

March 30, 2018

## HOMEWORK 2

### Problem 1. Programming: Estimation of the camera projection matrix

(a) **Linear estimation**

Estimate the camera projection matrix  $\mathbf{P}_{\text{DLT}}$  using the direct linear transformation (DLT) algorithm (with data normalization).

**Solution**

To get the projection matrix, we need to first vectorize  $\mathbf{P}$  and then solve the equation below.

$$\begin{bmatrix} [\mathbf{x}_1]^\perp \otimes \mathbf{X}_1^\top \\ [\mathbf{x}_2]^\perp \otimes \mathbf{X}_2^\top \\ \vdots \\ [\mathbf{x}_n]^\perp \otimes \mathbf{X}_n^\top \end{bmatrix} \mathbf{p} = \mathbf{0}$$

where  $[\mathbf{x}_1]^\perp$  is the left null space of  $\mathbf{x}_1$ . To get the left null space of  $\mathbf{x}_1$ , we need the Householder Matrix.

$$\mathbf{H}_\mathbf{V} = \mathbf{I} - 2 \frac{\mathbf{V}\mathbf{V}^\top}{\mathbf{V}^\top \mathbf{V}}$$
$$\mathbf{V} = \mathbf{x} + \text{sign}(x_1) \|\mathbf{x}\| \mathbf{e}_1$$

The 2 to 3 rows of  $\mathbf{H}_\mathbf{V}$  is the left null space of  $\mathbf{x}_1$ .

Since the DoF of  $\mathbf{p}$  is 11, we need at least 6 points to solve the equation. Suppose the left null space is  $\mathbf{A}$ , using Singular Value Decomposition we can get

$$\mathbf{A} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^\top$$

and  $\mathbf{p}$  is the last column of  $\mathbf{V}$ .

**Result**

$$\mathbf{P}_{\text{DLT}} = \begin{bmatrix} -0.0060446 & 0.0048386 & -0.0088225 & -0.8405 \\ -0.0090945 & 0.0023023 & 0.0061782 & -0.54156 \\ -5.0076 \times 10^{-6} & -4.4768 \times 10^{-6} & -2.5529 \times 10^{-6} & -0.0012515 \end{bmatrix}.$$

(b) **Nonlinear estimation**

Use  $\mathbf{P}_{\text{DLT}}$  as an initial estimate to an iterative estimation method, specifically the Levenberg-Marquardt algorithm, to determine the Maximum Likelihood estimate of the camera projection

matrix that minimizes the projection error.

### Solution

The algorithm works as follow:

$$\text{I } \lambda = 0.001;$$

$$\epsilon = \tilde{\mathbf{x}} - \hat{\hat{\mathbf{x}}}$$

$$\text{II } \mathbf{J} = \frac{\partial \hat{\mathbf{x}}}{\partial \mathbf{p}}$$

$$\text{III } \mathbf{J}^\top \boldsymbol{\Sigma}^{-1} \mathbf{J} \delta = \mathbf{J}^\top \boldsymbol{\Sigma}^{-1} \epsilon$$

$$\text{IV } (\mathbf{J}^\top \boldsymbol{\Sigma}^{-1} \mathbf{J} + \lambda \mathbf{I}) \delta = \mathbf{J}^\top \boldsymbol{\Sigma}^{-1} \epsilon, \text{ solve for } \delta.$$

$$\text{V } \hat{\mathbf{p}}_0 = \hat{\mathbf{p}} + \delta, \text{ candidate parameter vector.}$$

$$\text{VI } \hat{\mathbf{p}}_0 \mapsto \hat{\hat{\mathbf{x}}}_0;$$

$$\epsilon_0 = \tilde{\mathbf{x}} - \hat{\hat{\mathbf{x}}}_0$$

$$\text{VII If } \epsilon_0^\top \boldsymbol{\Sigma}_{\tilde{\mathbf{x}}}^{-1} \epsilon_0 \text{ cost less than } \epsilon^\top \boldsymbol{\Sigma}_{\tilde{\mathbf{x}}}^{-1} \epsilon,$$

$$\hat{\mathbf{p}} = \hat{\mathbf{p}}_0, \epsilon = \epsilon_0, \lambda = 0.1\lambda, \text{ go to step II or terminate.}$$

Else,

$$\lambda = 10\lambda, \text{ go to step IV}$$

Here, the termination condition is  $0.0001 \geq \text{previous\_cost} - \text{current\_cost}$ .

### Result

The costs of every step are

Iteration	Cost
0	84.0826
1	82.7913
2	82.7902
3	82.7902

The final estimate of the camera projection matrix is

$$\mathbf{P}_{\text{LM}} = \begin{bmatrix} 0.0060943 & -0.0047265 & 0.0087902 & 0.84364 \\ 0.0090202 & -0.0022929 & -0.0061333 & 0.53666 \\ 4.9909 \times 10^{-6} & 4.4521 \times 10^{-6} & 2.5371 \times 10^{-6} & 0.0012435 \end{bmatrix}.$$

## Appendix

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1 close all;
2 clear;
3 clc;
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4 %% Load Data
5 x = load('hw2_points2D.txt');
6 X = load('hw2_points3D.txt');
7 n = numel(x);
8 A = zeros(n,12);
9 %% Data Normalization
10 mu_x = mean(x);
11 sigma_x = sum(var(x));
12 s_x = sqrt(2/sigma_x);
13 T = [s_x      0      -mu_x(1)*s_x
14       0      s_x      -mu_x(2)*s_x
15       0       0       1];
16
17 mu_X = mean(X);
18 sigma_X = sum(var(X));
19 s_X = sqrt(3/sigma_X);
20 U = [s_X      0      0      -mu_X(1)*s_X
21       0      s_X      0      -mu_X(2)*s_X
22       0      0      s_X      -mu_X(3)*s_X
23       0      0      0      1];
24 x_bar = padarray(x,[0 1],1,'post');
25 X_bar = padarray(X,[0 1],1,'post');
26 x_bar_norm = T*x_bar';
27 X_bar_norm = U*X_bar';
28 %% P
29 for i = 1:2:n
30     xi = x_bar_norm(:,(i+1)/2);
31     Xi = X_bar_norm(:,(i+1)/2);
32     v = xi + sign(xi(1))*norm(xi,2)*[1;0;0];
33     Hv = eye(3) - 2 * (v*v')/(v'*v);
34     m = Hv(2:3,:)' ;
35     A(i:i+1,:) = kron(m',Xi');
36 end
37 [~,~,V] = svd(A);
38 p = V(:,end);
39 format shortg
40 P_DLT = T\reshape(p,4,3)'*U;
41 P_DLT = P_DLT/norm(P_DLT,'fro');
42 disp('P_DLT=')
43 disp(P_DLT)
44 %% Vectorization
45 x_norm = reshape(x_bar_norm(1:2,:),[],1);
46 %% Initialization
47 % P_init = reshape(p,4,3)';
48 % p_hat
49 p_bar = p;

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50 p_hat = parameterization(p_bar);
51 % x_hat
52 x_hat = reshape(p,4,3)'*X_bar_norm;
53 x_hat = x_hat(1:2,:) ./ x_hat(3,:);
54 x_hat = reshape(x_hat,[],1);
55 % sigma
56 sigma = T(1,1)^2 * eye(n);
57 % cost
58 previous_cost = inf;
59 tolerance = 0.0001;
60 %% LM
61 i = 0;
62 disp('LM: ')
63 fprintf('itr\tcost\n')
64 fprintf('-----\n')
65 % step_1
66 lambda = 0.001;
67 epsilon = x_norm - x_hat;
68 format short
69 current_cost = epsilon *(sigma\epsilon);
70 fprintf('%d\t%.4f\n', i, current_cost)
71 % step_2
72 J = jcb(x_hat,X_bar_norm,p_hat);
73 while tolerance < previous_cost - current_cost
74     i = i + 1;
75     % step_3_4
76     delta = (J'*(sigma\J)+lambda*eye(11))\ (J'*(sigma\epsilon));
77     % step_5
78     p_hat0 = p_hat + delta;
79     % step_6
80     x_hat0 = estimate(p_hat0,X_bar_norm);
81     epsilon0 = x_norm - x_hat0;
82     % step_7
83     format short
84     previous_cost = epsilon *(sigma\epsilon);
85     current_cost = epsilon0 *(sigma\epsilon0);
86     fprintf('%d\t%.4f\n', i, current_cost)
87     if current_cost < previous_cost
88         p_hat = p_hat0;
89         epsilon = epsilon0;
90         lambda = 0.1*lambda;
91         J = jcb(x_hat0,X_bar_norm,p_hat);
92     else
93         lambda = 10*lambda;
94     end
95 end

```

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96
97 p_bar_final = deparameterization(p_hat0);
98 format shortg
99 P_LM = T\reshape(p_bar_final,4,3)'*U;
100 P_LM = P_LM/norm(P_LM,'fro');
101 fprintf('\nP_LM=\n')
102 disp(P_LM)

1 function J = jcb(x_hat,X_bar_norm,p_hat)
2 % inputs:
3 % 1. inhomogeneous 2D points x vector;
4 % 2. homogeneous 3D points X;
5 % 3. p_bar(12*1)
6 p_bar = deparameterization(p_hat);
7 p_hat_norm = norm(p_hat,2);
8 r = size(x_hat,1);
9 c = numel(p_hat);
10 J = zeros(r,c);
11 for i = 1:2:r
12     w = p_bar(end-3:end)'*X_bar_norm(:,(i+1)/2);
13     dx_dpbar = [X_bar_norm(:,(i+1)/2)' zeros(1,4) -x_hat(i)*X_bar_norm(:,(i+1)/2)' % 2*12
14                 zeros(1,4) X_bar_norm(:,(i+1)/2)' -x_hat(i+1)*X_bar_norm(:,(i+1)/2)']/w;
15     da_dphat = -p_bar(2:end)'/2;
16     if p_hat_norm == 0
17         db_dphat = eye(c)/2;
18     else
19         db_dphat = sin(p_hat_norm/2)/p_hat_norm*eye(c) + ...
20             (p_hat_norm/2*cos(p_hat_norm/2)-sin(p_hat_norm/2))/p_hat_norm^3*(p_hat*p_hat')
21     end
22     dpbar_dphat = [da_dphat;db_dphat];
23     J(i:i+1,:) = dx_dpbar*dpbar_dphat;
24 end

1 function x_hat0 = estimate(p_hat0,X_bar_norm)
2 p_bar0 = deparameterization(p_hat0);
3 P_hat0 = reshape(p_bar0,4,3)';
4
5 x_bar0 = P_hat0*X_bar_norm;
6 x_hat0 = x_bar0(1:2,:)./x_bar0(3,:);
7 x_hat0 = reshape(x_hat0,[],1);
8 end

1 function v = parameterization(v_bar)
2 a = v_bar(1);
3 b = v_bar(2:end);
4 v = 2*acos(a)/sin(acos(a))*b;

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5  if norm(v,2)>pi
6      v = (norm(v,2)-2*pi)*v/norm(v,2);
7  end
8  end

1  function v_bar = deparameterization(v)
2  v_norm = norm(v,2);
3  a = cos(v_norm/2);
4  b = sin(v_norm/2)/v_norm*v;
5  v_bar = [a;b];
6  end

```