

198: Computer Vision: Homework #3

Camera Calibration & Augmented Reality

Due on Saturday, May 2, 2015

Prof. Elgammal

Eric Wengrowski

Contents

Part 1 - Camera calibration with 3D object	3
1.1 - Draw the image points, using small circles for each image point.	3
1.2	3
1.3 - Print matrix P	3
1.4	3
1.5	4
1.7 - RQ factorization of M (aka M3)	4
1.8 - Rotation in Z direction	5
1.9 - Compute K	5
Part 2 - Camera calibration with 2D calibration object	8
2.1 - Corner Extraction and Homography computation	8
2.2 - Computing Intrinsic and Extrinsic parameters	9
2.3 - Improving Accuracy	13
Fully automatic checkerboard grid detection	17
Part 3 - Augmented Reality 101	28
3.1 - Augmenting an Image	28
3.2 - Augmenting an Object	31
Extra Credit	37
Calibrate camera with only 2 images	37

Part 1 - Camera calibration with 3D object

```
worldCorners = [  
    2    2    2;  
   -2    2    2;  
   -2    2   -2;  
    2    2   -2;  
    2   -2    2;  
   -2   -2    2;  
   -2   -2   -2;  
    2   -2   -2;];  
  
cameraCorners = [  
    422 323;  
    178 323;  
    118 483;  
    482 483;  
    438 73;  
    162 73;  
     78 117;  
    522 117;];
```

1.1 - Draw the image points, using small circles for each image point.

```
figure(1), plot(cameraCorners(:,1),cameraCorners(:,2),'o'), title('World corners of 3D
```

1.2

```
% Write a function that takes as argument the homogeneous coordinates  
% of one cube corner and the homogeneous coordinates of its image, and  
% returns 2 rows of the matrix P (slide 30 of the Camera Calibration pdf  
% document). This matrix P will be used to compute the 12 elements of the  
% projection matrix M such that  $\lambda p_i = M \cdot P_i$   
P = matrixP(worldCorners,cameraCorners);
```

1.3 - Print matrix P

```
disp('Matrix P')  
disp(P);
```

1.4

```
% Now we need to solve the system  $Pm = 0$ . Find the singular value  
% decomposition of matrix P using matlab svd function. The last column  
% vector of V obtained by svd(P) should be the 12 elements in row  
% order of the projection matrix that transformed the cube corner  
% coordinates into their images. Print the matrix M.
```

```
[~,~,Vprime] = svd(P);

% Find M, where p=M*P
M(1,1:4) = Vprime(1:4,end)';
M(2,1:4) = Vprime(5:8,end)';
M(3,1:4) = Vprime(9:12,end)';
% Print matrix M
disp('Matrix M')
disp(M);
```

1.5

```
% Now we need to recover the translation vector which is a null vector of
% M. Find the singular value decomposition of matrix M = U*S*V'. The 4
% elements of the last column of V are the homogeneous coordinates of the
% position of the camera center of projection in the frame of reference of
% the cube (as in slide 36). Print the corresponding 3 Euclidean
% coordinates of the camera center in the frame of reference of the cube
[~,~,Vprime] = svd(M);
```

```
% V(:,end) are homogeneous coordinates of Camera center
camCenter = Vprime(:,end)'/Vprime(end,end)';
disp('Camera Center')
disp(camCenter)
```

```
\subsection{1.6}
```

```
% Consider the 3x3 matrix M composed of the first 3 columns of matrix M.
% Rescale the elements of this matrix so that its element m33 becomes equal
% to 1. Print matrix M . Now let the rotation matrices be as defined in
% slide 38 where the axes e1, e2, e3 are the x, y, z axes respectively.
% Therefore M can be written as  $M' = K * R_x' * R_y' * R_z'$ 
M3 = M(1:3,1:3);
M3 = M3/M3(end,end);
% Print matrix M' (M3)
disp('M''')
disp(M3)
```

1.7 - RQ factorization of M (aka M3)

```
% First, find a rotation matrix Rx that sets the term at position (3,2)
% to zero when Rx is multiplied to M. The cosine and sine used in this
% matrix are of the form:
%  $\cos(\theta_x) = m(3,3)/\sqrt{m(3,3)^2 + m(3,2)^2}$ 
%  $\sin(\theta_x) = -m(3,2)/\sqrt{m(3,3)^2 + m(3,2)^2}$ 
% Note that the term at position (3,2) would also be set to zero if the
% signs of  $\cos(\theta_x)$  and  $\sin(\theta_x)$  were reversed, but this would lead
% to finding a negative focal length for the camera. So we should choose
% the signs that leads to a positive focal length. Compute the angle  $\theta_x$  of
```

```
% this rotation in degrees. Compute matrix N = M*Rx. Print Rx, ?x and N.
    crx = M3(3,3)/sqrt(M3(3,3)^2 + M3(3,2)^2);
    srx = -M3(3,2)/sqrt(M3(3,3)^2 + M3(3,2)^2);
%     theta_x = asin(srx);
    theta_x = acos(crx);
%     Rx = [1      0      0
%           0      cos(theta_x)  -sin(theta_x)
%           0      sin(theta_x)   cos(theta_x)];

    Rx = [1      0      0
           0      crx  -srx
           0      srx   crx];
    N = M3*Rx;
    disp('R_x = ')
    disp(Rx)
    disp('theta_x = ')
    disp(theta_x)
    disp('Matrix N')
    disp(N)
```

1.8 - Rotation in Z direction

```
    crz = N(2,2)/sqrt(N(2,1)^2 + N(2,2)^2);
    srz = -N(2,1)/sqrt(N(2,1)^2 + N(2,2)^2);
%     theta_z = asin(srz);
    theta_z = acos(crz);
    Rz = [crz  -srz  0
           srz   crz  0
           0     0   1];
%     N = N*Rz;
    disp('theta_z = ')
    disp(theta_z)
```

1.9 - Compute K

```
% M3 = K*R
    R = Rx*eye(3)*Rz;
% R^-1 = transp(R) = R'
% M3 * R' = K
    K = M3 * R;
    K = K/K(3,3);
    disp('Matrix K')
    disp(K)
%{
    K = [f*mx    skew    u0
         0       f*my    v0
         0       0       1];
%}
```

```
% Compute image center
u0 = K(1,3);
v0 = K(2,3);
disp('Focal length = ')
disp((K(1,1)+K(2,2))/2)
disp('Image center = ')
disp([u0,v0])
```

Matrix P

Columns 1 through 6

2	2	2	1	0	0
0	0	0	0	2	2
-2	2	2	1	0	0
0	0	0	0	-2	2
-2	2	-2	1	0	0
0	0	0	0	-2	2
2	2	-2	1	0	0
0	0	0	0	2	2
2	-2	2	1	0	0
0	0	0	0	2	-2
-2	-2	2	1	0	0
0	0	0	0	-2	-2
-2	-2	-2	1	0	0
0	0	0	0	-2	-2
2	-2	-2	1	0	0
0	0	0	0	2	-2

Columns 7 through 12

0	0	-844	-844	-844	-422
2	1	-646	-646	-646	-323
0	0	356	-356	-356	-178
2	1	646	-646	-646	-323
0	0	236	-236	236	-118
-2	1	966	-966	966	-483
0	0	-964	-964	964	-482
-2	1	-966	-966	966	-483
0	0	-876	876	-876	-438
2	1	-146	146	-146	-73
0	0	324	324	-324	-162
2	1	146	146	-146	-73
0	0	156	156	156	-78
-2	1	234	234	234	-117
0	0	-1044	1044	1044	-522
-2	1	-234	234	234	-117

Matrix M

0.1925	0.0283	0.0786	0.7346
0.0000	0.2044	0.0001	0.6120
0.0000	0.0001	0.0003	0.0024

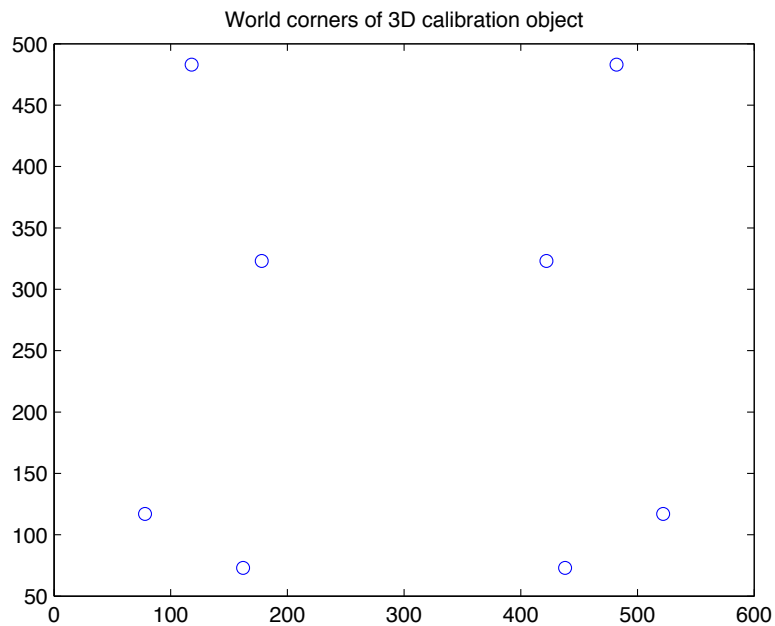
Camera Center

-0.0000	-2.9912	-8.2695	1.0000
---------	---------	---------	--------

```

M'
  734.6289  107.8955  299.9999
    0.0009  780.1442    0.2641
    0.0000    0.3597    1.0000
R_x =
  1.0000    0    0
    0    0.9410  0.3384
    0   -0.3384  0.9410
theta_x =
  0.3452
Matrix N
  734.6289  -0.0000  318.8125
    0.0009  734.0199  264.2723
    0.0000    0    1.0627
theta_z =
  1.2602e-06
Matrix K
  691.2797    0.0009  299.9999
    0.0000  690.7067  248.6780
    0.0000    0.0000    1.0000
Focal length =
  690.9932
Image center =
  299.9999  248.6780

```



Part 2 - Camera calibration with 2D calibration object

Checkerboard is 9 squares in width, 7 squares in height, 30x30mm squares Bottom left corner of grid is origin of world coordinate system. Checkerboard grid is plane at $Z=0$

```

grid1 = imread('images2.png');
grid2 = imread('images9.png');
grid3 = imread('images12.png');
grid4 = imread('images20.png');

gridWidth = 9;
gridHeight = 7;

% Corners in 3x4 homogeneous world coordinates
wc = [0,          gridHeight*30,  1;
      gridWidth*30, gridHeight*30,  1;
      gridWidth*30, 0,             1;
      0,            0,             1];
wc=wc';

```

2.1 - Corner Extraction and Homography computation

```

% Manually detect checkerboard corners: clockwise from top right
% Order: TopRight, TopLeft, BottomLeft, BottomRight
if ~exist('x1','var')
    figure(2), imshow(grid1), [x1,y1] = ginput(4);
    figure(2), imshow(grid2), [x2,y2] = ginput(4);
    figure(2), imshow(grid3), [x3,y3] = ginput(4);
    figure(2), imshow(grid4), [x4,y4] = ginput(4);
    close(2);
end

% Convert to 3xN homogenous coordinates, N=4
ic1 = [x1'; y1'; [1,1,1,1]];
ic2 = [x2'; y2'; [1,1,1,1]];
ic3 = [x3'; y3'; [1,1,1,1]];
ic4 = [x4'; y4'; [1,1,1,1]];

% Compute homography H that relates the grid 3d coordinates to the corners
H1 = homography2d(wc,ic1);
H2 = homography2d(wc,ic2);
H3 = homography2d(wc,ic3);
H4 = homography2d(wc,ic4);

% NOTE: It was not clear in the documentation, that the world
% coordinates WC should be the first input variable, rather than the
% pixel coordinates PC in homography2d(WC,PC).
% But that that seems to make a huge difference.

H1 = H1/H1(3,3);

```



```

H2 = H2/H2(3,3);
H3 = H3/H3(3,3);
H4 = H4/H4(3,3);

% Display results
disp('Homography for images2.png')
disp(H1)
disp('Homography for images9.png')
disp(H2)
disp('Homography for images12.png')
disp(H3)
disp('Homography for images20.png')
disp(H4)

```

```

Homography for images2.png
    1.7435    0.1589    67.0000
    0.0339   -1.5770   413.0000
    0.0000    0.0004    1.0000
Homography for images9.png
    2.1928    0.0615   132.0000
    0.2893   -1.8937   422.0000
    0.0010    0.0003    1.0000
Homography for images12.png
    1.1147    0.0814   104.0000
   -0.2860   -1.4058   394.0000
   -0.0009    0.0003    1.0000
Homography for images20.png
    1.6477    0.5275   128.0000
   -0.0289   -0.7825   277.0000
   -0.0001    0.0016    1.0000

```

2.2 - Computing Intrinsic and Extrinsic parameters

```

H = [H1, H2, H3, H4];
h = zeros(3,3);
V = [];

for i = 1:4
    Ho = eval(['H' num2str(i)]);
    h1 = Ho(:,1);
    h2 = Ho(:,2);
    h3 = Ho(:,3);

    k=1;j=2;
    v12 = [h1(1)*h2(1), h1(1)*h2(2)+h1(2)*h2(1), h1(2)*h2(2), h1(3)*h2(1)+h1(1)*h2(3),

    k=1;j=1;
    v11 = [h1(1)*h1(1), h1(1)*h1(2)+h1(2)*h1(1), h1(2)*h1(2), h1(3)*h1(1)+h1(1)*h1(3),

```

```

k=2;j=2;
v22 = [h2(1)*h2(1), h2(1)*h2(2)+h2(2)*h2(1), h2(2)*h2(2), h2(3)*h2(1)+h2(1)*h2(3),

V = [V; v12'; (v11-v22)'];
end

% Solve V*b=0,
% Solve for b by finding the eigenvector of V'*V associated with the
% smallest eigenvalue
%(equivalently, the right singular vector of V associated with the
% smallest singular value)
[U,S,Vprime] = svd(V);
b = Vprime(:,end)';

% b = [B11, B12, B22, B13, B23, B33]';
% B = inv(A')*inv(A), symmetric
B11 = b(1);
B12 = b(2);
B22 = b(3);
B13 = b(4);
B23 = b(5);
B33 = b(6);
B = [B11 B12 B13;
     B12 B22 B23;
     B13 B23 B33];

%Intrinsic parameters
v0 = (B12*B13 - B11*B23)/(B11*B22 - B12^2);
lambda = B33 - (B13^2 + v0*(B12*B13-B11*B23))/B11;
alpha = sqrt(lambda/B11);
beta = sqrt(lambda*B11/(B11*B22-B12^2));
gamma = -B12*alpha^2*beta/lambda;
u0 = gamma*v0/alpha - B13*alpha^2/lambda;

% B=lambda*inv(A)'*A
A = [alpha, gamma, u0;
     0, beta, v0;
     0, 0, 1];

disp('Intrinsic Parameters matrix K = ')
disp(A)

H = [H1, H2, H3, H4];
photoSet = [2,9,12,20];

for i = 1:4
    Ho = eval(['H' num2str(i)]);
    h1 = Ho(:,1);
    h2 = Ho(:,2);

```

```

h3 = Ho(:,3);
lambda = 1/norm(A\h1); %%% NEW LAMBDA - VERY CONFUSING NOTATION
r1 = lambda*inv(A)*h1;
r2 = lambda*inv(A)*h2;
r3 = cross(r1,r2);
t = lambda*inv(A)*h3;

%      R(:, :, i) = [r1, r2, r3];
%      t(:, i) = t;
R = [r1, r3, r2]; %%% Not sure why this has to be the case

disp(['Rotation matrix for images' num2str(photoSet(i)) '.png'])
disp(R)
disp(['Translation vector for images' num2str(photoSet(i)) '.png'])
disp(t)
disp(['R''*R for images' num2str(photoSet(i)) '.png'])
disp(R'*R)

% R'*R is not eye(3)
% Better method of estimating R: use SVD, set singular values to 1s
% New Rotation matrix = Rnew = U*V', where R = U*S*V'

[U,S,Vprime] = svd(R);
Rnew = U*Vprime;

disp(['New R via SVD for images' num2str(photoSet(i)) '.png'])
disp(Rnew)
disp(['New R''*R via SVD for images' num2str(photoSet(i)) '.png'])
disp(Rnew'*Rnew)
end

Intrinsic Parameters matrix K =
718.0150    2.9850   316.9536
    0   703.3625   232.5124
    0         0    1.0000
Rotation matrix for images2.png
0.9998    0.0108    0.0165
0.0173   -0.1790   -0.9857
0.0079   -0.9858    0.1792
Translation vector for images2.png
-144.2853
106.0317
413.2068
R'*R for images2.png
1.0000         0    0.0008
         0    1.0040         0
0.0008         0    1.0040
New R via SVD for images2.png
0.9998    0.0108    0.0160

```

```
0.0177 -0.1787 -0.9837
0.0078 -0.9838 0.1788
New R' * R via SVD for images2.png
1.0000 0.0000 -0.0000
0.0000 1.0000 -0.0000
-0.0000 -0.0000 1.0000
Rotation matrix for images9.png
0.9322 0.3616 -0.0087
0.0277 -0.0948 -0.9948
0.3608 -0.9272 0.0983
Translation vector for images9.png
-92.4713
96.2931
357.4320
R' * R for images9.png
1.0000 -0.0000 -0.0002
-0.0000 0.9994 -0.0000
-0.0002 -0.0000 0.9994
New R via SVD for images9.png
0.9322 0.3617 -0.0086
0.0276 -0.0948 -0.9951
0.3608 -0.9274 0.0984
New R' * R via SVD for images9.png
1.0000 0 0.0000
0 1.0000 0
0.0000 0 1.0000
Rotation matrix for images12.png
0.9117 -0.4101 -0.0041
-0.0572 -0.1257 -0.9884
-0.4068 -0.9014 0.1397
Translation vector for images12.png
-140.2684
108.2363
471.4255
R' * R for images12.png
1.0000 0 -0.0040
0 0.9964 0.0000
-0.0040 0.0000 0.9964
New R via SVD for images12.png
0.9117 -0.4108 -0.0023
-0.0592 -0.1259 -0.9903
-0.4065 -0.9030 0.1391
New R' * R via SVD for images12.png
1.0000 0.0000 -0.0000
0.0000 1.0000 0
-0.0000 0 1.0000
Rotation matrix for images20.png
0.9997 -0.0231 0.0103
-0.0104 -0.7014 -0.7117
```

```

-0.0223   -0.7113    0.7014
Translation vector for images20.png
-113.6192
  27.2807
 431.3167
R'*R for images20.png
    1.0000         0    0.0020
         0    0.9985         0
    0.0020         0    0.9985
New R via SVD for images20.png
    0.9997   -0.0232    0.0093
   -0.0097   -0.7019   -0.7122
   -0.0230   -0.7119    0.7019
New R'*R via SVD for images20.png
    1.0000   -0.0000    0.0000
   -0.0000    1.0000   -0.0000
    0.0000   -0.0000    1.0000

```

2.3 - Improving Accuracy

compute the approximate location of each grid corner in the image use previously computed homographies and known 3d locations of the grid corners

```

% known 3d locations of the grid corners
wc_allpoints = [];

for i = 0:gridWidth
    for j = 0:gridHeight
        wc_allpoints = [wc_allpoints; i*30, j*30, 1];
    end
end

% Compute all grid locations with homography- NOW WORKING PROPERLY :D
p_approx = zeros((gridWidth+1)*(gridHeight+1), 3);
H = [H1, H2, H3, H4];
Hnew = zeros(3,3,4);

for i = 1:4      % For all 4 calibration images
    H = eval(['H' num2str(i)]);
    p_approx = H*wc_allpoints';
    for j=1:length(p_approx)      % Normalize
        p_approx(:,j) = p_approx(:,j) / p_approx(3,j);
    end

    grid = eval(['grid' num2str(i)]);
    figure(), imshow(grid), title(['Figure1: Projected grid corners for images' num2str(i)]);
    hold on
    plot(p_approx(1,:),p_approx(2:3,:),'ro');
end
hold off

```

```

% Harris corner detection
sigma = 2;
thresh = 500;
radius = 2;
[cim,r,c,rsubp,csubp]=harris(rgb2gray(grid),sigma,thresh,radius,1);
title(['Figure 2 : Harris corners for images' num2str(photoSet(i)) '.png'])

% Compute the closest Harris corner to each approx grid corner
D = dist2(p_approx(1:2,:)',[csubp, rsubp]);
[D_sorted, D_index] = sort(D, 2);
p_correct(:, :, i) = [csubp(D_index(:,1)),rsubp(D_index(:,1)),ones((gridWidth+1)*(gr
figure(), imshow(grid), title(['Figure3: Grid Points for images' num2str(photoSet(i)) '.png'])
hold on
plot(p_correct(:,1,i),p_correct(:,2,i),'g+')
hold off

% Compute new homography from p_correct
Hnew(:, :, i) = homography2d(wc_allpoints',p_correct(:, :, i)');
Hnew(:, :, i) = Hnew(:, :, i)/Hnew(3,3,i);
disp(['Recomputed Homography H of ' num2str(photoSet(i)) '.png'])
disp(Hnew(:, :, i))

end % for all 4 images

Hn1 = Hnew(:, :, 1);
Hn2 = Hnew(:, :, 2);
Hn3 = Hnew(:, :, 3);
Hn4 = Hnew(:, :, 4);

% Use Hnew to estimate K,R,t for each image
Hn = [Hn1, Hn2, Hn3, Hn4];
H = [H1, H2, H3, H4];
%h = zeros(3,3);
V = [];

for i = 1:4
    Hnn = eval(['Hn' num2str(i)]);
    h1 = Hnn(:,1);
    h2 = Hnn(:,2);
    h3 = Hnn(:,3);

    k=1;j=2;
    v12 = [h1(1)*h2(1), h1(1)*h2(2)+h1(2)*h2(1), h1(2)*h2(2), h1(3)*h2(1)+h1(1)*h2(3),

    k=1;j=1;
    v11 = [h1(1)*h1(1), h1(1)*h1(2)+h1(2)*h1(1), h1(2)*h1(2), h1(3)*h1(1)+h1(1)*h1(3),

    k=2;j=2;

```

```

v22 = [h2(1)*h2(1), h2(1)*h2(2)+h2(2)*h2(1), h2(2)*h2(2), h2(3)*h2(1)+h2(1)*h2(3),

V = [V; v12'; (v11-v22)'];
end

% Solve V*b=0,
% Solve for b by finding the eigenvector of V'*V associated with the
% smallest eigenvalue
%(equivalently, the right singular vector of V associated with the
% smallest singular value)
[U,S,Vprime] = svd(V);
b = Vprime(:,end)';

% b = [B11, B12, B22, B13, B23, B33]';
% B = inv(A')*inv(A), symmetric
B11 = b(1);
B12 = b(2);
B22 = b(3);
B13 = b(4);
B23 = b(5);
B33 = b(6);
B = [B11 B12 B13;
     B12 B22 B23;
     B13 B23 B33];

%Intrinsic parameters
v0 = (B12*B13 - B11*B23)/(B11*B22 - B12^2);
lambda = B33 - (B13^2 + v0*(B12*B13-B11*B23))/B11;
alpha = sqrt(lambda/B11);
beta = sqrt(lambda*B11/(B11*B22-B12^2));
gamma = -B12*alpha^2*beta/lambda;
u0 = gamma*v0/alpha - B13*alpha^2/lambda;

% B=lambda*inv(A)'*A
A = [alpha, gamma, u0;
     0, beta, v0;
     0, 0, 1];
disp('Intrinsic Parameters matrix K = ')
disp(A)

photoSet = [2,9,12,20];
Hn = [Hn1, Hn2, Hn3, Hn4];
H = [H1, H2, H3, H4];

for i = 1:4 % for all 4 images
    Hnn = eval(['Hn' num2str(i)]);
    h1 = Hnn(:,1);
    h2 = Hnn(:,2);
    h3 = Hnn(:,3);

```

```

lambda = 1/norm(A\h1); %%% NEW LAMBDA - VERY CONFUSING NOTATION
r1 = lambda*inv(A)*h1;
lambda = 1/norm(A\h2); %%% NEW LAMBDA - VERY CONFUSING NOTATION
r2 = lambda*inv(A)*h2;
r3 = cross(r1,r2);
t(:,i) = lambda*inv(A)*h3;
R = [r1, r3, r2]; %%% Not sure why this has to be the case

% Better method of estimating R: use SVD, set singular values to 1s
% New Rotation matrix = Rnew = U*V', where R = U*S*V'

[U,S,Vprime] = svd(R);
Rnew(:, :, i) = U*Vprime;

disp(['Rotation matrix R for images' num2str(photoSet(i)) '.png'])
disp(Rnew(:, :, i))
disp(['Translation vector for images' num2str(photoSet(i)) '.png'])
disp(t(:, i))

% Compute reprojection error
% compute the errors between points in p_correct and points you get
% by projecting grid corners to the image
Hnn = eval(['Hn' num2str(i)]);
Hh = eval(['H' num2str(i)]);
p_projection = Hnn*wc_allpoints';

for j=1:length(p_projection) % Normalize
    p_projection(:, j) = p_projection(:, j) /p_projection(3, j);
end
p_projection = p_projection';

err_xline = [p_correct(:,1,i) p_projection(:,1)];
err_yline = [p_correct(:,2,i) p_projection(:,2)];

grid = eval(['grid' num2str(i)]);
figure(), imshow(grid), title(['Figure4: Grid Point Reprojection Error for images'
hold on
plot(p_correct(:,1,i), p_correct(:,2,i), 'g+')
plot(p_projection(:,1), p_projection(:,2), 'bo')
plot(err_xline', err_yline', 'r-')
hold off

err_reprojection = [err_xline,err_yline];
tot_err_reprojection = sum(sqrt((err_xline(:,1)-err_xline(:,2)).^2 + (err_yline(:,1)-err_yline(:,2)).^2));
avg_err_reprojection = tot_err_reprojection/80;

% Display reprojection error
disp(['Total Grid Point Reprojection Error (in pixels) for images' num2str(photoSet(i)) '.png'])
disp(tot_err_reprojection)

```



```

disp(['Average Grid Point Reprojection Error (in pixels) for images' num2str(photos)
disp(avg_err_reprojection)

% Compare reprojection error to part 2 - manual only 4 corner input
p_projection_old = Hh*wc_allpoints';
for j=1:length(p_projection_old)
    p_projection_old(:,j) = p_projection_old(:,j) /p_projection_old(3,j);
end
p_projection_old = p_projection_old';
err_xline_old = [p_correct(:,1,i) p_projection_old(:,1)];
err_yline_old = [p_correct(:,2,i) p_projection_old(:,2)];
err_reprojection_old = [err_xline_old,err_yline_old];
tot_err_reprojection_old = sum(sqrt((err_xline_old(:,1)-err_xline_old(:,2)).^2 + (
avg_err_reprojection_old = tot_err_reprojection_old/80;

disp(['Manual Only Grid Point Input - Total Reprojection Error (in pixels) for ima
disp(tot_err_reprojection_old)
disp(['Manual Only Grid Point Input - Average Reprojection Error (in pixels) for in
disp(avg_err_reprojection_old)

end % for all 4 images

```

Fully automatic checkerboard grid detection

To calibrate a camera with no user manual input (not even the 4 corners), the user can simply specify the number of blocks, as well as the block dimensions (measurements in mm). This establishes the world coordinates of the checkerboard grid. To determine the image coordinates of the checkerboard grid, first run corner detection. Then, search you image for sets of colinear corners. In particular, you are looking for colinear points that correspond to the already known number of checkerboard grid points in the row and column direction. The sets of colinear corners should approximate a rectangular grid, with parallel and perpendicular line segmemnts with a projective transformation applied. In practice, Matlab's function `detectCheckerboard()` can be used.

```

Recomputed Homography H of 2.png
    1.7456    0.1571    63.4936
    0.0316   -1.6043   414.4186
    0.0000    0.0004    1.0000
Recomputed Homography H of 9.png
    2.2440    0.0727   128.7522
    0.3056   -1.9304   424.4314
    0.0011    0.0003    1.0000
Recomputed Homography H of 12.png
    1.1305    0.0819   101.1891
   -0.2824   -1.4298   394.5842
   -0.0009    0.0003    1.0000
Recomputed Homography H of 20.png
    1.6909    0.5302   125.9504
   -0.0143   -0.7965   277.1073
    0.0000    0.0016    1.0000
Intrinsic Parameters matrix K =

```

```
723.2192  -0.9648  329.6334
          0  709.8053  234.3268
          0          0  1.0000
Rotation matrix R for images2.png
          0.9999  0.0043  0.0154
          0.0159 -0.1644 -0.9863
          0.0017 -0.9864  0.1645
Translation vector for images2.png
-151.6065
 104.6242
 412.3610
Total Grid Point Reprojection Error (in pixels) for images2.png
143.9755
Average Grid Point Reprojection Error (in pixels) for images2.png
1.7997
Manual Only Grid Point Input - Total Reprojection Error (in pixels) for images2.png
256.3953
Manual Only Grid Point Input - Average Reprojection Error (in pixels) for images2.png
3.2049
Rotation matrix R for images9.png
          0.9238  0.3827 -0.0109
          0.0271 -0.0937 -0.9952
          0.3819 -0.9191  0.0970
Translation vector for images9.png
-98.2373
 94.8461
354.1330
Total Grid Point Reprojection Error (in pixels) for images9.png
149.1836
Average Grid Point Reprojection Error (in pixels) for images9.png
1.8648
Manual Only Grid Point Input - Total Reprojection Error (in pixels) for images9.png
222.6190
Manual Only Grid Point Input - Average Reprojection Error (in pixels) for images9.png
2.7827
Rotation matrix R for images12.png
          0.9151 -0.4032 -0.0052
         -0.0567 -0.1157 -0.9917
         -0.3993 -0.9078  0.1288
Translation vector for images12.png
-148.6400
 106.3454
 471.0204
Total Grid Point Reprojection Error (in pixels) for images12.png
166.4552
Average Grid Point Reprojection Error (in pixels) for images12.png
2.0807
Manual Only Grid Point Input - Total Reprojection Error (in pixels) for images12.png
255.2531
```

```
Manual Only Grid Point Input - Average Reprojection Error (in pixels) for images12.png
3.1907
Rotation matrix R for images20.png
1.0000 -0.0044 -0.0076
-0.0085 -0.7011 -0.7130
0.0022 -0.7130 0.7011
Translation vector for images20.png
-120.8294
25.8653
429.1528
Total Grid Point Reprojection Error (in pixels) for images20.png
135.8244
Average Grid Point Reprojection Error (in pixels) for images20.png
1.6978
Manual Only Grid Point Input - Total Reprojection Error (in pixels) for images20.png
172.9386
Manual Only Grid Point Input - Average Reprojection Error (in pixels) for images20.png
2.1617
```

Figure1: Projected grid corners for images2.png

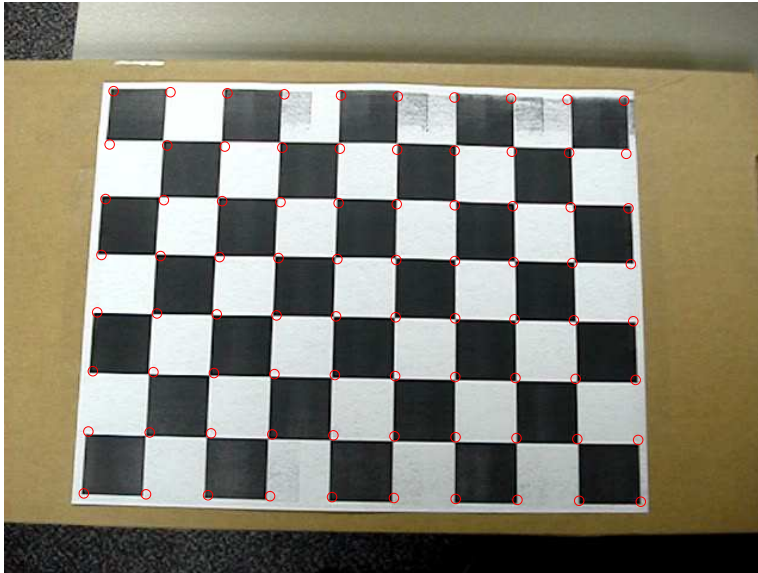


Figure 2 : Harris corners for images2.png

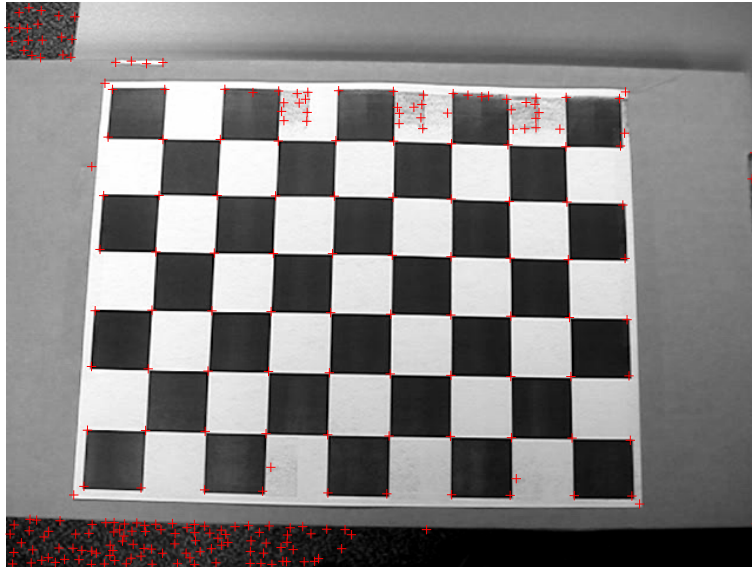


Figure3: Grid Points for images2.png



Figure1: Projected grid corners for images9.png

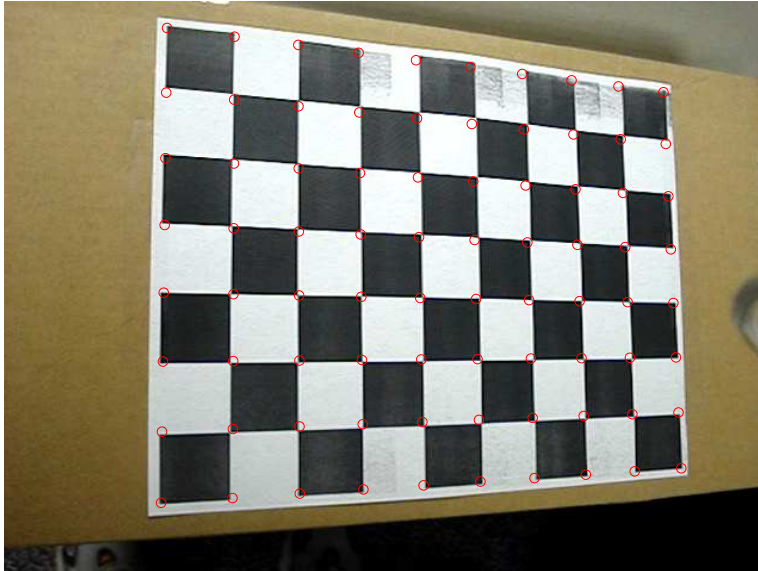


Figure 2 : Harris corners for images9.png

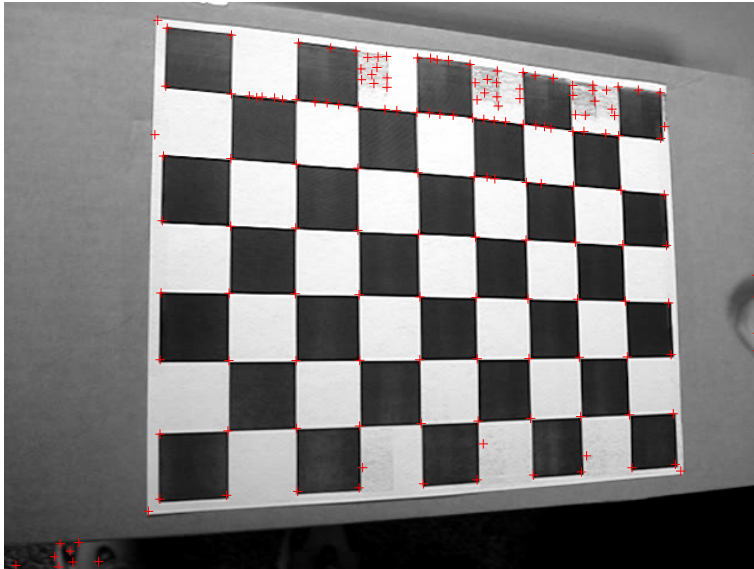


Figure3: Grid Points for images9.png

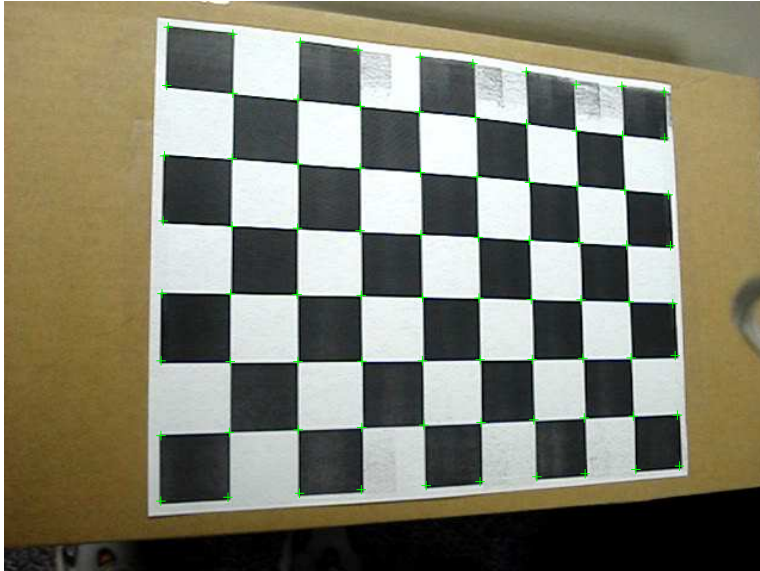


Figure1: Projected grid corners for images12.png



Figure 2 : Harris corners for images12.png

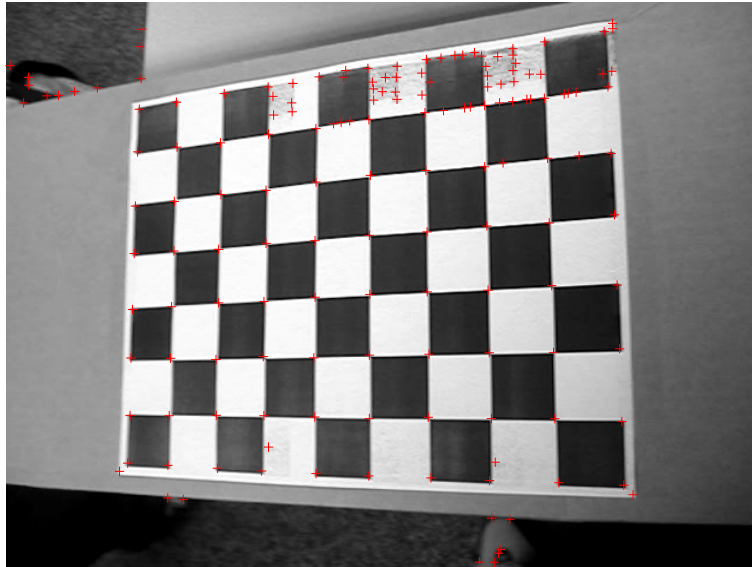


Figure3: Grid Points for images12.png

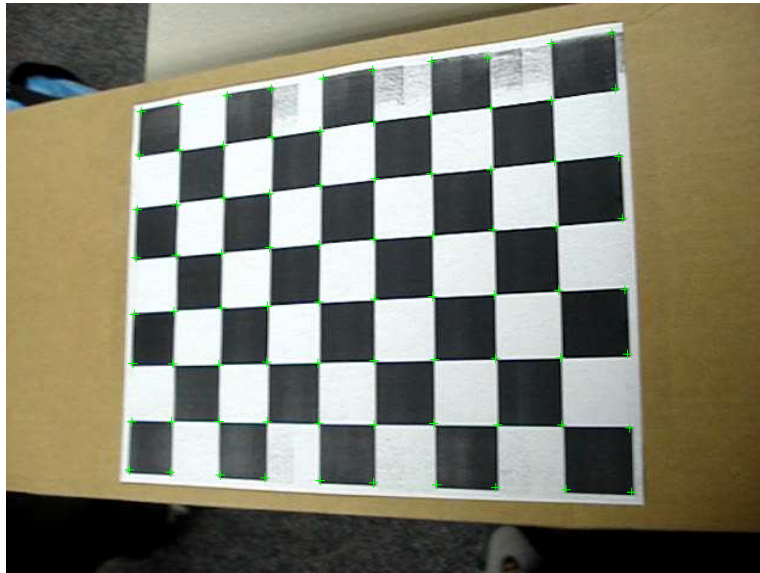


Figure1: Projected grid corners for images20.png



Figure 2 : Harris corners for images20.png

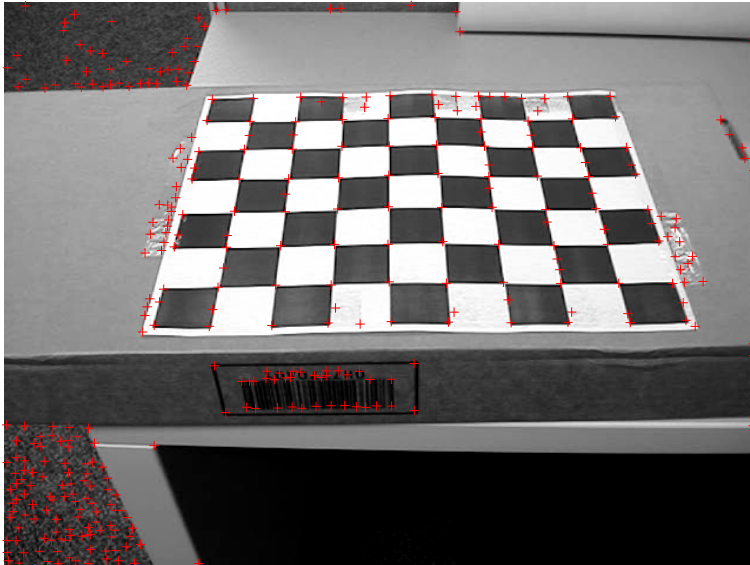


Figure3: Grid Points for images20.png



Figure4: Grid Point Reprojection Error for images2.png



Figure4: Grid Point Reprojection Error for images9.png



Figure4: Grid Point Reprojection Error for images12.png



Figure4: Grid Point Reprojection Error for images20.png



Part 3 - Augmented Reality 101

3.1 - Augmenting an Image

```

mouseIn = imread('0.png');
scale = [gridHeight*30 NaN];
%scale = [NaN gridWidth*30];
mouseIn = imresize(mouseIn,scale);
[rowsM, colsM, ~] = size(mouseIn);
Hn = [Hn1, Hn2, Hn3, Hn4];

mouseIn = mouseIn + 1;
mouseIn = imrotate(mouseIn,-90);

for k = 1:4 % all checkerboard images

    grid = eval(['grid' num2str(k)]);
    [rowsG, colsG, ~] = size(grid);
    Hnn = eval(['Hn' num2str(k)]);

    mouse_homo = [];
    for i = 1:colsM
        for j = 1:rowsM
            mouse_homo = [mouse_homo; i, j, 1, mouseIn(i,j,1), mouseIn(i,j,2), mouseIn(i,j,3)];
        end
    end

    mouse_homo_tformed = double(mouse_homo(:,1:3))*Hnn';
    mouse_homo_tformed(:,1) = mouse_homo_tformed(:,1)./mouse_homo_tformed(:,3);
    mouse_homo_tformed(:,2) = mouse_homo_tformed(:,2)./mouse_homo_tformed(:,3);
    mouse_homo_tformed = abs(round(mouse_homo_tformed+1));

    mouseNew = zeros(max(mouse_homo_tformed(:,1)), max(mouse_homo_tformed(:,2)), 3);
    for i = 1:length(mouse_homo_tformed)
        r = mouse_homo_tformed(i,2);    %%%
        c = mouse_homo_tformed(i,1);    %%%
        mouseNew(r,c,1) = mouse_homo(i,4);
        mouseNew(r,c,2) = mouse_homo(i,5);
        mouseNew(r,c,3) = mouse_homo(i,6);
    end
    mouseNew = uint8(mouseNew);
%     figure, imshow(mouseNew)

%     mouseNew(mouseNew == 0) = [];
%     L = zeros(size(mouseNew));
%     L(:, :, 1) = medfilt2(mouseNew(:, :, 1), [5 5]);
%     L(:, :, 2) = medfilt2(mouseNew(:, :, 2), [5 5]);
%     L(:, :, 3) = medfilt2(mouseNew(:, :, 3), [5 5]);

%     h = fspecial('average', [3 3]);

```

```
% L = imfilter(mouseNew,h)*3;
% figure, imshow(L)

mouse = mouseNew;

% tform = projective2d(Hnn');
% mouse = imwarp(mouse,tform,'FillValues', 255);

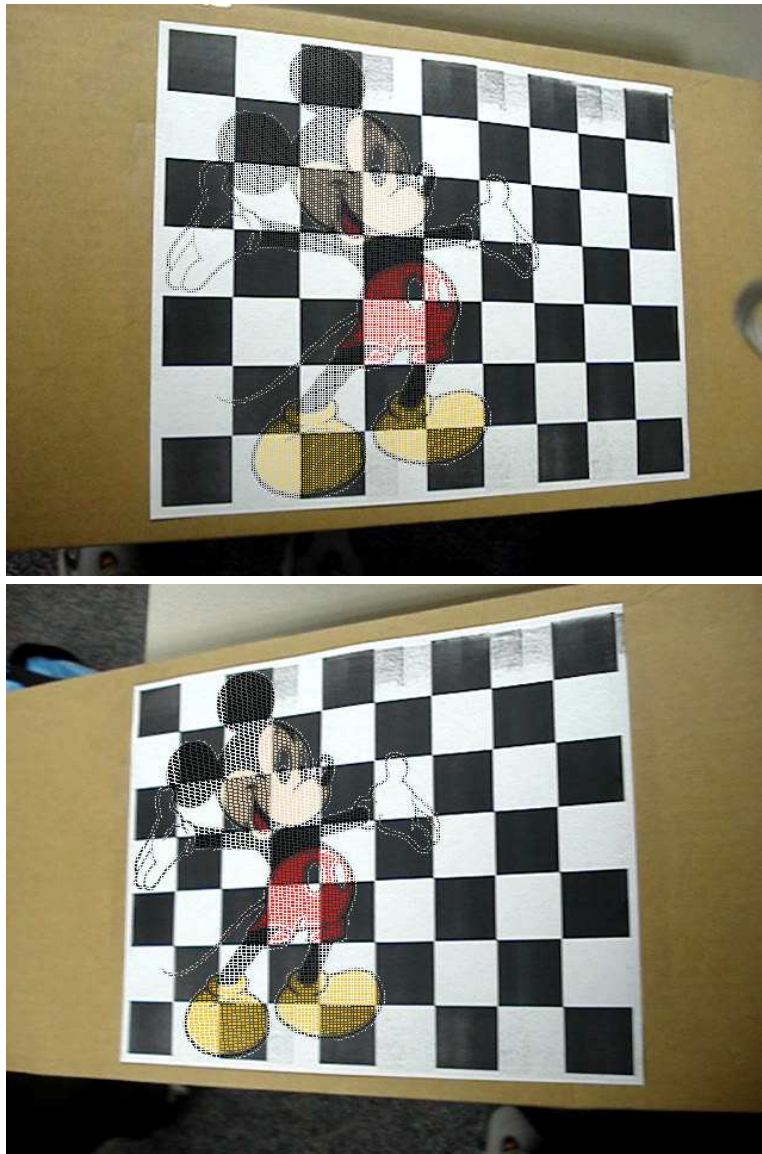
% % Overlay onto image
bw = (mouse > 0) & (mouse < 255);

% Pad with zeros
dif = abs(size(grid)-size(mouse));
mask_pad = padarray(bw, [dif(1),dif(2)], 'post');
img_masked_pad = mouse .* uint8(bw);

new_img = zeros(rowsG,colsG,3);
for i = 1:rowsG
for j = 1:colsG
    if mask_pad(i,j,:)
        new_img(i,j,:) = img_masked_pad(i,j,:);
    else
        new_img(i,j,:) = grid(i,j,:);
    end
end
end
figure(), imshow(uint8(new_img))

end
```







3.2 - Augmenting an Object

```

scale = 30;
cube = [0,          0,          0,          1;
        3*scale,    0,          0,          1;
        0,          3*scale,    0,          1;
        0,          0,          3*scale,    1;
        0,          3*scale,    3*scale,    1;
        3*scale,    0,          3*scale,    1;
        3*scale,    3*scale,    0,          1;
        3*scale,    3*scale,    3*scale,    1;];

newCube(:,1) = cube(:,3);
newCube(:,2) = cube(:,2);
newCube(:,3) = cube(:,1);
newCube(:,4) = cube(:,4);
cube=newCube;

cubeEdges = [cube(1,1:3) cube(2,1:3);
             cube(1,1:3) cube(3,1:3);
             cube(1,1:3) cube(4,1:3);
             cube(2,1:3) cube(6,1:3);
             cube(2,1:3) cube(7,1:3);
             cube(3,1:3) cube(5,1:3);
             cube(3,1:3) cube(7,1:3);
             cube(4,1:3) cube(5,1:3);
             cube(4,1:3) cube(6,1:3);
             cube(8,1:3) cube(5,1:3);
             cube(8,1:3) cube(6,1:3);
             cube(8,1:3) cube(7,1:3)];

cubeEdgesX = [cubeEdges(:,1), cubeEdges(:,4)]';

```

```

cubeEdgesY = [cubeEdges(:,2), cubeEdges(:,5)]';
cubeEdgesZ = [cubeEdges(:,3), cubeEdges(:,6)]';

figure(), plot3(cube(:,1), cube(:,2), cube(:,3), 'ro')
hold on
plot3(cubeEdgesX, cubeEdgesY, cubeEdgesZ)
hold off

extrinsic = zeros(3,4,4);
Projection = zeros(3,4,4);

Hn = [Hn1, Hn2, Hn3, Hn4];

for k = 1:4
    grid = eval(['grid' num2str(k)]);
    Hnn = eval(['Hn' num2str(k)]);
    %t(:,k)
    %Rnew(:, :, k)
    %A
    extrinsic(:, :, k) = [Rnew(:, :, k), t(:, k)];
    intrinsic = A;
    Projection(:, :, k) = intrinsic*extrinsic(:, :, k);

    pixels = Projection(:, :, k)*cube';
    pixels = pixels';

%     Hnnew = [Hnn, [0,0,0]'; 0,0,0,1];
%     pixels = Hnn*cube(:,1:3)';
%     pixels = pixels';

% Normalize by homogenous coordinate
for i=1:length(pixels)
    pixels(i,:) = pixels(i,:)/pixels(i,3);
end

pixelEdges = [pixels(1,1:3) pixels(2,1:3);
               pixels(1,1:3) pixels(3,1:3);
               pixels(1,1:3) pixels(4,1:3);
               pixels(2,1:3) pixels(6,1:3);
               pixels(2,1:3) pixels(7,1:3);
               pixels(3,1:3) pixels(5,1:3);
               pixels(3,1:3) pixels(7,1:3);
               pixels(4,1:3) pixels(5,1:3);
               pixels(4,1:3) pixels(6,1:3);
               pixels(8,1:3) pixels(5,1:3);
               pixels(8,1:3) pixels(6,1:3);
               pixels(8,1:3) pixels(7,1:3)];

```



```

pixelEdgesX = [pixelEdges(:,1),pixelEdges(:,4)]';
pixelEdgesY = [pixelEdges(:,2),pixelEdges(:,5)]';
pixelEdgesZ = [pixelEdges(:,3),pixelEdges(:,6)]';

figure, imshow(grid)
hold on
plot(pixelEdgesX, pixelEdgesY)
plot(pixels(:,1), pixels(:,2), 'ro')
title(['3D cubic grid projected onto images' num2str(photoSet(k)) '.png'])
hold off

end

```

Reprojected cube coordinates on images2.png

63.4936	414.4186	1.0000
75.2674	260.6822	1.0000
-8.6060	431.3644	1.0000
221.3573	416.8171	1.0000
192.5805	434.4125	1.0000
227.6583	263.0537	1.0000
9.4105	236.5551	1.0000
201.7919	239.5595	1.0000

Reprojected cube coordinates on images9.png

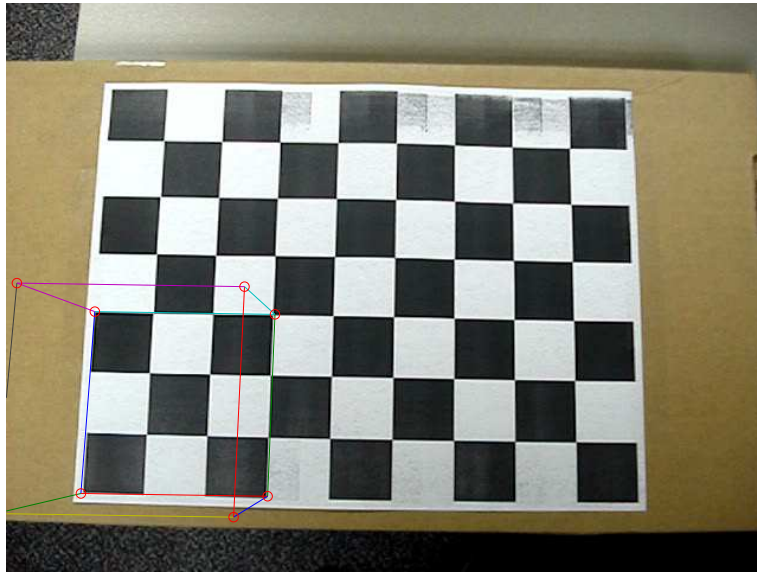
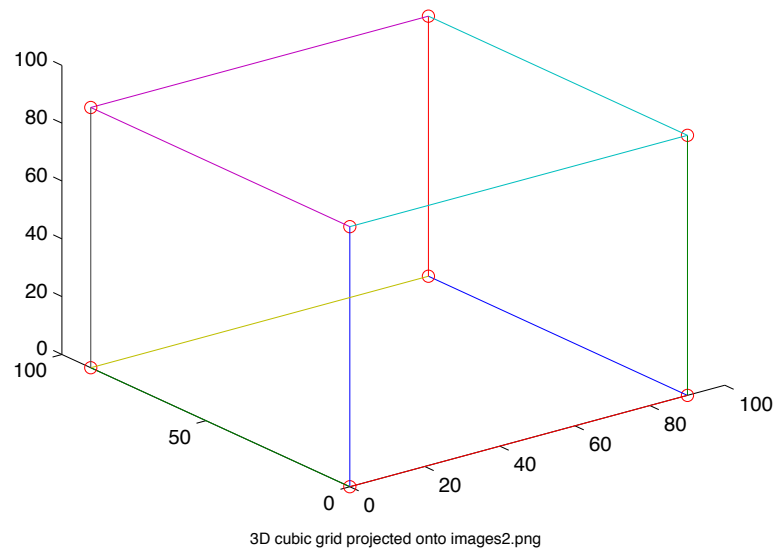
128.7522	424.4314	1.0000
131.8714	244.6465	1.0000
159.3308	460.3117	1.0000
301.2940	412.0723	1.0000
375.1122	440.5763	1.0000
300.3530	248.1139	1.0000
162.4185	226.3215	1.0000
371.8755	232.7034	1.0000

Reprojected cube coordinates on images12.png

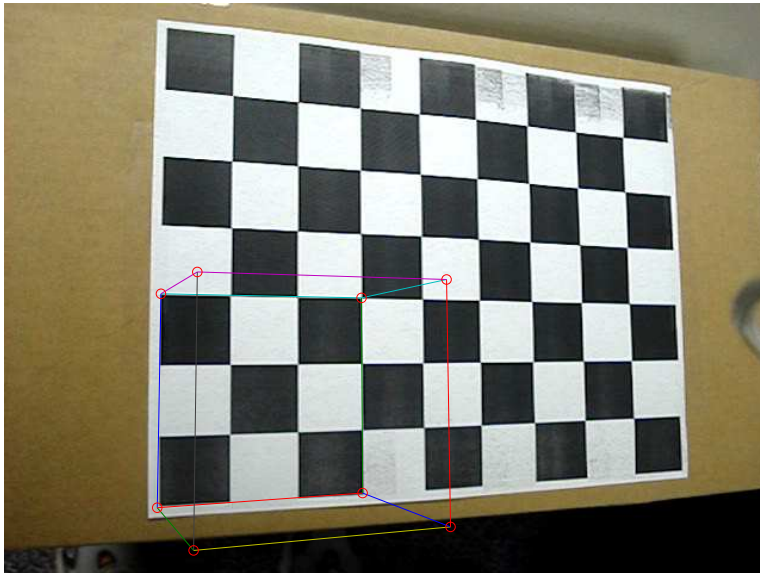
101.1891	394.5842	1.0000
106.1484	259.4707	1.0000
-14.1361	409.2226	1.0000
219.2325	399.5005	1.0000
119.4708	416.7638	1.0000
221.5283	253.3903	1.0000
-4.8328	246.1523	1.0000
125.4480	237.3996	1.0000

Reprojected cube coordinates on images20.png

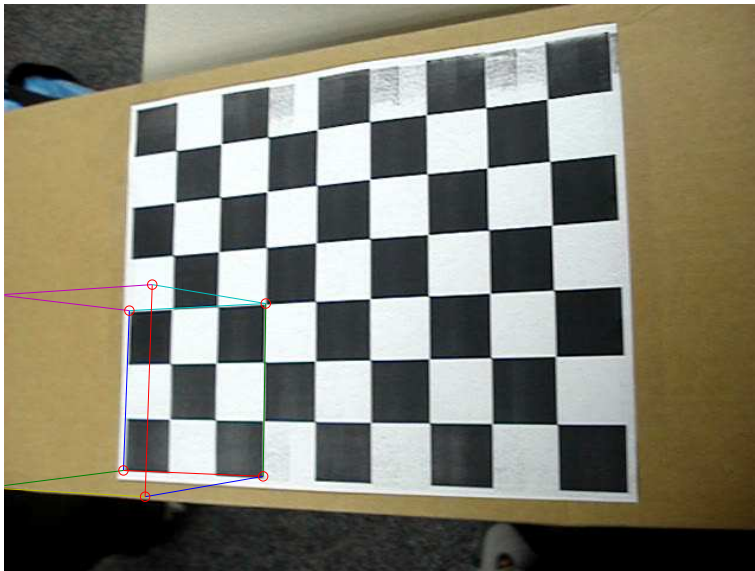
125.9504	277.1073	1.0000
151.1820	179.0929	1.0000
89.5154	161.9140	1.0000
277.6402	275.8212	1.0000
267.8818	160.4634	1.0000
283.4248	178.0105	1.0000
123.9001	66.1862	1.0000
275.9709	64.9930	1.0000

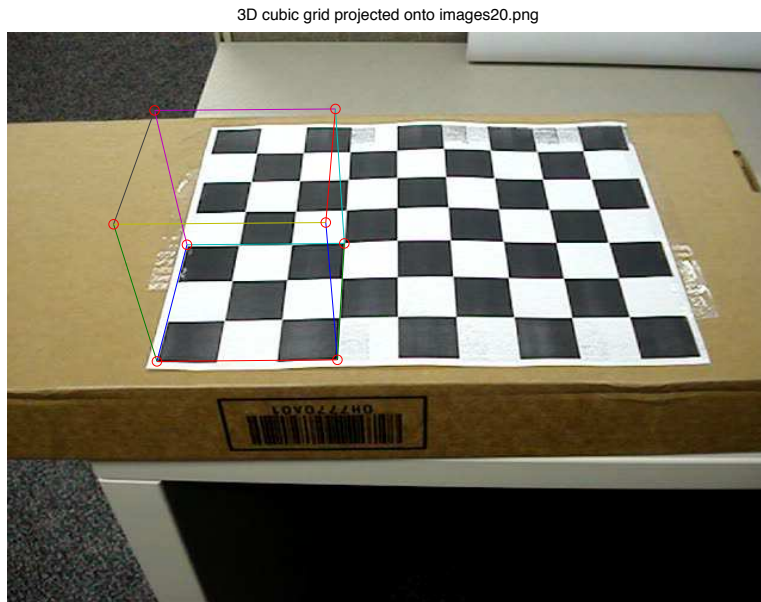


3D cubic grid projected onto images9.png



3D cubic grid projected onto images12.png





Extra Credit

Calibrate camera with only 2 images

The intrinsic and extrinsic parameters of a camera can be estimated using only 2 calibration images by treating the system as a stereo calibration system. Zhang describes this in section 2.4.9:

Let (R_s, t_s) be the rigid transformation between the two cameras such that $(R', t') = (R, t) * (R_s, t_s)$ or more precisely:

$$R' = R * R_s \text{ and } t' = R * t_s + t.$$

Stereo calibration is then to solve:

$A, A', k_1, k_2, k'_1, k'_2, \{(R_i, t_i) | i = 1, \dots, n\}$, and (R'_s, t'_s) by minimizing the following function:

$$\sum_{i=1}^n \sum_{j=1}^m [\delta_{ij} \|m_{ij} - m(A, k_1, k_2, R_i, t_i, M_j)\|^2 + [\delta'_{ij} \|m'_{ij} - m(A', k'_1, k'_2, R'_i, t'_i, M'_j)\|^2]$$

subject to $R'_i = R_i R_s$ and $t'_i = R_i t_s + t_i$.

The problem is then solved with nonlinear optimization. To obtain an initial solution, the camera is independently calibrated for each image. SVD is used to compute R_s from $R'_i = R_i R_s$ (for all n point correspondences). t_s is solved with least-squares from $t'_i = R_i t_s + t_i$ (also for all n point correspondences).

The nice part, is that now the number of point correspondences needed to estimate extrinsic parameters is reduced from $12n$ to $6n + 6$. This is the same principle the the fundamental matrix F operates by for stereo camera systems. This is why the 7 point correspondences are needed to estimate the fundamental matrix. The fundamental matrix can be used to derive a projective transformation relating the scene coordinates to world coordinates.