

HW2

January 24, 2018

CSE 252B: Computer Vision II, Winter 2018 – Assignment 2

Instructor: Ben Ochoa

Due: Wednesday, February 7, 2018, 11:59 PM

Instructions

- Review the academic integrity and collaboration policies on the course website.
- This assignment must be completed individually.
- This assignment contains both math and programming problems.
- All solutions must be written in this notebook
- Math problems must be done in Markdown/LATEX. Remember to show work and describe your solution.
- Programming aspects of this assignment must be completed using Python in this notebook.
- This notebook contains skeleton code, which should not be modified (This is important for standardization to facilitate efficient grading).
- You may use python packages for basic linear algebra, but you may not use packages that directly solve the problem. Ask the instructor if in doubt.
- You must submit this notebook exported as a pdf. You must also submit this notebook as an .ipynb file.
- You must submit both files (.pdf and .ipynb) on Gradescope. You must mark each problem on Gradescope in the pdf.
- It is highly recommended that you begin working on this assignment early.

Problem 1 (Programming): Linear estimation of the camera projection matrix (15 points)

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 camera projection matrix (i.e., $x_i = PX_i$), 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 $x_i = PX_i$ as $[x_i]^\perp PX_i = \mathbf{0}$ (not $x_i \times PX_i = \mathbf{0}$), where $[x_i]^\perp x_i = \mathbf{0}$, when forming the solution. Return P_{DLT} , scaled such that $\|P_{DLT}\|_{Fro} = 1$

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In [1]: import numpy as np
import matplotlib.pyplot as plt
```

```

x=np.loadtxt('hw2_points2D.txt').T
X=np.loadtxt('hw2_points3D.txt').T
print('x is', x.shape)
print('X is', X.shape)

def toHomo(x):
    # converts points from inhomogeneous to homogeneous coordinates
    return np.vstack((x,np.ones((1,x.shape[1])))

def fromHomo(x):
    # converts points from homogeneous to inhomogeneous coordinates
    return x[:-1,:]/x[-1,:]

def computeP_DLT(x,X):
    # inputs:
    # x 2D points
    # X 3D points
    # output:
    # P_DLT the (3x4) DLT estimate of the camera projection matrix

    """your code here"""
    P = np.eye(3,4)+np.random.randn(3,4)/10
    return P/np.sqrt(np.sum(P**2))

def proj(P,X):
    # projects 3d points X to 2d using projection matrix P
    return fromHomo(np.matmul(P,toHomo(X)))

def rmse(x,y):
    # calculates the root mean square error (RMSE)
    # used to measure reprojection error
    return np.mean(np.sqrt(np.sum((x-y)**2,0)))

def displayResults(P, x, X, title):
    print (title+' =')
    print (P)
    print ('||s||=%f'%(title, np.sqrt(np.sum(P**2)) ))

    x_proj = proj(P,X)
    plt.plot(x[0,:], x[1:], '.k')
    plt.plot(x_proj[0,:], x_proj[1:], '.r')
    for i in range(x.shape[1]):
        plt.plot([x[0,i], x_proj[0,i]], [x[1,i], x_proj[1,i]], '-r')

    plt.title('mean projection error is %f'%rmse(x,x_proj))
    plt.show()

P_DLT = computeP_DLT(x,X)

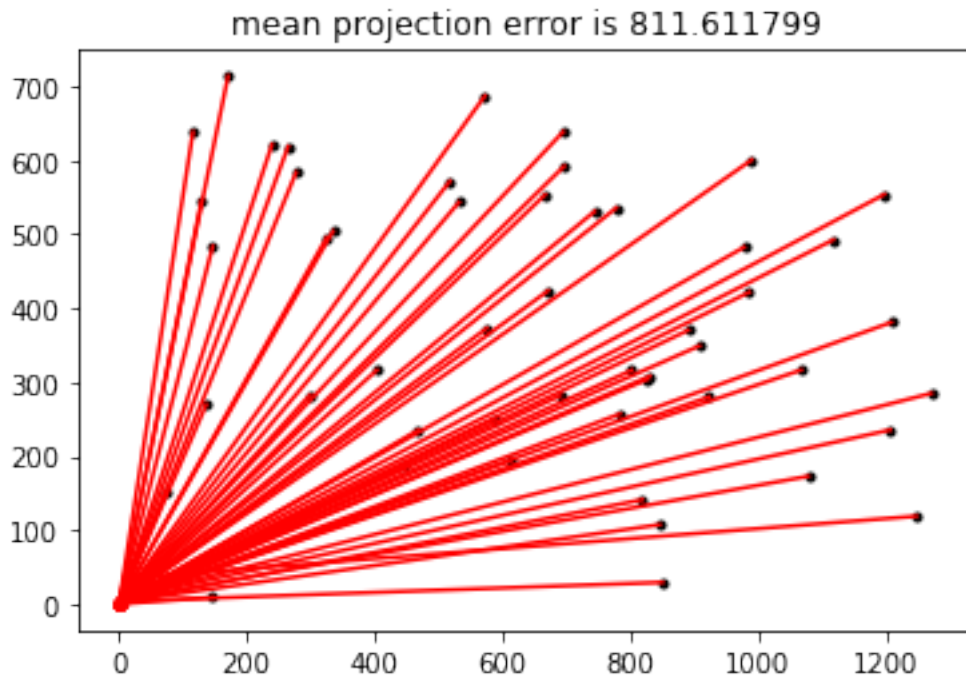
```

```

displayResults(P_DLT, x, X, 'P_DLT')

x is (2, 50)
X is (3, 50)
P_DLT =
[[ 0.59344377 -0.08964572  0.0116238  -0.0919074 ]
 [ 0.03159558  0.53853317  0.02790091 -0.01749567]
 [-0.01372009  0.12111904  0.56553239 -0.06648533]]
||P_DLT||=1.000000

```



Problem 2 (Programming): Nonlinear estimation of the camera projection matrix (30 points)

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 homogeneous vector $p = vec(P^T)$. 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. Return P_{LM} , scaled such that $\|P_{LM}\|_{Fro} = 1$. You may need to change the max iterations or implement another stopping criteria.

```

In [2]: def LMstep(P, x, X, l, v):
         # inputs:
         # P current estimate of P

```

```

# x 2D points
# X 3D points
# l LM lambda parameter
# v LM change of lambda parameter
# output:
# P updated by a single LM step
# l accepted lambda parameter

"""your code here"""
return P, l

# use P_DLT as an initialization for LM
P_LM = P_DLT.copy()

# LM hyperparameters
l=.001
v=10
max_iters=10

# LM optimization loop
for i in range(max_iters):
    P_LM, l = LMstep(P_LM, x, X, l, v)
    print ('iter %d mean reprojection error %f'%(i+1, rmse(x,proj(P_LM,X))))

displayResults(P_LM, x, X, 'P_LM')

iter 1 mean reprojection error 811.611799
iter 2 mean reprojection error 811.611799
iter 3 mean reprojection error 811.611799
iter 4 mean reprojection error 811.611799
iter 5 mean reprojection error 811.611799
iter 6 mean reprojection error 811.611799
iter 7 mean reprojection error 811.611799
iter 8 mean reprojection error 811.611799
iter 9 mean reprojection error 811.611799
iter 10 mean reprojection error 811.611799
P_LM =
[[ 0.59344377 -0.08964572  0.0116238 -0.0919074 ]
 [ 0.03159558  0.53853317  0.02790091 -0.01749567]
 [-0.01372009  0.12111904  0.56553239 -0.06648533]]
||P_LM||=1.000000

```

