

# CSE 252B - Homework 4

Lingting Ge    A53212800

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## 1 Feature detection

Download input data from the course website. The file *price\_center20.JPG* contains image1 and the file *price\_center21.JPG* contains image 2. In your report, include a figure containing the pair of input images.

For each input image, calculate an image where each pixel value is the minor eigenvalue of the gradient matrix

$$N = \begin{bmatrix} \Sigma_w I_x^2 & \Sigma_w I_x I_y \\ \Sigma_w I_x I_y & \Sigma_w I_y^2 \end{bmatrix} \quad (1)$$

where  $w$  is the window about the pixel, and  $I_x$  and  $I_y$  are the gradient images in the  $x$  and  $y$  direction, respectively. Calculate the gradient images using the five point central difference operator. Set resulting values that are below a specified threshold value to zero (hint: calculating the mean instead of the sum in  $N$  allows for adjusting the size of the window without changing the threshold value). Apply an operation that suppresses (sets to 0) local (i.e., about a window) nonmaximum pixel values in the minor eigenvalue image. Vary these parameters such that around 600-650 features are detected in each image. For resulting nonzero pixel values, determine the subpixel feature coordinate using the Forstner corner point operator.

In your report, state the size of the feature detection window (i.e., the size of the window used to calculate the elements in the gradient matrix  $N$ ), the minor eigenvalue threshold value, the size of the local nonmaximum suppression window, and the resulting number of features detected in each image. Additionally, include a figure containing the pair of images, where the detected features (after local nonmaximum suppression) in each of the images are indicated by a square about the feature, where the size of the square is the size of the detection window.

### Solution:

The parameters I used are as follows:

Size of the feature detection window is  $9 * 9$ ;

The minor eigenvalue threshold value is 380;

The size of the local non maximum suppression window is  $9 * 9$ .

The resulting numbers of features detected are 646 and 631 for the first and second image respectively.

Here is the procedure that I solve this problem:

- Read the image and transform the image into gray scale image.
- Calculate gradient images  $I_x$  and  $I_y$  respectively.
- Select a window size and calculate gradient matrix.
- Calculate the minor eigenvalue image.
- Compute the non maxima suppression.



Figure 1: Original figure

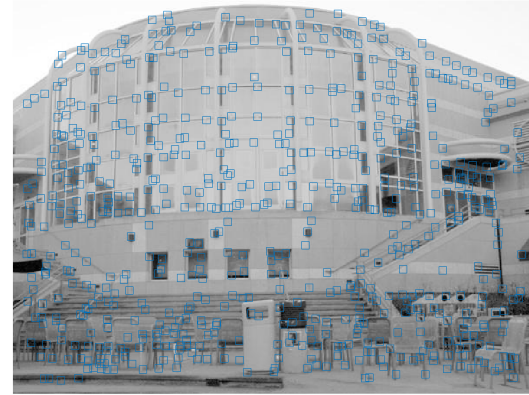
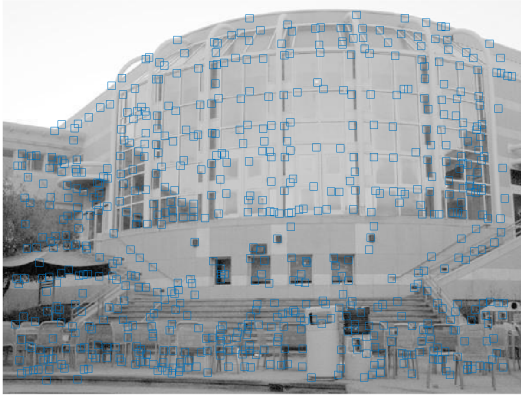


Figure 2: Corner detection

- Using Forstner corner point method to find the coordinates of the corners.

The original figures are shown in Figure 1.

The detected features are shown in Figure 2.

## 2 Feature matching

Determine the set of one-to-one putative feature correspondences by performing a brute-force search for the greatest correlation coefficient value (in the range  $[-1, 1]$ ) between the detected features in image 1 and the detected features in image 2. Only allow matches that are above a specified correlation coefficient threshold value (note that calculating the correlation coefficient allows for adjusting the size of the matching window without changing the threshold value). Further, only allow matches that are above a specified distance ratio threshold value, where distance is measured to the next best match for a given feature. Vary these parameters such that around 200 putative feature correspondences are established. Optional: constrain the search to coordinates in image 2 that are within a proximity of the detected feature coordinates in image 1.

In your report, state the size of the proximity window (if used), the correlation coefficient threshold value, the distance ratio threshold value, and the resulting number of putative feature correspondences (i.e., matched features). Additionally, include a figure containing the pair of images, where the matched features in each of the images are indicated by a square about the feature, where the size of the square is the size of the matching window, and a line segment is drawn from the feature to the coordinates of the corresponding feature in the other image (see Fig. 4.9(e) in the Hartley & Zisserman book as an example).

### Solution:

The parameters I used are as follows:

The correlation coefficient threshold value is 0.6;

The distance ratio threshold value is 0.7;

The window size is  $21 * 21$ .

I didn't use the proximity window.

The resulting number of putative feature correspondences is 201.

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

- Fetch the corners of two features from the result of question (a).
- Take out all windows corresponding to their corners.
- Calculate correlation coefficients of window pair between all window in two figures.
- Do the one-to-one matching as follows:
  - Find the indices of element with maximum value.
  - If the maximum value is larger than the similarity threshold, do the follows:
    - Store the best match value.
    - Set this element value to -1.
    - Find the next best match value as the following equation:
$$nextbestmatch = \max(nextbestmatchvalueinrow, nextbestmatchvalueincolumn) \quad (2)$$
  - If the  $(1 - bestmatchvalue) < (1 - nextbestmatchvalue) * distanceratiothreshold$ , then store the feature match. Otherwise, this match is not unique enough.
  - Set the row and column to be -1.
- Otherwise, stop the iteration.

The final feature matching images are shown in Figure 3:

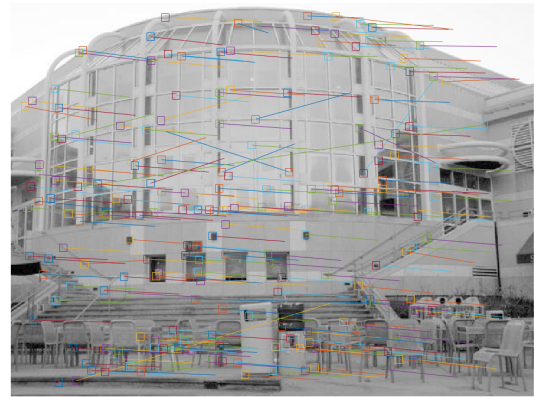
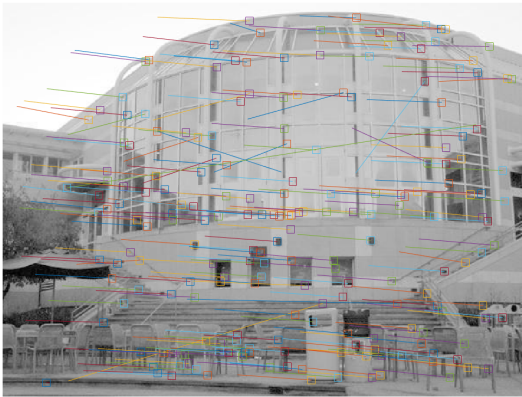


Figure 3: Feature mapping

### 3 Outlier rejection

The resulting set of putative point correspondences should contain both inlier and outlier correspondences (i.e., false matches). Determine the set of inlier point correspondences using the M-estimator Sample Consensus (MSAC) algorithm, where the maximum number of attempts to find a consensus set is determined adaptively. For each trial, you must use the 4-point algorithm (as described in lecture) to estimate the planar projective transformation from the 2D points in image 1 to the 2D points in image 2. Calculate the (squared) Sampson error as a first order approximation to the geometric error.

In your report, describe any assumptions, including the probability  $p$  that at least one of the random samples does not contain any outliers (used to determine the number of attempts to find a consensus set), and the probability  $\alpha$  that a given data point is an inlier and the variance  $\sigma^2$  of the measurement error (both used to determine the distance threshold; hint: this problem has codimension 2). State the resulting number of inliers and the number of attempts to find the consensus set.

Additionally, include a figure containing the pair of images, where the inlier features in each of the images are indicated by a square about the feature, where the size of the square is the size of the matching window, and a line segment is drawn from the feature to the coordinates of the corresponding feature in the other image (see Fig. 4.9(g) in the Hartley & Zisserman book as an example).

#### Solution:

The parameters I used are as follows:

Probability  $p = 0.99$ ;

Probability  $\alpha = 0.95$ ;

Variance  $\sigma^2$  assumed to be 1;

The number of inliers I find is 163;

The number of trials is 11.

The random seed I used is `rand('seed', 0)`;

Here are the general steps that I used to solve this question is as follows:

- For initialization, set max trials and minimum cost to be infinity. And number of trials to be 0;
- Begin the iteration of MASC method.
- Select four random points for two figures respectively.
- Compute the matrix  $H_1^{-1}$  for figure 1, using four-point method.
- Compute the matrix  $H_2^{-1}$  for figure 2, using four-point method.
- Calculate the matrix  $H$  using following equation:

$$H = H_2^{-1} * (H_1^{-1})^{-1} \quad (3)$$

- Calculate the corresponding cost and model, the error is computed as the squared Sampson error.
- If the cost is less then current minimum cost, do the follows:
  - Update the minimum cost and model.
  - Calculate the number inliers and update the max trials using parameter  $w$ , where  $w = \frac{\text{number of inliers}}{\text{total number of data points}}$ , and  $\text{max\_trials} = \frac{\log(1-P)}{\log(1-w^s)}$ , where  $s = 4$  since we have three random points for each iteration.
- If current number of trials is bigger than the current max trials, then stop the iteration. Otherwise, continue.

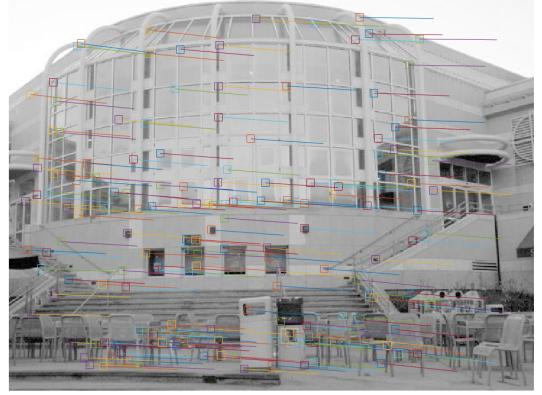
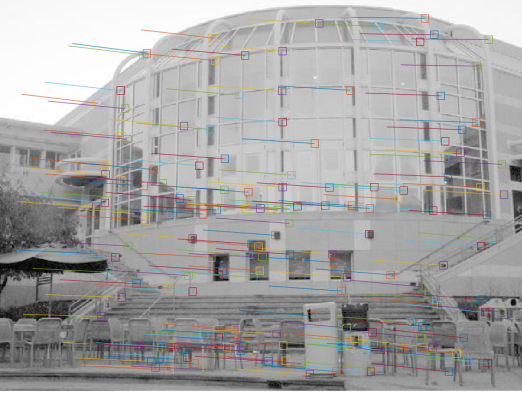


Figure 4: Feature mapping using inliers

- After the iteration, we can get the inliers by compare the error of each point with the tolerance, using the model we get from the iteration.

The matching figures are shown in Figure 4.

## 4 Linear estimation

Estimate the planar projective transformation  $H_{DLT}$  from the resulting set of inlier correspondences using the direct linear transformation (DLT) algorithm (with data normalization). You must express  $\mathbf{x}'_i = \mathbf{H}\mathbf{x}_i$  as  $[\mathbf{x}']_i^\perp \mathbf{H}\mathbf{x}_i = 0$  (not  $\mathbf{x}'_i \times \mathbf{H}\mathbf{x}_i = 0$ ), 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  $\|H_{DLT}\|_{Fro} = 1$ , in your report with sufficient precision such that it can be evaluated (hint: use format longg in MATLAB prior to displaying your results).

### Solution:

The planar projective transformation  $H_{DLT}$  is as follows:

$$H_{DLT} = \begin{bmatrix} -0.0106540525548768 & -0.000322565823387382 & 0.175433007787968 \\ 1.50813373020026e-05 & -0.0109447323490494 & 0.984320115185873 \\ -1.18906447804917e-07 & -1.23974438128738e-06 & -0.0101867727565862 \end{bmatrix} \quad (4)$$

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

- Do the data normalization for both figures.
- Then we can get the normalized data and matrix  $T_1$  and  $T_2$  for both figures respectively.
- Using Householder matrix to compute the left null space of each point in figure 2.
- Form the big matrix  $A$  using kron operations for each pair of points in both figures.
- Compute the vector form of matrix  $H$ , using SVD operation of matrix  $A$ .
- Reshape the vector form of matrix  $H$ , then we can get the matrix  $H_{norm}$ .
- Calculate the matrix  $H_{DLT}$ , using the following equation:

$$H_{DLT} = inv(T_2) * P_{norm} * T_1. \quad (5)$$

- Scale the matrix  $H_{DLT}$  so that its *fro* norm is equal to 1.

## 5 Nonlinear estimation

Use  $H_{DLT}$  and the Sampson corrected points (in image 1) as an initial estimate to an iterative estimation method, specifically the sparse Levenberg-Marquardt algorithm, to determine the Maximum Likelihood estimate of the planar projective transformation that minimizes the reprojection error. You must parameterize the planar projective transformation matrix and the homogeneous 2D scene points that are being adjusted using the parameterization of homogeneous vectors (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 planar projective transformation matrix HLM, scaled such that  $\|H_{LM}\|_{Fro} = 1$ , in your report with sufficient precision such that it can be evaluated.

### Solution:

The initial cost is 79.7774830417331.

And the cost of each successive iteration are as follows:

```
79.7774830417331
79.7579930299769
79.6976116725415
79.6966414533895
79.696641450062
```

The number of iterations that used to be convergence is 4.

The final estimate of the matrix is as follows:

$$H_{LM} = \begin{bmatrix} 0.0106660499793628 & 0.000320913162721748 & -0.174173928321309 \\ -1.92852986465492e-05 & 0.0109602143976192 & -0.984543171425123 \\ 1.05082564703225e-07 & 1.23568286685395e-06 & 0.0102074488860498 \end{bmatrix} \quad (6)$$

For this problem, the process of Levenberg algorithm (nonlinear estimation) is very clear according to the lecture note. And here is the general process:

- For initialization, we have initial matrix  $H_{DLT}$ , which is from the result of question (d), and the inlier points for both images, which are from the result of question (c).
- Set the initial value  $\lambda = 0.001$ .
- Compute the scene point using the first image and Sampson correction.
- Calculate initial measurement vector  $[\hat{h}^T, \hat{x}_1^T, \dots, \hat{x}_n^T]$ , where  $\hat{h}$  is the parameterization of the transformation matrix  $H$ , and  $\hat{x}_i$  are the parameterization of scene points.
- Calculate the projections using following equations, where  $x - scene$  is the scene points, and  $H$  is the initial transformation matrix  $H_{DLT}$ .

$$proj1 = I * x_{scene} \quad (7)$$

$$proj2 = H * x_{scene} \quad (8)$$

- Compute the measurement vector  $[x_1^T, x_2^T, \dots, x_n^T, x''_1^T, x''_2^T, \dots, x''_n^T]$ .
- Compute the initial error vector and further compute the initial cost.
- Begin the iteration of Levenberg method, do the following until convergence.



- First, compute the Jacobian matrix using parameter vector and inlier points for both images. And the Jacobian matrix is a sparse matrix, which contains three parts:  $A$ ,  $B1$  and  $B2$ .
- Second, using the three parts of Jacobian matrix to compute the normal equations matrix, which also contains three parts:  $U$ ,  $V$ , and  $W$ .
- Third, compute the normal equations vector, which is in the form of  $(\epsilon_a^T, \epsilon_{b_1}^T, \epsilon_{b_2}^T, \dots, \epsilon_{b_n}^T)^T$ .
- Forth, compute the augmented normal equations, solve the equations and we can get the increment  $\delta$ .
- Then, add  $\delta$  to the parameter vector, we can get a new vector.
- Deparameterize the two parts of the new parameter vector, then we can get the new transformation matrix and the new scene points.
- Recompute the new error and cost, using the new transformation matrix and new scene points.
- If the current cost is less than the current minimum cost, then update the error, cost and model, and go to the first step, with setting  $\lambda = 0.1\lambda$ . Otherwise, go to the forth step by setting  $\lambda = 10\lambda$ .
- Finally, after convergence, we can get the result.

## Appendix: Source code

```
1 % main.m
2
3 clc , clear , close all;
4 format longg;
5
6 % input image
7 image1 = 'price_center20.JPG';
8 image2 = 'price_center21.JPG';
9
10 figure(1)
11 subplot(1, 2, 1);
12 imshow(rgb2gray(imread(image1)));
13 subplot(1, 2, 2)
14 imshow(rgb2gray(imread(image2)));
15
16
17 %———— Question (a) —————%
18 % feature detection %
19
20 % set parameter
21 w_size1 = 9;
22 threshold = 380;
23 w_size2 = 9;
24 w_sizeb = 21;
25 simThresh = 0.6;
26 ratioThresh = 0.7;
27
28 % corner detection
29 [row1, col1] = featureDetection(image1, w_size1, threshold, w_size2);
30 [row2, col2] = featureDetection(image2, w_size1, threshold, w_size2);
31
32 % count # features
33 x1 = row1(:);
34 x2 = row2(:);
35 y1 = col1(:);
36 y2 = col2(:);
37 disp('Question (a):');
38 disp('number of features in figure 1:');
39 disp(size(x1, 1));
40 disp('number of features in figure 2:');
41 disp(size(x2, 1));
42
43 % show the feature image
44 figure(2)
45 subplot(1, 2, 1);
46 imshow(rgb2gray(imread(image1)));
47 hold on;
48 scatter(y1, x1, w_size1 * w_size1, 's');
49 subplot(1, 2, 2)
50 imshow(rgb2gray(imread(image2)));
51 hold on;
52 scatter(y2, x2, w_size1 * w_size1, 's');
53
54
55
56 %———— Question (b) —————%
57 % feature matching %
58
59 % feature matching
60 match = featureMatching(image1, image2, row1, col1, row2, col2, w_sizeb, simThresh,
    ratioThresh);
61 disp('Question (b):');
62 disp('number of matchings:');
```

```

63 disp(sum(sum(match)));
64
65 % show the feature matching image
66 figure(3)
67 subplot(1, 2, 1);
68 imshow(rgb2gray(imread(image1)));
69 hold on;
70 length1 = size(row1);
71 length2 = size(row2);
72 for i = 1 : length1(1)
73     for j = 1 : length2(1)
74         if match(i, j) == 1
75             plot([col1(i), col2(j)], [row1(i), row2(j)], '-');
76             scatter(col1(i), row1(i), w_size1 * w_size1, 's');
77         end
78     end
79 end
80 subplot(1, 2, 2);
81 imshow(rgb2gray(imread(image2)));
82 hold on;
83 length1 = size(row1);
84 length2 = size(row2);
85 for i = 1 : length1(1)
86     for j = 1 : length2(1)
87         if match(i, j) == 1
88             plot([col1(i), col2(j)], [row1(i), row2(j)], '-');
89             scatter(col2(j), row2(j), w_size1 * w_size1, 's');
90         end
91     end
92 end
93
94
95 %————— Question (c) —————%
96 % outliers rejection %
97
98 % extract coordinates of matching in question (b)
99 point2DOrig1 = [];
100 point2DOrig2 = [];
101 for i = 1 : size(row1, 1)
102     for j = 1 : size(row2, 1)
103         if match(i, j) == 1
104             point2DOrig1 = [point2DOrig1; [row1(i), col1(i)]];
105             point2DOrig2 = [point2DOrig2; [row2(j), col2(j)]];
106         end
107     end
108 end
109
110 % MSAC method
111 [inlierIndex, trials] = MSAC(point2DOrig1, point2DOrig2);
112 inlier1 = [];
113 inlier2 = [];
114 for i = 1 : length(inlierIndex)
115     if inlierIndex(i) == 1
116         inlier1 = [inlier1; point2DOrig1(i, :)];
117         inlier2 = [inlier2; point2DOrig2(i, :)];
118     end
119 end
120 disp('Question (c):');
121 disp('number of inliers:');
122 disp(sum(inlierIndex));
123 disp('number of trials:');
124 disp(trials);
125
126 % show the feature matching image
127 figure(4)

```

```

128 subplot(1, 2, 1);
129 imshow(rgb2gray(imread(image1)));
130 hold on;
131 for i = 1 : length(inlierIndex)
132     if inlierIndex(i) == 1
133         plot([point2DOrig1(i, 2), point2DOrig2(i, 2)], ...
134             [point2DOrig1(i, 1), point2DOrig2(i, 1)], '—');
135         scatter(point2DOrig1(i, 2), point2DOrig1(i, 1), w_size1 * w_size1, 's');
136     end
137 end
138 subplot(1, 2, 2);
139 imshow(rgb2gray(imread(image2)));
140 hold on;
141 for i = 1 : length(inlierIndex)
142     if inlierIndex(i) == 1
143         plot([point2DOrig2(i, 2), point2DOrig1(i, 2)], ...
144             [point2DOrig2(i, 1), point2DOrig1(i, 1)], '—');
145         scatter(point2DOrig2(i, 2), point2DOrig2(i, 1), w_size1 * w_size1, 's');
146     end
147 end
148
149
150
151 %————— Question (d) —————%
152 % linear estimation %
153
154 [H_norm, T2, T1] = linearEstimation(inlier2, inlier1);
155 format longg;
156 H_norm = - H_norm;
157
158 % scale P with ||P||Fro = 1
159 H = T2 \ H_norm * T1;
160 H = H / norm(H, 'fro');
161 H_DLT = - H;
162 disp('Question (d):');
163 disp('H matrix DLT:');
164 disp(H_DLT);
165
166 uni = ones(size(inlier1, 1), 1);
167 xEst = -H_DLT * [inlier1, uni]';
168 paramW = xEst(3, :);
169 xEst = xEst ./ paramW;
170 % disp(xEst);
171
172
173
174 %————— Question (e) —————%
175 % nonlinear estimation %
176
177 H_init = -H_DLT;
178 HLM = levenbergEst(H_init, inlier1, inlier2);
179 HLM = HLM / norm(HLM, 'fro');
180 disp('Question (e):')
181 disp('HLM:')
182 disp(HLM)

```

```

1 % featureDetection.m
2
3 % feature detection
4 function [row, col] = featureDetection(image, w_size1, threshold, w_size2)
5     % read the image in RGB format
6     i = imread(image);
7
8     % convert RGB to gray scale
9     grayImage = rgb2gray(i);

```

```

10 %grayImage = double(grayImage);
11
12 % calculate gradient images
13 K = [-1, 8, 0, -8, 1] / 12;
14 Ix = imfilter(grayImage, K);
15 Iy = imfilter(grayImage, K');
16
17 % calculate Isquare and IxIy
18 IxSquare = Ix .* Ix;
19 IxIy = Ix .* Iy;
20 IySquare = Iy .* Iy;
21
22 % calculate minor eigenvalue image
23 eigenImage = calEigenImage(IxSquare, IxIy, IySquare, w_size1);
24
25 % set 0 if below threshold
26 threshEigenImage = eigenImage .* (eigenImage >= threshold);
27
28 % non maximum suppression
29 % maximum filter
30 Imax = ordfilt2(threshEigenImage, w_size2 * w_size2, ones(w_size2, w_size2));
31 % compare two image, generate image J
32 imageJ = threshEigenImage .* (threshEigenImage >= Imax);
33
34 % find the coordinate of corner
35 [row, col] = findCorner(IxSquare, IxIy, IySquare, imageJ, w_size1);
36 end
37
38 % calculate minor eigenvalue image
39 function m = calEigenImage(IxSquare, IxIy, IySquare, w_size)
40     len = size(IxIy);
41     m = zeros(len(1), len(2));
42     for i = 1 : len(1)
43         for j = 1 : len(2)
44             [N, b] = calGradMatrix(IxSquare, IxIy, IySquare, i, j, w_size);
45             m(i, j) = 0.5 * (trace(N) - sqrt(trace(N) ^ 2 - 4 * det(N)));
46         end
47     end
48 end
49
50 % Calculate gradient matrix
51 function [m, b] = calGradMatrix(IxSquare, IxIy, IySquare, i, j, w_size)
52     m = zeros(2, 2);
53     b = zeros(2, 1);
54     half = (w_size - 1) / 2;
55     len = size(IxIy);
56     i_start = max(i - half, 1);
57     j_start = max(j - half, 1);
58     i_end = min(i + half, len(1));
59     j_end = min(j + half, len(2));
60     m(1, 1) = sum(sum(IxSquare(i_start : i_end, j_start : j_end)));
61     m(1, 2) = sum(sum(IxIy(i_start : i_end, j_start : j_end)));
62     m(2, 1) = m(1, 2);
63     m(2, 2) = sum(sum(IySquare(i_start : i_end, j_start : j_end)));
64     for p = i_start : i_end
65         for q = j_start : j_end
66             b(1) = b(1) + double(p) * double(IxSquare(p, q)) + double(q) * double(IxIy(p, q))
67             b(2) = b(2) + double(q) * double(IySquare(p, q)) + double(p) * double(IxIy(p, q))
68         end
69     end
70 end
71
72 % find corner coordinates

```

```

73 function [row, col] = findCorner(IxSquare, IxIy, IySquare, imageJ, w_size)
74     len = size(imageJ);
75     row = [];
76     col = [];
77     for i = 1 : len(1)
78         for j = 1 : len(2)
79             if (imageJ(i, j) > 0)
80                 [N, b] = calGradMatrix(IxSquare, IxIy, IySquare, i, j, w_size);
81                 coord = N \ b;
82                 coord = coord';
83                 if coord(1) >= 15 && coord(1) <= len(1) - 15 && ...
84                     coord(2) >= 15 && coord(2) <= len(2) - 15
85                     row = [row; coord(1)];
86                     col = [col; coord(2)];
87                 end
88             end
89         end
90     end
91 end
92
93 % extract the corner coordinates
94 function [row, col] = extractCorner(corner)
95     row = [];
96     col = [];
97     for i = 15 : size(corner, 1) - 15
98         for j = 15 : size(corner, 2) - 15
99             if corner(i, j) == 1
100                 row = [row, i];
101                 col = [col, j];
102             end
103         end
104     end
105     row = row';
106     col = col';
107 end

```

```

1 % featureMatching.m
2
3 % feature matching
4 function match = featureMatching(image1, image2, row1, col1, row2, col2, w_size, simThresh,
5     ratioThresh)
6     I1 = imread(image1);
7     I2 = imread(image2);
8     Image1 = rgb2gray(I1);
9     Image2 = rgb2gray(I2);
10    length1 = size(row1);
11    len1 = length1(1);
12    length2 = size(row2);
13    len2 = length2(1);
14    match = zeros(len1, len2);
15    % calculate correlation coefficient matrix
16    correl = zeros(len1, len2);
17    for i = 1 : len1
18        [win1, size1] = fetchWindow(Image1, size(Image1), row1, col1, i, w_size);
19        for j = 1 : len2
20            [win2, size2] = fetchWindow(Image2, size(Image2), row2, col2, j, w_size);
21            if size1 == w_size^2 && size2 == w_size^2
22                correl(i, j) = corr2(win1, win2);
23            else
24                correl(i, j) = -1.0;
25            end
26        end
27    end
28    % one to one match
29    maxValue = max(max(correl));

```

```

29     count = 0;
30     while maxValue > simThresh
31         [X, Y] = find(correl == maxValue);
32         x = X(1);
33         y = Y(1);
34         correl(x, y) = -1;
35         nextMaxValue = max(max(correl(x,:)), max(correl(:,y)));
36         if (1.0 - maxValue) < (1.0 - nextMaxValue) * ratioThresh
37             count = count + 1;
38             match(x, y) = 1;
39         end;
40         correl(x,:) = -1;
41         correl(:,y) = -1;
42         maxValue = max(max(correl));
43     end
44 end
45
46 % fetch the window
47 function [win, size] = fetchWindow(image, len, row, col, i, w_size)
48     half = (w_size - 1) / 2;
49     i_start = max(round(row(i)) - half, 1);
50     j_start = max(round(col(i)) - half, 1);
51     i_end = min(round(row(i)) + half, len(1));
52     j_end = min(round(col(i)) + half, len(2));
53     win = image(i_start : i_end, j_start : j_end);
54     size = (i_end - i_start + 1) * (j_end - j_start + 1);
55 end

```

```

1 % MSAC.m
2
3 % MSAC method
4 function [inlierIndex, trials] = MSAC(point2DOrig1, point2DOrig2)
5     format longg;
6     % transfer to homogeneous
7     num_point = size(point2DOrig1, 1);
8     point2DHomo1 = [point2DOrig1, ones(num_point, 1)];
9     point2DHomo2 = [point2DOrig2, ones(num_point, 1)];
10
11     % MSAC algorithm
12     consensus_min_cost = Inf;
13     trials = 0;
14     max_trials = Inf;
15     threshold = 0;
16     prob = 0.99;
17     alpha = 0.95;
18     variance = 1;
19     codimension = 2;
20     tolerance = chi2inv(alpha, codimension);
21
22     rand('seed', 0);
23
24     % begin iteration
25     while (trials < max_trials && consensus_min_cost > threshold)
26         % generate three random samples
27         sampleIndex = randperm(num_point, 4);
28         % compute model H
29         H1_inv = fourPoint(point2DHomo1, sampleIndex);
30         H2_inv = fourPoint(point2DHomo2, sampleIndex);
31         H = H2_inv / H1_inv;
32         % compute cost
33         cost = 0;
34         for i = 1 : num_point
35             % compute sampson error
36             error_i = sampsonError(H, point2DHomo1(i, :), point2DHomo2(i, :));
37             if error_i < tolerance

```

```

38         cost = cost + error_i;
39     else
40         cost = cost + tolerance;
41     end
42 end
43 % update model
44 if cost < consensus_min_cost
45     consensus_min_cost = cost;
46     model_H = H;
47     % count number of inliers
48     dist_error = zeros(1, num_point);
49     for i = 1 : num_point
50         dist_error(i) = sampsonError(model_H, point2DHomo1(i, :), point2DHomo2(i, :));
51     end
52     % update max_trials
53     num_inliers = sum(dist_error <= tolerance);
54     w = num_inliers / num_point;
55     max_trials = log(1 - prob) / log(1 - w^4);
56 end
57 trials = trials + 1;
58 end
59 % count inliers
60 dist_error = zeros(1, num_point);
61 for i = 1 : num_point
62     dist_error(i) = sampsonError(model_H, point2DHomo1(i, :), point2DHomo2(i, :));
63 end
64 inlierIndex = (dist_error <= tolerance);
65 end
66
67 % four point method for 2D projective transformation
68 function H_inv = fourPoint(pointHomo, sampleIndex)
69     format longg;
70     point1 = pointHomo(sampleIndex(1), :)';
71     point2 = pointHomo(sampleIndex(2), :)';
72     point3 = pointHomo(sampleIndex(3), :)';
73     point4 = pointHomo(sampleIndex(4), :)';
74     part1 = [point1, point2, point3];
75     lam = part1 \ point4;
76     H_inv = [lam(1) * point1, lam(2) * point2, lam(3) * point3];
77 end
78
79 % calculate Sampson error %
80 function error = sampsonError(H, point1, point2)
81     % compute epsilon (Ah) and J
82     point1 = point1';
83     point2 = point2';
84     epsilon = [-point1' * H(2, :) + point2(2) * point1' * H(3, :)'; ...
85               point1' * H(1, :) - point2(1) * point1' * H(3, :)'];
86     J = [-H(2, 1) + point2(2) * H(3, 1), -H(2, 2) + point2(2) * H(3, 2), ...
87          0, point1(1) * H(3, 1) + point1(2) * H(3, 2) + H(3, 3); ...
88          H(1, 1) - point2(1) * H(3, 1), H(1, 2) - point2(1) * H(3, 2), ...
89          -(point1(1) * H(3, 1) + point1(2) * H(3, 2) + H(3, 3)), 0];
90     % compute sampson error
91     error = epsilon' / (J * J') * epsilon;
92 end

```

```

1 % linearEstimation.m
2
3 % DLT linear estimation %
4 function [H_norm, T1, T2] = linearEstimation(inlier1, inlier2)
5     % data normalization
6     [point1, T1] = dataNormalization(inlier1, 2);
7     [point2, T2] = dataNormalization(inlier2, 2);
8

```



```

9      % using DLT compute matrix A
10     %  $H * point2 = point1$ 
11     A = DLTAAlgorithm(point1, point2);
12
13     % using svd compute projection matrix P
14     H_norm = calProjMat(A);
15 end
16
17 % Data Normalization
18 function [point, T] = dataNormalization(data, dim)
19     num_point = size(data, 1);
20     % calculate mean and variance
21     m = mean(data);
22     v = var(data);
23     % calculate normalized vector
24     if (dim == 2)
25         s = sqrt(2.0 / sum(v));
26         T = zeros(3, 3);
27         T(1, 1) = s;
28         T(2, 2) = s;
29         T(3, 3) = 1.0;
30         T(1, 3) = -1.0 * m(1) * s;
31         T(2, 3) = -1.0 * m(2) * s;
32     else
33         s = sqrt(3.0 / sum(v));
34         T = zeros(4, 4);
35         T(1, 1) = s;
36         T(2, 2) = s;
37         T(3, 3) = s;
38         T(4, 4) = 1.0;
39         T(1, 4) = -1.0 * m(1) * s;
40         T(2, 4) = -1.0 * m(2) * s;
41         T(3, 4) = -1.0 * m(3) * s;
42     end
43     % transfer inhomogeneous to homogeneous data
44     unit = ones(num_point, 1);
45     point = [data, unit];
46     % normalize the data
47     point = T * point';
48     point = point';
49 end
50
51 % DLT algorithm
52 function matA = DLTAAlgorithm(point1, point2)
53     num_point = size(point1, 1);
54     point1 = point1';
55     point2 = point2';
56     matA = [];
57     % using house holder matrix
58     % to calculate left null space of x
59     for i = 1 : num_point
60         x = point1(:, i);
61         v = x + sign(x(1)) * norm(x) * [1, 0, 0]';
62         Hv = eye(3) - 2.0 * (v * v') / (v' * v);
63         leftNull = Hv(2 : 3, :);
64         matA = [matA; kron(leftNull, point2(:, i)')];
65     end
66 end
67
68 % using svd compute projection matrix P
69 function P = calProjMat(A)
70     [U, S, V] = svd(A);
71     P = V(:, size(V, 2));
72     P = reshape(P, [3, 3]);
73     P = P';

```

74 end

```
1 % levenbergEst.m
2
3 function HLM = levenbergEst(H_init, inlier1, inlier2)
4     inlier1 = inlier1';
5     inlier2 = inlier2';
6     num_point = size(inlier1, 2);
7     pntHomo1 = [inlier1; ones(1, num_point)];
8     pntHomo2 = [inlier2; ones(1, num_point)];
9     H = H_init;
10
11 % compute scene point
12 pnt_scene_deparam = zeros(2, num_point);
13 pnt_scene_param = zeros(2, num_point);
14 for i = 1 : num_point
15     pnt = sampsonCorrection(H, pntHomo1(:, i)', pntHomo2(:, i)');
16     pnt = pnt';
17     pnt_scene_deparam(:, i) = pnt;
18     pnt = [pnt; 1] / norm(pnt);
19     pnt_scene_param(:, i) = parameterize(pnt);
20 end
21
22 % compute initial cost
23 error1 = inlier1 - pnt_scene_deparam;
24 proj2 = zeros(3, num_point);
25 proj2_homo = zeros(3, num_point);
26 for i = 1:num_point
27     proj2(:, i) = H * deparameterize(pnt_scene_param(:, i));
28     proj2_homo(:, i) = proj2(:, i)/proj2(3, i);
29 end
30 proj2_inhomo = proj2_homo(1:2, :);
31 error2 = inlier2 - proj2_inhomo;
32 cost = norm(error1(:))^2 + norm(error2(:))^2;
33 disp('cost for each iteration:');
34 disp(cost);
35
36 h = H';
37 h = h(:);
38 paramH = parameterize(h);
39 lam = 0.001;
40 n = 1;
41
42 while 1
43     % compute Jacobian matrix
44     [A, B1, B2] = calJacobian(num_point, proj2, pnt_scene_param, H, paramH);
45
46     % compute normal equations matrix
47     U = zeros(8, 8);
48     V = zeros(2, 2, num_point);
49     W = zeros(8, 2, num_point);
50     error_part1 = zeros(8, 1);
51     error_part2 = zeros(2, 1, num_point);
52     for i = 1:num_point
53         U = U + A(:, :, i)' * A(:, :, i);
54         V(:, :, i) = B1(:, :, i)' * B1(:, :, i) + ...
55             B2(:, :, i)' * B2(:, :, i);
56         W(:, :, i) = A(:, :, i)' * B2(:, :, i);
57         error_part1 = error_part1 + A(:, :, i)' * ...
58             error2(:, i);
59         error_part2(:, :, i) = B1(:, :, i)' * error1(:, i) + ...
60             B2(:, :, i)' * error2(:, i);
61     end
62
63     % compute augmented normal euations
```

```

64     S = U + lam * eye(8);
65     epsilon = error_part1;
66     for i = 1 : num_point
67         S = S - W(:, :, i) * inv(V(:, :, i) + lam * eye(2)) * ...
68             W(:, :, i)';
69         epsilon = epsilon - W(:, :, i) * inv(V(:, :, i) + lam * eye(2)) * ...
70             error_part2(:, :, i);
71     end
72     delata_part1 = linsolve(S, epsilon);
73     delata_part2 = zeros(2, 1, num_point);
74     for i = 1 : num_point
75         delata_part2(:, :, i) = inv(V(:, :, i) + lam * eye(2)) * ...
76             (error_part2(:, :, i) - W(:, :, i)' * ...
77             delata_part1);
78     end
79
80     % update
81     paramH_update = paramH + delata_part1;
82     pnt_scene_param_update = zeros(2, num_point);
83     for i = 1 : num_point
84         pnt_scene_param_update(:, i) = pnt_scene_param(:, i) + ...
85             delata_part2(:, :, i);
86     end
87     h_update = deparameterize(paramH_update);
88     deparamH_update = reshape(h_update, 3, 3);
89     deparamH_update = deparamH_update';
90     proj1_update = zeros(2, num_point);
91     for i = 1 : num_point
92         pnt = deparameterize(pnt_scene_param_update(:, i));
93         pnt = pnt / pnt(3);
94         proj1_update(:, i) = pnt(1 : 2);
95     end
96
97     % compute new error
98     error1_update = inlier1 - proj1_update;
99     proj2_inhomo_update = zeros(3, num_point);
100    for i = 1 : num_point
101        proj2_update(:, i) = deparamH_update * ...
102            deparameterize(pnt_scene_param_update(:, i));
103        proj2_inhomo_update(:, i) = proj2_update(:, i) / proj2_update(3, i);
104    end
105    proj2_inhomo_update = proj2_inhomo_update(1 : 2, :);
106    error2_update = inlier2 - proj2_inhomo_update;
107    cost_update = norm(error2_update(:))^2 + norm(error1_update(:))^2;
108
109    % jump the loop
110    if(cost_update > cost)
111        lam = 10 * lam;
112    else
113        disp(cost_update);
114        if((cost - cost_update) / cost < 1e-8)
115            break;
116        end
117        n = n + 1;
118        lam = lam / 10;
119        paramH = paramH_update;
120        H = deparamH_update;
121        error1 = error1_update;
122        error2 = error2_update;
123        cost = cost_update;
124        pnt_scene_param = pnt_scene_param_update;
125        proj2 = proj2_update;
126    end
127 end
128 disp('number of iterations:');

```

```

129     disp(n);
130     HLM = H;
131 end
132
133 % parameterize
134 function paramVector = parameterize(P)
135     a = P(1);
136     b = P(2 : length(P));
137     paramVector = (2.0 / (sinc(acos(a)))) * b;
138     normP = norm(paramVector);
139     if (normP > pi)
140         paramVector = (1.0 - 2 * pi / normP * ceil((normP - pi) / 2 * pi)) * paramVector;
141     end
142 end
143
144 % deparameterize
145 function deparamVector = deparameterize(P)
146     normP = norm(P);
147     deparamVector = [cos(normP / 2.0), ((sinc(normP / 2.0)) / 2.0) * P']';
148 end
149
150 % sinc(x)
151 function res = sinc(x)
152     if x == 0
153         res = 1.0;
154     else
155         res = (sin(x)) / x;
156     end
157 end
158
159 % derivative of sinc(x)
160 function res = derivSinc(x)
161     if x == 0
162         res = 0.0;
163     else
164         res = cos(x) / x - sin(x) / (x * x);
165     end
166 end
167
168 % calculate Sampson error %
169 function point = sampsonCorrection(H, point1, point2)
170     x_hat = [point1(1 : 2), point2(1 : 2)]';
171     point1 = point1';
172     point2 = point2';
173     % compute epsilon (Ah) and J
174     epsilon = [-point1' * H(2, :) + point2(2) * point1' * H(3, :)'; ...
175               point1' * H(1, :) - point2(1) * point1' * H(3, :)'];
176     J = [-H(2, 1) + point2(2) * H(3, 1), -H(2, 2) + point2(2) * H(3, 2), ...
177          0, point1(1) * H(3, 1) + point1(2) * H(3, 2) + H(3, 3); ...
178          H(1, 1) - point2(1) * H(3, 1), H(1, 2) - point2(1) * H(3, 2), ...
179          -(point1(1) * H(3, 1) + point1(2) * H(3, 2) + H(3, 3)), 0];
180     % compute sampson error
181     lam = (J * J') \ (-epsilon);
182     delta = J' * lam;
183     x_hat = x_hat + delta;
184     point = x_hat(1 : 2)';
185 end
186
187 % compute jacobian matrix
188 function [A, B1, B2] = calJacobian(num_point, proj2, pnt_scene_param, H, paramH)
189     A = zeros(2, 8, num_point);
190     B1 = zeros(2, 2, num_point);
191     B2 = zeros(2, 2, num_point);
192     for i = 1:num_point
193         pnt = proj2(:, i);

```

```

194     pnt_scene = deparameterize(pnt_scene_param(:, i));
195
196     % compute A
197     A1_i = [1 / pnt(3), 0, -pnt(1) / pnt(3)^2;
198            0, 1 / pnt(3), -pnt(2) / pnt(3)^2];
199     A2_i = zeros(2,9);
200     A2_i(1,1:3) = pnt_scene';
201     A2_i(2,4:6) = pnt_scene';
202     A2_i(3,7:9) = pnt_scene';
203
204     part_H = zeros(9, 8);
205     part_H(1, :) = -0.25 * (sinc(norm(norm(paramH) / 2))) * paramH';
206
207
208     part_H(2:9, :) = sinc(norm(paramH) / 2) * 0.5 * eye(8) + ...
209                        (1 / (4 * norm(paramH))) * ...
210                        (derivSinc(norm(paramH) / 2)) * paramH * paramH';
211
212     A_i = A1_i * A2_i * part_H;
213     A(:, :, i) = A_i;
214
215     % Compute B1
216     B1_1_i = [1 / pnt_scene(3), 0, -pnt_scene(1) / pnt_scene(3)^2;
217             0, 1 / pnt_scene(3), -pnt_scene(2) / pnt_scene(3)^2];
218
219     B1_2_i = zeros(3, 2);
220     B1_2_i(1, :) = -0.25 * (sinc(norm(pnt_scene_param(:, i)) / 2)) * ...
221                    pnt_scene_param(:, i)';
222     B1_2_i(2 : 3, :) = sinc(norm(pnt_scene_param(:, i)) / 2) * 0.5 * ...
223                        eye(2) + (1/(4 * norm(pnt_scene_param(:, i)))) * ...
224                        (derivSinc(norm(pnt_scene_param(:, i)) / 2)) * ...
225                        pnt_scene_param(:, i) * pnt_scene_param(:, i)';
226
227     B1_i = B1_1_i * B1_2_i;
228     B1(:, :, i) = B1_i;
229
230     % compute B2
231     B2_1_i = [1 / pnt(3), 0, -pnt(1) / pnt(3)^2;
232            0, 1 / pnt(3), -pnt(2) / pnt(3)^2];
233
234     B2_2_i = H;
235
236     B2_3_i = zeros(3,2);
237     B2_3_i(1, :) = -0.25 * (sinc(norm(pnt_scene_param(:, i)) / 2)) * ...
238                    pnt_scene_param(:, i)';
239     B2_3_i(2 : 3, :) = sinc(norm(pnt_scene_param(:, i)) / 2) * 0.5 * ...
240                        eye(2) + (1/(4 * norm(pnt_scene_param(:, i)))) * ...
241                        (derivSinc(norm(pnt_scene_param(:, i)) / 2)) * ...
242                        pnt_scene_param(:, i) * pnt_scene_param(:, i)';
243     B2_i = B2_1_i * B2_2_i * B2_3_i;
244     B2(:, :, i) = B2_i;
245 end
246 end

```