

# CS-E4850 Computer Vision, Answers to Exercise Round 12

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## Exercise 2. Epipolar geometry.

Here we use the position of the camera 2 as our origin. Let's first write the equation (1) out using the notation from  $\mathbf{x}$  and  $\mathbf{x}'$ :

$$\vec{O'O} = \mathbf{t} = (t_1, t_2, t_3)^\top$$

$$\vec{O'p'} = \mathbf{x}'$$

$$\vec{Op} = R\mathbf{x}$$

Thus we can derive that:

$$\vec{O'p'} \cdot (\vec{O'O} \times \vec{Op}) = \mathbf{x}' \cdot (\mathbf{t} \times R\mathbf{x}) = 0$$

where  $\mathbf{t} \times R\mathbf{x}$  can be written as  $[\mathbf{t}]_\times R\mathbf{x}$  and  $\mathbf{t} \times \mathbf{t} = 0$ . Therefore finally we get:

$$\mathbf{x}'^\top [\mathbf{t}]_\times R\mathbf{x} = 0$$

where  $[\mathbf{t}]_\times R$  is the essential matrix  $E$ .

### Exercise 3. Stereo vision.

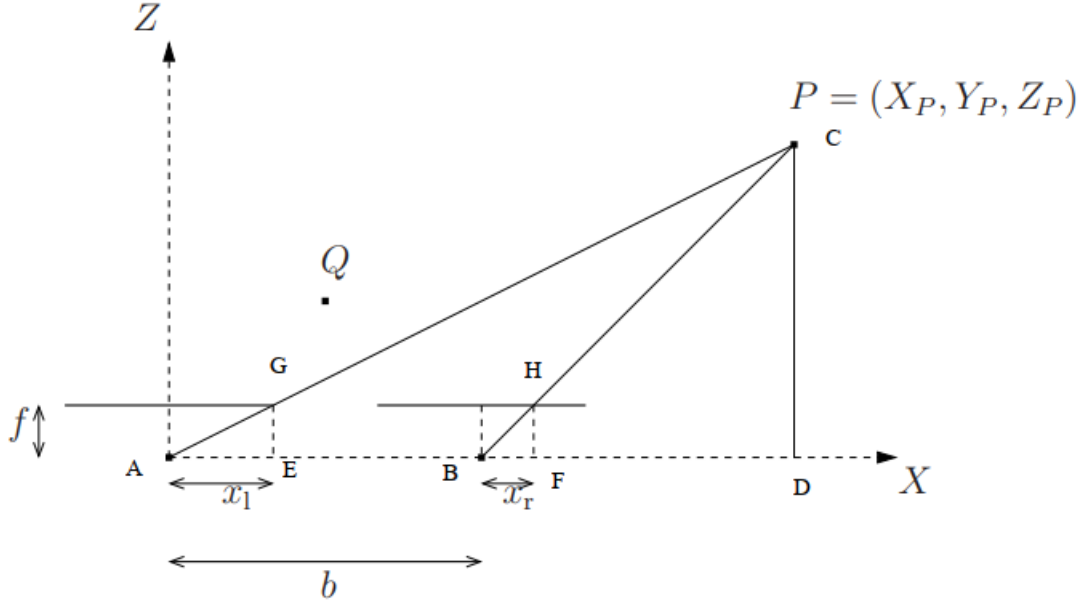


Figure 1: : Top view of a stereo configuration where two pinhole cameras are placed side by side

- a) We have 2 pairs of similar triangles in Figure 1:  $\triangle AGE$  and  $\triangle ADC$ ,  $\triangle BHF$  and  $\triangle BDC$ . Let's assume that  $DF = a$ , thus we can have the following formulas:

$$\frac{f}{x_l} = \frac{Z_p}{b + x_r + a}$$

$$\frac{f}{x_r} = \frac{Z_p}{x_r + a}$$

$$x_l = 1 + x_r$$

Then we can get:

$$\frac{1}{x_l} = \frac{Z_p}{6 + x_r + a}$$

$$\frac{1}{x_r} = \frac{Z_p}{x_r + a}$$

$$x_l = 1 + x_r$$

Finally we can substitute  $x_l$  with  $x_r + 1$  and we can derive that:

$$1 + x_r = \frac{6 + x_r + a}{Z_p}$$

$$x_r = \frac{x_r + a}{Z_p}$$

Therefore, we get that  $Z_p = 6cm$

- b) Actually we can use the similar method to derive that in the general case  $\frac{d}{f} = \frac{b}{Z_p}$  (because  $\frac{f}{x_l} = \frac{Z_p}{b+x_r+a}$ ,  $\frac{f}{x_r} = \frac{Z_p}{x_r+a}$  and  $|x_l - x_r| = d$ ), and therefore  $Z_p = \frac{bf}{d}$ . Thus, if  $d$  is below than 1 pixel, we can say that  $0 \leq d < 0.01mm$ . So  $Z_p$  should fall into the range  $(100bf, \infty)mm$
- c)  $Q$  on the left image plane is:

$$q_l = P_r Q = (1, 0, 1)$$

Then the essential matrix is:

$$E = [t]_{\times} R = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 6 \\ 0 & -6 & 0 \end{bmatrix}$$

So then the corresponding epipolar line  $l'$  with  $q_l$  is  $Eq_l = (0, 1, 0)^T$ . And since  $q_r = (-1, 0, 1)^T$  should be on the line  $l'$  too, thus we have the formula for the coefficients  $a, b, c, d$  of  $l'$ :

$$a = 0$$

$$b = 1$$

$$c = 0$$

$$d = 0$$

And also because  $l'$  is on the second image plane, thus  $l'$  should be  $y = 0, z = 0$

## Exercise 4. Fundamental matrix estimation.

The python code for the two functions are shown below.

```

1 def estimateF(x1, x2):
2     # Return the fundamental matrix F (3 by 3), based on two sets
      of homogeneous 2D points x1 and x2.
3     # Input: x1, x2 numpy ndarray (3 by N) containing matching 2D
      homogeneous points.
4     # Output: F numpy ndarray (3 by 3) containing the fundamental
      matrix.
5     n = x1.shape[1]
6     A = np.zeros((n, 9))
7     for i in range(n):

```

```

8         u,v,u_,v_ = x1[0,i]/x1[2,i],x1[1,i]/x1[2,i],x2[0,i]/x2[2,
          i],x2[1,i]/x2[2,i]
9         A[i] = [u_*u,u_*v,u_,v_*u,v_*v,v_,u,v,1]
10        # compute linear least square solution
11        U,S,V = np.linalg.svd(A)
12        F = V[-1].reshape(3,3)
13        print(F)
14        # rank 2 constrain on F
15        U,S,V = np.linalg.svd(F)
16        S[2] = 0
17        F = (U*S)@V
18        print(F)
19        return F
20
21    def estimateFnorm(x1,x2):
22        # Return the fundamental matrix F (3 by 3), based on two sets
          of homogeneous 2D points x1 and x2.
23        # Input: x1,x2 numpy ndarray (3 by N) containing matching 2D
          homogeneous points.
24        # Output: F numpy ndarray (3 by 3) containing the fundamental
          matrix based on normalized homogeneous points.
25        n = x1.shape[1]
26
27        # normalize image coordinates
28        x1 = x1 / x1[2]
29        mean_1 = np.mean(x1[:2],axis=1)
30        s1 = np.sqrt(2) / np.std(x1[:2])
31        T1 = np.array([[s1,0,-s1*mean_1[0]],[0,s1,-s1*mean_1
          [1]],[0,0,1]])
32        x1 = np.dot(T1,x1)
33
34        x2 = x2 / x2[2]
35        mean_2 = np.mean(x2[:2],axis=1)
36        s2 = np.sqrt(2) / np.std(x2[:2])
37        T2 = np.array([[s2,0,-s2*mean_2[0]],[0,s2,-s2*mean_2
          [1]],[0,0,1]])
38        x2 = np.dot(T2,x2)
39
40        # compute F with the normalized coordinates
41        F = estimateF(x1,x2)
42
43        # reverse normalization
44        F = np.dot(T1.T,np.dot(F,T2))

```

```
return F
```