# CSE 252B - Homework 2

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# 1 Programming: Estimation of the camera projection matrix

### 1.1 Linear estimation

Download input data from the course website. The file hw2-points3D.txt contains the coordinates of 50 scene points in 3D (each line of the file gives the  $\tilde{X}_i$ ,  $\tilde{Y}_i$ , and  $\tilde{Z}_i$  inhomogeneous coordinates of a point). The file hw2-points2D.txt contains the coordinates of the 50 corresponding image points in 2D (each line of the file gives the  $\tilde{x}_i$  and  $\tilde{y}_i$  inhomogeneous coordinates of a point). The scene points have been randomly generated and projected to image points under a cam- era projection matrix (i.e.,  $\mathbf{x}_i = \mathbf{P}\mathbf{X}_i$ ), then noise has been added to the image point coordinates.

Estimate the camera projection matrix  $P_{DLT}$  using the direct linear transformation (DLT) algorithm (with data normalization). You must express  $\mathbf{x}_i = \mathbf{P}\mathbf{X}_i$  as  $[\mathbf{x}]_i^{\perp}\mathbf{P}\mathbf{X}_i = 0$  (not  $\mathbf{x}_i \times \mathbf{P}\mathbf{X}_i = 0$ ), where  $[\mathbf{x}]_i^{\perp}\mathbf{x}_i = 0$ , when forming the solution. Include the numerical values of the resulting  $P_{DLT}$ , scaled such that  $\|P_{DLT}\|_{Fro} = 1$ , in your report with sufficient precision such that it can be evaluated (hint: use format shortg in MATLAB prior to displaying your results).

#### Solution:

My result is as follows:

$$P_{DLT} = \begin{bmatrix} -0.0060446 & 0.0048386 & -0.0088225 & -0.8405 \\ -0.0090945 & 0.0023023 & 0.0061782 & -0.54156 \\ -5.0076e - 06 & -4.4768e - 06 & -2.5529e - 06 & -0.0012515 \end{bmatrix}$$
(1)

Here is the general process that I used to solve this problem:

First, read the data, do the data normalization, then we can get normalized data and matrix  $\mathbf{T}$  and  $\mathbf{U}$  for 2D and 3D points respectively. Then, using Householder matrix, we can compute the left null space for each corresponding 2D point. After that, we can get the matrix  $\mathbf{A}$ . Then using this matrix, we can get the vector form of  $P_{norm}$ . At last, reshape it, using the formula  $P_{DLT} = \text{inv}(T) * P_{norm} * U$ , then scale it by the "Fro" norm, we can get the final answer.

#### 1.2 Nonlinear estimation

Use  $P_{DLT}$  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. You must parameterize the camera projection matrix as a parameterization of the

Table 1: cost at each iteration	
iteration	cost
0	84.082583222450751
1	82.791273148649665
2	82.790238005509423
3	82.790238005407218
4	82.790238005407673
5	82.790238005407673
6	82.790238005407417
7	82.790238005408284
8	82.790238005407360
9	82.790238005407588
10	82.790238005406891
11	82.790238005407645
12	82.790238005407204
13	82.790238005407858
14	82.790238005407147
15	82.790238005406124
16	82.790238005408071
17	82.790238005406678
18	82.790238005408142
19	82.790238005405968
20	82.790238005407588
21	82.790238005407971
22	82.790238005407161
23	82.790238005405968
24	82.790238005405968
25	82.790238005405968
26	82.790238005405968
27	82.790238005405968
28	82.790238005405968
29	82.790238005405968
30	82.790238005405968

homogeneous vector  $\mathbf{p} = vec(\mathbf{P}^{T})$ . It is highly recommended to implement a parameterization of homogeneous vector method where the homogeneous vector is of arbitrary length, as this will be used in following assignments (see section A6.9.2 (page 624) of the textbook, and the corrections and errata).

In your report, show the initial cost (i.e., the cost at iteration 0) and the cost at the end of each successive iteration. Show the numerical values for the final estimate of the camera projection matrix PLM, scaled such that  $||P_{LM}||_{Fro} = 1$ , in your report with sufficient precision such that it can be evaluated.

## Solution:

First, the initial cost is 84.082583222450751.

Then, the cost at the end of each successive iteration are show as table 1.

At last, the projection matrix is as follows:

$$P_{LM} = \begin{bmatrix} 0.0060943 & -0.0047265 & 0.0087902 & 0.84364 \\ 0.0090202 & -0.0022929 & -0.0061333 & 0.53666 \\ 4.9909e - 06 & 4.4521e - 06 & 2.5371e - 06 & 0.0012435 \end{bmatrix}$$
 (2)

For this problem, the process is very clear according to the lecture note. And here is the general process:

First, compute the initial measurement vector, initial cost, and parameterized vector. For initialization, set lambda  $\lambda=0.001$ . Then for each iteration, calculate the Jocabian matrix and error, and using Jocabian matrix, lamba, and error to compute the delta for each iteration. Then, plus the vector  $\mathbf{P}$  with delta and then calculate the new cost. After that, if the new cost is less than the old cost, then set these parameters to the new ones, and set  $\lambda=0.1\lambda$ . However, if the new cost is greater than the old cost, then set  $\lambda=10\lambda$ , and don't update other parameters. Keep doing the iteration until convergence.

Besides, there are several points that we should pay attention to: First, we should use normalized data, and  $\mathbf{P_{norm}}$ , instead of  $\mathbf{P_{DLT}}$  as the input of the iterative method. Second, we should pay attention to the correctness of computing Jocabian matrix, since this is the most important part of the whole process.

### Appendix: Source code for problem 1

```
1 % projectionMatrix.m
3 % Question (a) %
4 % Linear Estimation %
6 % DLT algorithm to estimate camera projection matrix
8 % read the data
9 point2Dorig = readPoint('hw2_points2D.txt', 2);
point3Dorig = readPoint('hw2_points3D.txt', 3);
12 % data normalization
{\tiny 13} \ [\ point2D\ ,\ T\ ] \ = \ dataNormalization \left(\ point2Dorig\ ,\ 2\right);
[point3D, U] = dataNormalization(point3Dorig, 3);
_{16} % using DLT compute matrix A
_{17} A = DLTAlgorithm(point2D, point3D);
19 % using svd compute projection matrix P
P_norm = calProjMat(A);
_{21} % P_norm = - P_norm;
23 % scale P with ||P|| Fro = 1
P = inv(T) * P_norm * U;
25 P = P / norm(P, 'fro');
26 format shortg;
_{27} \frac{disp}{(P)};
uni = ones(50, 1);
xEst = P * [point3Dorig, uni]';
paramW = xEst(3, :)
xEst = xEst ./ paramW;
33 \% \operatorname{disp}(xEst);
34
35
36 % Problem 2%
37 % Iterative Method %
_{39} % use original data instead of normalized
unit = ones (50, 1);
x2D = [point2Dorig, unit]';
42 x3D = [point3Dorig, unit];
43
44 % data normalization
  [x2D_norm, T] = dataNormalization(point2Dorig, 2);
46 [x3D_norm, U] = dataNormalization(point3Dorig, 3);
^{48} x2D = x2D\_norm;
x3D = x3D_norm;
51 % main function
52 format long;
_{53} lambda = 0.001;
measureVector = calMeasureVector(x2D);
55 \% \text{ covar} = \text{calCovar}(\text{x2D}, \text{T});
covar = eye(100);
covar = covar * T(1, 1)^2;
58 \% \text{ deparamP} = P\_norm;
59 deparamP = -[P_{norm}(1, :), P_{norm}(2, :), P_{norm}(3, :)];
paramP = parameterize(deparamP);
61 % compute error and cost
62 proj2D = projection (deparamP, x3D);
63 error = measureVector - calMeasureVector(proj2D);
```

```
64 cost = error ' * inv(covar) * error;
65 disp(cost);
66 % begin iteration
67 \text{ for } i = 1 : 30
       % compute Jocabian
68
       J = calJocabian(x2D, x3D, deparamP, paramP);
69
70
       % compute delta
       delta = (J' * inv(covar) * J + lambda * eye(11)) \setminus (J' * inv(covar) * error);
71
       % update P
72
       paramPUpdate = paramP + delta;
73
74
       deparamPUpdate = deparameterize(paramPUpdate);
       % compute error and cost
75
       proj2DUpdate = projection(deparamPUpdate, x3D);
76
       errorUpdate = measureVector - calMeasureVector(proj2DUpdate);
77
       costUpdate = errorUpdate ' * inv(covar) * errorUpdate;
78
       disp(costUpdate);
79
80
       % make decsion
        if (costUpdate < cost)</pre>
81
            paramP = paramPUpdate;
82
            deparamP = deparamPUpdate;
83
84
            error = errorUpdate;
            cost = costUpdate;
85
            lambda = 0.1 * lambda;
86
87
            lambda = 10.0 * lambda;
88
89
90
   end
91
   proMat_norm = reshape(deparamP, [4, 3]);
   proMat = inv(T) * proMat_norm * U;
proMat = proMat / norm(proMat, 'fro');
93
   format shortg;
   disp (proMat);
97
98
99
   % read the data
100
   function point = readPoint(fileName, dim)
        file = fopen(fileName);
103
        if dim = 2
            point = textscan(file, '%f %f');
104
            point = textscan(file, '%f %f %f');
106
       end
107
        fclose (file);
108
        point = cell2mat(point);
   end
110
112 % Data Normalization
   function [point, T] = dataNormalization(data, dim)
114
       % calculate mean and variance
       m = mean(data);
116
       v = var(data);
       % calculate normalized vector
117
118
        if (dim == 2)
            s = sqrt(2.0 / sum(v));
119
            T = zeros(3, 3);
120
           T(1, 1) = s;

T(2, 2) = s;
122
123
            T(3, 3) = 1.0;
            T(1, 3) = -1.0 * m(1) * s;
124
            T(2, 3) = -1.0 * m(2) * s;
125
        else
126
            s = sqrt(3.0 / sum(v));
127
128
            T = zeros(4, 4);
```

```
\begin{array}{lll} T(\,1\,\,,\,\,\,1\,) \;=\; s\;;\\ T(\,2\,\,,\,\,\,2\,) \;=\; s\;; \end{array}
129
130
             T(3, 3) = s;
132
             T(4, 4) = 1.0;
            T(1, 4) = -1.0 * m(1) * s;
133
             T(2, 4) = -1.0 * m(2) * s;

T(3, 4) = -1.0 * m(3) * s;
135
136
        % transfer inhomo to homo data
137
        unit = ones(50,1);
138
        point = [data, unit];
139
        % normalize the data
140
        point = T * point;
141
142
143
   % DLT algorithm
144
   function matA = DLTAlgorithm(point2D, point3D)
145
        matA = [];
146
        % using house holder matrix
147
        \% to calculate left null space of \boldsymbol{x}
148
149
        for i = 1 : 50
             x = point2D(:, i);
             v = x + sign(x(1)) * norm(x) * [1, 0, 0]';
             Hv = eye(3) - 2.0 * (v * v') / (v' * v);

leftNull = Hv(2:3, :);
152
             matA = [matA; kron(leftNull, point3D(:, i)')];
154
        end
   end
156
157
% using svd compute projection matrix P
    function P = calProjMat(A)
        [U, S, V] = svd(A);
160
        P = V(:, 12);
161
        P = reshape(P, [4, 3]);
162
        P = P';
163
164
   end
165
167
168 % Question (b)%
169 % construct measurement vector
   function measureVector = calMeasureVector(point)
170
        measureVector = [];
        for i = 1 : 50
             measureVector = [measureVector, point(1 : 2, i)'];
173
174
        measureVector = measureVector ';
176
   \% projection from 3D to 2D
178
   function res = projection (deparamP, x3D)
179
        P = reshape(deparamP, [4, 3]);
180
        res = P * x3D;
181
        w = res(3, :);
182
183
        res = res . / w;
184
   end
185
186 % construct associated covariance
187
   function covar = calCovar(point, T)
188
        covar = eye(100);
189 %
          for i = 1 : 50
               covar(2 * i - 1: 2 * i, 2 * i - 1: 2 * i) = cov(point(1 : 2, i)), point(1 : 2, i)
190 %
         <sup>'</sup>);
191 %
          end
192
        covar = T(1, 1) * T(1, 1) * covar;
```

```
193 end
194
195 % parameterize
   function paramVector = parameterize(P)
       a = P(1);
197
       b = P(2 : length(P));
198
        paramVector = (2.0 / (sinc(acos(a)))) * b;
199
       normP = norm(paramVector);
200
        if (normP > pi)
201
            paramVector = (1.0 - 2 * pi / normP * ceil((normP - pi) / 2 * pi)) * paramVector;
202
            \% paramVector = (1.0 - 2 * pi / normP) * paramVector;
203
204
       end
205
   end
206
207 % deparameterize
   function deparamVector = deparameterize(P)
208
       normP = norm(P);
209
       deparam Vector = [\cos(normP / 2.0), ((\sin c(normP / 2.0)) / 2.0) * P']';
210
   end
211
212
213 % sinc(x)
   function res = sinc(x)
214
       if x == 0
215
216
            res = 1.0;
        else
217
            res = (sin(x)) / x;
218
       end
219
220 end
221
222 % compute Jocabian
_{223} % x2D and x3D are homogeneous
   function jocabian = calJocabian(x2D, x3D, deparamP, paramP)
224
       jocabian = [];
226
       projX2D = projection(deparamP, x3D);
        part2 = jocab2(deparamP, paramP);
227
228
        for i = 1:50
            part1 = jocab1(projX2D(:, i), x3D(:, i), deparamP);
229
230
            jocabian = [jocabian; part1 * part2];
       end
231
232
   end
233
234 % compute partial xi partial P bar
   function res = jocab1(point2D, point3D, deparamP)
235
       w = deparamP(9 : 12)' * point3D;
236
       tmp = zeros(1, 4);
237
       res = 1 / w * [point3D', tmp, -1.0 * point2D(1) * point3D'; ...
238
                        tmp, point3D', -1.0 * point2D(2) * point3D'];
239
   end
240
241
_{242} % compute partial P bar partial P
243
   function res = jocab2 (deparamP, paramP)
       normP = norm(paramP);
244
        res = -0.5 * deparamP(2 : length(deparamP))';
245
        if (normP == 0)
246
            res = [res; 0.5 * eye(length(paramP))];
247
248
            tmp = 0.5 * (sinc(normP / 2)) * eye(length(paramP)) + 0.25 / normP ...
249
                  * derivSinc(normP / 2) * paramP * paramP';
251
            res = [res; tmp];
252
       \quad \text{end} \quad
   end
253
255 % derivative of sinc(x)
function res = derivSinc(x)
   if x == 0
```