

Introduction to Computer Vision : HW 1

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1 Camera Calibration

a

From the result of SVD,

$$\mathbf{A}\mathbf{V} = \mathbf{U}\mathbf{\Sigma} \quad (1)$$

Since $\mathbf{V} \in \mathbf{O}(\mathbf{n})$, the column vector of \mathbf{V} , denoting \mathbf{v}_i , can form the basis of \mathbb{R}^n . That is, $\forall \mathbf{x} \in \mathbb{R}^n, \mathbf{x} = \sum_i a_i \mathbf{v}_i$, for $a_i \in \mathbb{R}$. This results in $\mathbf{A}\mathbf{p} = \sum_i a_i \mathbf{A}\mathbf{v}_i = \sum_i a_i \sigma_i \mathbf{u}_i$. Thus,

$$\|\mathbf{A}\mathbf{v}\|^2 = \sum_i a_i^2 \sigma_i^2 \quad (2)$$

It is a convention to make the diagonal entries of $\mathbf{\Sigma}$, σ_i , be ordered, that is, $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_r$. Thus, to minimize equation 2, $a_1 = a_2 = \dots = a_{r-1} = 0$ and $a_r = 1$, since \mathbf{p} is normalized. This implies $\mathbf{p} = \mathbf{v}_n$. (note that $r = n$ since we assumed over-determined system.)

b

The following code is the implmentation to calculate the camera matrix for given corresponding points.

```
x = [[880, 214],
[43, 203],
[270, 197],
[886, 347],
[745, 302],
[943, 128],
[476, 590],
[419, 214],
[317, 335],
[783, 521],
[235, 427],
[665, 429],
[655, 362],
[427, 333],
[412, 415],
[746, 351],
[434, 415],
[525, 234],
[716, 308],
[602, 187]]

X = [[312.747, 309.140, 30.086],
[305.796, 311.649, 30.356],
[307.694, 312.358, 30.418],
[310.149, 307.186, 29.298],
[311.937, 310.105, 29.216],
[311.202, 307.572, 30.682],
[307.106, 306.876, 28.660],
[309.317, 312.490, 30.230],
[307.435, 310.151, 29.318],
[308.253, 306.300, 28.881],
[306.650, 309.301, 28.905],
[308.069, 306.831, 29.189],
[309.671, 308.834, 29.029],
[308.255, 309.955, 29.267],
[307.546, 308.613, 28.963],
[311.036, 309.206, 28.913],
[307.518, 308.175, 29.069],
[309.950, 311.262, 29.990],
[312.160, 310.772, 29.080],
[311.988, 312.709, 30.514]]
```

```

A = []
for i in range(len(X)):
    xx = X[i]
    u,v = x[i]
    A.append(
        [xx[0], xx[1], xx[2], 1, 0, 0, 0, 0, -u*xx[0], -u*xx[1], -u*xx[2], -u]
    )
    A.append(
        [0, 0, 0, 0, xx[0], xx[1], xx[2], 1, -v*xx[0], -v*xx[1], -v*xx[2], -v]
    )
import numpy as np
A = np.array(A)
[U,S,V] = np.linalg.svd(A)
p = V[-1,:]
P_1 = p.reshape((3,4))
print(P_1)

```

c

Before determining \mathbf{P} , I proved that $\mathbf{p} = \mathbf{A}^\dagger \mathbf{b}$. Consider SVD of $\mathbf{A} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^T \in \mathbb{R}^{m \times n}$, where $\mathbf{U} \in O(m)$, $\mathbf{\Sigma} \in \mathbb{R}^{m \times n}$, $\mathbf{V} \in O(n)$.

$$\|\mathbf{A}\mathbf{p} - \mathbf{b}\|^2 = \|\mathbf{U}\mathbf{\Sigma}\mathbf{V}^T\mathbf{p} - \mathbf{b}\|^2 = \|\mathbf{\Sigma}\mathbf{V}^T\mathbf{p} - \mathbf{U}^T\mathbf{b}\|(\cdot: \mathbf{U} \in O(m)) \quad (3)$$

Let $\mathbf{V}^T\mathbf{p} = \mathbf{q}$, $\mathbf{U}^T\mathbf{b} = \mathbf{r}$ and rewrite the problem as follow.

$$\text{Find } \arg \min_{\mathbf{q}} \|\mathbf{\Sigma}\mathbf{q} - \mathbf{r}\|^2 \quad (4)$$

This problem can be solved as follow.

$$\|\mathbf{\Sigma}\mathbf{q} - \mathbf{r}\|^2 = \sum_{i=1}^r (\sigma_i q_i - r_i)^2 \text{ where } r = \min\{m, n\} \quad (5)$$

We can uniquely select the $q_i = r_i/\sigma_i$, for $i = 1, \dots, r$, or $\mathbf{q} = \mathbf{\Sigma}^{-1}\mathbf{r}$, to minimize this expression. This implies $\mathbf{p} = \mathbf{V}\mathbf{\Sigma}^{-1}\mathbf{U}^T\mathbf{b}$. Thus, proof is done, noting that $\mathbf{A}^\dagger = (\mathbf{A}^T\mathbf{A})^{-1}\mathbf{A}^T = (\mathbf{V}\mathbf{\Sigma}^T\mathbf{\Sigma}\mathbf{V}^T)^{-1}\mathbf{\Sigma}^T\mathbf{U}^T = \mathbf{V}\mathbf{\Sigma}^{-1}\mathbf{U}^T$

I used following code to calculate the camera matrix.

```

def pseudo_inverse(A):
    return np.linalg.pinv(A)

A = []
b = []
for i in range(len(X)):
    xx = X[i]
    u,v = x[i]
    A.append(
        [xx[0], xx[1], xx[2], 1, 0, 0, 0, 0, -u*xx[0], -u*xx[1], -u*xx[2]]
    )
    A.append(
        [0, 0, 0, 0, xx[0], xx[1], xx[2], 1, -v*xx[0], -v*xx[1], -v*xx[2]]
    )
    b.append(u)
    b.append(v)

A = np.array(A)
b = np.array(b)
p = np.matmul(pseudo_inverse(A), b)
p = np.append(p, 1)
P_2 = p.reshape((3,4))
print(P_2)

```

I used following code to check whether the result of problem 1-(b) and problem 1-(c) agree by setting $m_{34} = 1$ in the camera matrix calculated on problem 1-(b). Since the result of following code agrees to camera matrix above, I can verify that both methodology are equivalent.

```

print(P_2[-1, -1] / P_1[-1, -1] * P_1)

```