2, F, int(temple_pts1['x1'][i]), int(temple_pts1['y1'][i]))
    x2[0][i] = x2_
    y2[0][i] = y2_
     # homograpy, error_ = triangulate(C1, temple_pts1[0], C2, temple_pts1[1])

    Integrating everything together.
    Loads necessary files from ../data/ and visualizes 3D reconstruction using scatter

if __name__ == "__main ":
   temple_coords_path = np.load('code/data/templeCoords.npz')
    correspondence = np.load('code/data/some_corresp.npz') # Loading correspondences
    intrinsics = np.load('code/data/intrinsics.npz') # Loading the intrinscis of the camera
    K1, K2 = intrinsics['K1'], intrinsics['K2']
   pti1, pts2 = correspondence['pts1'], correspondence['pts2']
im1 = plt.imread('code/data/im1.png')
    im2 = plt.imread('code/data/im2.png')
    F = eightpoint(pts1, pts2, M=np.max([*im1.shape, *im2.shape]))
    P = compute3D_pts(temple_coords_path, intrinsics, F, im1, im2)
    xs = P[:,0]
   ys = P[:,1]
zs = P[:,2]
    fig = plt.figure()
    ax = fig.add_subplot(projection='3d')
    ax.scatter(xs,ys,zs)
    plt.show()
```





```
def ransacF(pts1, pts2, M, nIters=1000, tol=10):
   current inliers = 0
   inliers = []
   numb_inliers = 0
   ct_inliers = []
   p_prime = np.zeros((pts1.shape[0],3))
    for i in range(nIters):
       print("Here:
                              ',i)
       index = np.random.choice(pts1.shape[0],8,False)
       x1 = pts1[index]
       x2 = pts2[index]
       F_ = eightpoint(x1,x2,M) #My sevenpoint is not that accurate...
        for k in range(pts1.shape[0]):
           p_prime = np.append(pts2[k],1)
           error = np.dot(F_,p_prime)
           x2_x = error[0]
           x2_y = error[1]
```

```
distance_1 = np.sqrt(x2_x**2+x2_y**2)
    distance = abs(np.dot(p_prime.T,error)/distance_1)

#Find the inliers
# error_ = error/np.sqrt(np.sum(error[:,2:]**2,axis = 0))
# dist = abs(np.sum(homo_2*error_,axis = 0))
if (distance<= tol).all():
    numb_inliers+1
    ct_inliers.append(1)
# else:
# ct_inliers.append(0)
# numb_inliers = 0

if numb_inliers > current_inliers:
    current_inliers = numb_inliers
    inliers = ct_inliers
    F = F_

if F[2,2] != 1:
    F = F/F[2,2]

return F, inliers
```

The Ransac method improved the epipolar line correspondences. I played around with raising and lowering the iterations, and lowering the number of iterations made the Ransac method less accurate versus raising the number of iterations actually yielded better results (though I defaulted to the 1000 used in the hw assignment for the write-up). Using a similar implementation to the previous homework, I implemented the Ransac method by checking for inliers where the computed error (distance) was less than the tolerance. For the error computation, I looked at the distance between the point and the error/distance\_1 (this expression was meant to represent where I would predict where the points would actually fall on the epipolar line).

```
Q5.2: Rodrigues formula.
def rodrigues(r):
     theta = np.linalg.norm(r) #theta = ||r||
     u = r/theta
     if theta <= np.pi:</pre>
          if theta == 0:
               R = np.diag([1,1,1])
               ux = np.array([[0,-u[2],u[1]],[u[2],0,-u[0]],[-u[1],u[0],0]])
               u_t = (u.reshape(3,1) @ u.reshape(3,1).T)
               R = np.diag([1,1,1])*np.cos(theta)+(1-np.cos(theta))*u_t+ux*np.sin(theta)
          R = np.eye(3)
     return R
def invRodrigues(R):
   A = (R-R.T)//2
    s = np.linalg.norm(rho)
    c = (R[0][0]+R[1][1]+R[2][2]-1)//2
    if (s == 0 \text{ and } c == 1):
       r = np.zeros((3,1))
       # index = np.where((R+np.diag[1,1,1]) != 0)
# v = (R+np.diag[1,1,1])[:,index]
I = R + np.diag([1,1,1])
        for i in range(3):
           if (np.count_nonzero(I[:,i]))>0 and (np.count_nonzero(I[:,i]))!=0:
       v = I[:, i]
u = v/np.linalg.norm(v)
       if ((np.linalg.norm(r) == np.pi) and (r[0][0] == 0 and r[1][0] == 0 and r[3][0]<0) or (r[0][0] == 0 and r[1][0]<0) or (r[0][0]<0)):
         u = rho/s
         theta = np.arctan2(s,c)
         r = u*theta
```

```
def rodriguesResidual(K1, M1, p1, K2, p2, x):
    # Replace pass by your implementation
    C1 = np.dot(K1,M1)

w = np.reshape(x[:-6],shape = (p1.shape[0],3))
t2 = np.reshape(x[-6:-3],shape = (3,1))
r2 = np.reshape(x[-3:],shape = (3,1))
R2 = rodrigues(r2)

M2 = np.htsack(R2,x[-3:].reshape(3,1))
P_homo = np.hstack(w,np.ones(p1.shape[0],1))
C2 = np.dot(K2,M2)

p1_= np.dot(C1,P_homo.T).T

p2_ = np.dot(C2,P_homo.T).T

p1_hat = p1_[:2,:]/p1_[2,:]
p1_hat = p1_[:2,:]/p1_[2,:]
residuals = np.concatenate([(p1 - p1_hat).reshape([-1]), (p2 - p2_hat).reshape([-1])))
return residuals
```

I was not able to get the correct results for running this question, I believe this is due to not computing the inliers correctly in the RansacF function but the results would output incorrectly for each iteration. I also did not have enough time to finish the implementation of this question (specifically the debugging process in the bundle adjustment portion of the question).

Note: I missed some parts of the questions where a .npz file was required to save the results. I did go back and try to capture as many as I could before the deadline.