

ECE 4554 / 5554: Computer Vision: Homework 3

Name : Ankit Parekh

VT Username : ankitparekh

Program : MS CPE (Non-Thesis)

Problem 1) Solution:

2D Planar Perspective Transformation or 2D-Homography:

$$\begin{bmatrix} s.x' \\ s.y' \\ 1 \end{bmatrix} = H \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \quad \text{where } H = \begin{bmatrix} h_{00} & h_{01} & h_{02} \\ h_{10} & h_{11} & h_{12} \\ h_{20} & h_{21} & h_{22} \end{bmatrix}$$

To normalize H ; $\sqrt{\sum (h_{ij})^2} = 1$ which leaves us with 8 degrees of freedom instead of 9

a) Computing Homography for a transformation:

Condition: $n \geq 4$, where n is the number of corresponding pair of points

(Considering we have n pairs of points (mappings):

$$(x'_1, y'_1) \leftrightarrow (x_1, y_1)$$

$$(x'_2, y'_2) \leftrightarrow (x_2, y_2)$$

\vdots

$$(x'_n, y'_n) \leftrightarrow (x_n, y_n)$$

We can represent the transformation as shown below:

$$\underbrace{\begin{bmatrix} \tilde{x} \\ \tilde{y} \\ \tilde{z} \end{bmatrix}}_{\text{Transformed Destination Coordinates}} = \underbrace{\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix}}_{\text{Image Coordinates}} = \underbrace{\begin{bmatrix} h_{00} & h_{01} & h_{02} \\ h_{10} & h_{11} & h_{12} \\ h_{20} & h_{21} & h_{22} \end{bmatrix}}_H \underbrace{\begin{bmatrix} x \\ y \\ 1 \end{bmatrix}}_{\text{Source Image Coordinates}}$$

For a given pair (i) of corresponding pts.:

$$x'_{(i)} = \frac{\tilde{x}_{(i)}}{\tilde{z}_{(i)}} = \frac{h_{00}x_{(i)} + h_{01}y_{(i)} + h_{02}}{h_{20}x_{(i)} + h_{21}y_{(i)} + h_{22}} \dots \text{--- (I)}$$

$$y'_{(i)} = \frac{\tilde{y}_{(i)}}{\tilde{z}_{(i)}} = \frac{h_{10}x_{(i)} + h_{11}y_{(i)} + h_{12}}{h_{20}x_{(i)} + h_{21}y_{(i)} + h_{22}} \dots \text{--- (II)}$$

Rearranging terms in (I) & (II) we get:

$$x'_{(i)} (h_{20} x_{(i)} + h_{21} y_{(i)} + h_{22}) = h_{00} x_{(i)} + h_{01} y_{(i)} + h_{02}$$

$$y'_{(i)} (h_{20} x_{(i)} + h_{21} y_{(i)} + h_{22}) = h_{10} x_{(i)} + h_{11} y_{(i)} + h_{12}$$

Rearranging terms and writing in matrix notation:

$$\begin{bmatrix} x_{(i)} & y_{(i)} & 1 & 0 & 0 & 0 & -x'_{(i)} x_{(i)} & -x'_{(i)} y_{(i)} & -x'_{(i)} \\ 0 & 0 & 0 & x_{(i)} & y_{(i)} & 1 & -y'_{(i)} x_{(i)} & -y'_{(i)} y_{(i)} & -y'_{(i)} \end{bmatrix} \begin{bmatrix} h_{00} \\ h_{01} \\ h_{02} \\ h_{10} \\ h_{11} \\ h_{12} \\ h_{20} \\ h_{21} \\ h_{22} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

Combining the equations for all corresponding pts.:

$$\underbrace{\begin{bmatrix} x_1 & y_1 & 1 & 0 & 0 & 0 & -x'_1 x_1 & -x'_1 y_1 & -x'_1 \\ 0 & 0 & 0 & x_1 & y_1 & 1 & -y'_1 x_1 & -y'_1 y_1 & -y'_1 \\ x_2 & y_2 & 1 & 0 & 0 & 0 & -x'_2 x_2 & -x'_2 y_2 & -x'_2 \\ 0 & 0 & 0 & x_2 & y_2 & 1 & -y'_2 x_2 & -y'_2 y_2 & -y'_2 \\ \vdots & & & \vdots & & & \vdots & & \vdots \\ x_n & y_n & 1 & 0 & 0 & 0 & -x'_n x_n & -x'_n y_n & -x'_n \\ 0 & 0 & 0 & x_n & y_n & 1 & -y'_n x_n & -y'_n y_n & -y'_n \end{bmatrix}}_{2n \times 9} \underbrace{\begin{bmatrix} h_{00} \\ h_{01} \\ h_{02} \\ h_{10} \\ h_{11} \\ h_{12} \\ h_{20} \\ h_{21} \\ h_{22} \end{bmatrix}}_{9 \times 1} = \underbrace{\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}}_{2n \times 1}$$

$Q \quad a \quad 0$

We can write the above as: $Qa = 0$

Solving for a such that $\|a\|^2 = 1$. We can use least squares method to solve the problem.

Defining Least Squares Problem:

$$\min_a \|Qa\|^2 \text{ such that } \|a\|^2 = 1$$

We know that: $\|Qa\|^2 = (Qa)^T(Qa) = a^T Q^T Q a$
 and $\|a\|^2 = a^T a = 1$

∴ We need to solve: $\min_a (a^T Q^T Q a)$ such that $a^T a = 1$

Defining Loss function: $L(a, \lambda) = a^T Q^T Q a - \lambda (a^T a - 1)$

and we need to find a that minimizes L

Taking derivative of $L(a, \lambda)$ w.r.t. a :

$$2Q^T Q a - 2\lambda a = 0$$

$$Q^T Q a = \lambda a \quad \text{Eigen Value Problem}$$

Eigen vector a with smallest eigen value λ of matrix $Q^T Q$ minimizes the loss function $L(\lambda)$.

1b) Given set of Key-point pairs:

$$(x_i', y_i') \leftrightarrow (x_i, y_i)$$

$$(3.0, 2.0) \leftrightarrow (0, 0)$$

$$(3.67, 2.0) \leftrightarrow (1, 0)$$

$$(3.53, 2.5) \leftrightarrow (1, 1)$$

$$(3.0, 3.0) \leftrightarrow (0, 1)$$

Creating Q matrix using above:

$$Q = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & -3 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & -2 \\ 1 & 0 & 1 & 0 & 0 & 0 & -3.67 & 0 & -3.67 \\ 0 & 0 & 0 & 1 & 0 & 0 & -2.0 & 0 & -2.0 \\ 1 & 1 & 1 & 0 & 0 & 0 & -3.5 & -3.5 & -3.5 \\ 0 & 0 & 0 & 1 & 1 & 1 & -2.5 & -2.5 & -2.5 \\ 0 & 1 & 1 & 0 & 0 & 0 & 0 & -3.0 & -3.0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 0 & -3.0 & -3.0 \end{bmatrix}$$

Solving the above Eigen Value problem using Python code.

Python Code to Solve the Above Eigen Value Problem:

```
1. def step_break(): # function for output clarity, draws lines between steps
2.     for i in range(70):
3.         print("=", end="")
4.         print()
5.
6. print("Python code for solving Eigen Value problem [transpose(Q).Q.a =  $\lambda$ .a]")
7. import numpy as np
8.
9. step_break()
10. print("Step 1 - Initializing matrix Q:")
11. Q = np.array([[0, 0, 1, 0, 0, 0, 0, 0, -3], [0, 0, 0, 0, 0, 1, 0, 0, -2], [1, 0,
    1, 0, 0, 0, -3.67, 0, -3.67], [0, 0, 0, 1, 0, 1, -2, 0, -2], [1, 1, 1, 0, 0, 0, -
    3.5, -3.5, -3.5], [0, 0, 0, 1, 1, 1, -2.5, -2.5, -2.5], [0, 1, 1, 0, 0, 0, 0, -3,
    3], [0, 0, 0, 0, 1, 1, 0, -3, -3]])
12. print(Q)
13.
14. step_break()
15. print("Step 2 - Computing matrix = transpose(Q).Q:")
16. matrix = np.matmul(np.transpose(Q), Q)
17. print(matrix)
18.
19. step_break()
20. print("Step 3 - Computing eigen values of matrix:") #np.linalg.eigh returns eigen
    values as well as vectors, [0]: values, [1]: vectors (columns in the matrix)
21. eigen_values = np.linalg.eigh(matrix)[0]
22. print(eigen_values)
23.
24. step_break()
25. print("Step 4 - Computing eigen vectors of matrix:") #np.linalg.eigh returns
    eigen values as well as vectors, [0]: values, [1]: vectors (columns in the matrix)
26. eigen_vectors = np.transpose(np.linalg.eigh(matrix)[1])
27. print(eigen_vectors)
28.
29. step_break()
30. print("Step 5 - Smallest eigen value of matrix:")
31. min_eigen_value = min(eigen_values)
32. print(min_eigen_value)
33.
34. step_break()
35. print("Step 6 - Index of smallest eigen value of the matrix:")
36. idx_min_eigen_value = eigen_values.tolist().index(min_eigen_value)
37. print(idx_min_eigen_value)
38.
39. step_break()
40. print("Step 7 - Eigen vector corresponding to smallest eigen value:")
41. eigen_vector = np.linalg.eigh(matrix)[1][:, idx_min_eigen_value]
42. print(eigen_vector)
43.
44. step_break()
45. print("Step 8 - Magnitude of eigen vector in Step 6:")
46. magnitude = sum([x**2 for x in eigen_vector])
47. print(magnitude)
```

```

48. print("Approximately equal to 1")
49.
50. step_break()
51. print("Step 9 - Solution to our eigen value problem:")
52. print("2D Homography matrix H:")
53. h_string = "h00,h01,h02,h10,h11,h12,h20,h21,h22"
54. SUB = str.maketrans("012", "012")
55. h_parameters = h_string.translate(SUB).split(",")
56. h = np.array([h_parameters[0:3],h_parameters[3:6],h_parameters[6:9]])
57. print(h)
58.
59. step_break()
60. print("Step 10 - Arranging values from eigen vector in H matrix:")
61. print("H =")
62. H = np.array([eigen_vector[0:3],eigen_vector[3:6], eigen_vector[6:9]])
63. print(H)
64.
65. step_break()
66. print("Step 11 - Normalizing H - Dividing all parameters of H by
    {}: ".format(h_parameters[-1]))
67. normalized_H = H/H[2][2]
68. print(normalized_H)

```

Output:

Python code for solving Eigen Value problem $[transpose(Q) \cdot Q \cdot a = \lambda \cdot a]$

=====

Step 1 - Initializing matrix Q:

```

[[ 0.  0.  1.  0.  0.  0.  0.  0. -3. ]
 [ 0.  0.  0.  0.  0.  1.  0.  0. -2. ]
 [ 1.  0.  1.  0.  0.  0. -3.67 0. -3.67]
 [ 0.  0.  0.  1.  0.  1. -2.  0. -2. ]
 [ 1.  1.  1.  0.  0.  0. -3.5 -3.5 -3.5 ]
 [ 0.  0.  0.  1.  1.  1. -2.5 -2.5 -2.5 ]
 [ 0.  1.  1.  0.  0.  0.  0. -3. -3. ]
 [ 0.  0.  0.  0.  1.  1.  0. -3. -3. ]]

```

=====

Step 2 - Computing matrix = transpose(Q).Q:

```

[[ 2.  1.  2.  0.  0.  0.  0. -7.17 -3.5
 -7.17 ]
 [ 1.  2.  2.  0.  0.  0. -3.5 -6.5
 -6.5 ]
 [ 2.  2.  4.  0.  0.  0. -7.17 -6.5
 -13.17 ]
 [ 0.  0.  0.  2.  1.  2. -4.5 -2.5
 -4.5 ]
 [ 0.  0.  0.  1.  2.  2. -2.5 -5.5
 -5.5 ]
 [ 0.  0.  0.  2.  2.  4. -4.5 -5.5
 -9.5 ]
 [ -7.17 -3.5 -7.17 -4.5 -2.5 -4.5 35.9689 18.5
 35.9689 ]
 [ -3.5 -6.5 -6.5 -2.5 -5.5 -5.5 18.5 36.5
 36.5 ]
 [ -7.17 -6.5 -13.17 -4.5 -5.5 -9.5 35.9689 36.5
 66.9689 ]]

```

=====

Step 3 - Computing eigen values of matrix:

```

[1.44492540e-14 3.23775075e-03 1.17328773e-02 6.28086068e-01
 1.05035523e+00 6.29874446e+00 9.88257262e+00 1.87961201e+01
 1.18766951e+02]

```

=====

Step 4 - Computing eigen vectors of matrix:

```

[[ 7.18057522e-01  2.73290549e-01  2.65252592e-01  3.59028761e-01
  3.61708080e-01  1.76835061e-01  1.79514380e-01  9.10968498e-02
  8.84175307e-02]
[-4.68653807e-03  5.00438751e-01 -6.54552704e-01  6.56928604e-02
  2.58398623e-01 -4.28997984e-01  2.20950428e-02  1.48279603e-01
 -2.08566893e-01]
[ 4.07730520e-01 -4.84488207e-01 -3.24353129e-01  3.88046463e-01
 -4.58755182e-01 -2.79928161e-01  1.40707551e-01 -1.47206781e-01
 -1.13830779e-01]
[-3.32909483e-01 -2.89584122e-01  3.54788984e-01  4.34083050e-01
 4.52219902e-01 -5.35246885e-01 -3.12081578e-03  9.97485289e-04
 -2.48873938e-03]
[ 3.35554163e-01 -4.88329187e-01 -1.56639859e-01 -6.01849029e-01
 4.96304364e-01 -1.16856122e-01 -2.01472277e-02 -1.92615327e-02
 -3.78076235e-02]
[-2.36105681e-01 -2.98819894e-01 -4.45424089e-01  3.89196755e-01
 3.42505169e-01  6.18675813e-01 -4.51864574e-02  5.42285401e-02
 -5.65175407e-03]
[ 9.04568314e-02  1.01654722e-01 -1.60267366e-01  7.64971115e-02
 6.45653836e-02 -1.01836981e-01 -5.12604777e-01 -5.18284718e-01
 6.35629040e-01]
[ 1.50909611e-01 -1.06411560e-01  4.05220697e-02  6.99782104e-02
 -1.22604415e-01 -5.09702230e-02 -6.90550855e-01  6.81816058e-01
 6.73648288e-04]
[-8.94421224e-02 -8.28837628e-02 -1.40908882e-01 -5.77019885e-02
 -6.78963620e-02 -1.02260644e-01  4.53217579e-01  4.59608273e-01
 7.28170627e-01]]

```

```

=====
Step 5 - Smallest eigen value of matrix:
1.444925396309616e-14
=====

```

```

Step 6 - Index of smallest eigen value of the matrix:
0
=====

```

```

Step 7 - Eigen vector corresponding to smallest eigen value:
[0.71805752 0.27329055 0.26525259 0.35902876 0.36170808 0.17683506
 0.17951438 0.09109685 0.08841753]
=====

```

```

Step 8 - Magnitude of eigen vector in Step 6:
0.9999999999999999
Approximately equal to 1
=====

```

```

Step 9 - Solution to our eigen value problem:
2D Homography matrix H:
[['h00' 'h01' 'h02']
 ['h10' 'h11' 'h12']
 ['h20' 'h21' 'h22']]
=====

```

```

Step 10 - Arranging values from eigen vector in H matrix:
H =
[[0.71805752 0.27329055 0.26525259]
 [0.35902876 0.36170808 0.17683506]
 [0.17951438 0.09109685 0.08841753]]
=====

```

```

Step 11 - Normalizing H - Dividing all parameters of H by h22:
[[8.12121212 3.09090909 3.          ]
 [4.06060606 4.09090909 2.          ]
 [2.03030303 1.03030303 1.          ]]

```


Problem 2) Solution:

2D Affine Transformation:

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = A \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}, \text{ where } A = \begin{bmatrix} a_{00} & a_{01} & a_{02} \\ a_{10} & a_{11} & a_{12} \\ 0 & 0 & 1 \end{bmatrix}$$

2a) let A be an invertible matrix, let \vec{b} be a vector, and let $f: \mathbb{R}^2 \rightarrow \mathbb{R}^2$ be defined as an Affine Transformation via $f(\vec{x}) \mapsto A\vec{x} + \vec{b}$.

$$f(\vec{x}) = \vec{y}$$

$$A\vec{x} + \vec{b} = \vec{y}$$

$$A\vec{x} = \vec{y} - \vec{b}$$

$$A^{-1}(A\vec{x}) = A^{-1}(\vec{y} - \vec{b})$$

Multiplying A^{-1} on both sides

$$I_2 \vec{x} = A^{-1}\vec{y} - A^{-1}\vec{b}$$

$$\vec{x} = A^{-1}(\vec{y} - \vec{b})$$

We can conclude that f^{-1} exists and can be given by $f^{-1}(\vec{x}) = A^{-1}(\vec{x} - \vec{b})$

This is also an Affine transformation.

$$\text{For every vector } \vec{x}: (f \circ f^{-1})(\vec{x}) = (f \circ f^{-1})(\vec{x}) = \vec{x}$$

\therefore Both f & f^{-1} are bijections on \mathbb{R}^2

2b) Computing transformed coordinates:

$$(x, y) \mapsto (0, 0) \quad ; \quad (x, y) \mapsto (1, 0) \quad ; \quad (x, y) \mapsto (0, 1)$$

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} a_{00} & a_{01} & a_{02} \\ a_{10} & a_{11} & a_{12} \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \quad ; \quad \begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} a_{00} & a_{01} & a_{02} \\ a_{10} & a_{11} & a_{12} \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix} \quad ; \quad \begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} a_{00} & a_{01} & a_{02} \\ a_{10} & a_{11} & a_{12} \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}$$

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} a_{02} \\ a_{12} \\ 1 \end{bmatrix}$$

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} a_{00} + a_{02} \\ a_{10} + a_{12} \\ 1 \end{bmatrix}$$

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} a_{01} + a_{02} \\ a_{11} + a_{12} \\ 1 \end{bmatrix}$$

$$(x', y') \Rightarrow (a_{02}, a_{12})$$

$$(x', y') \Rightarrow (a_{00} + a_{02}, a_{10} + a_{12})$$

$$(x', y') \Rightarrow (a_{01} + a_{02}, a_{11} + a_{12})$$

2c) A & B are both 3x3 affine transformation matrices

let $f(\vec{x}) = A\vec{x} + \vec{a}$ represent transformation using matrix A
 $g(\vec{x}) = B\vec{x} + \vec{b}$ represent transformation using matrix B

$$\begin{aligned}\text{Then, } (g \circ f)(\vec{x}) &= g(f(\vec{x})) \\ &= B(A\vec{x} + \vec{a}) + \vec{b} \\ &= (BA)\vec{x} + (B\vec{a} + \vec{b})\end{aligned}$$

Since A & B are invertible, (BA) is invertible as well.
∴ (g ∘ f) or BA is also an affine transformation.

We can show this through matrix multiplication as well:

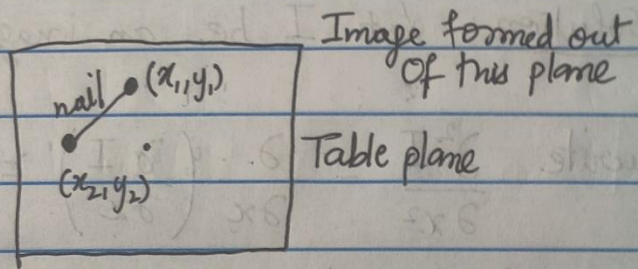
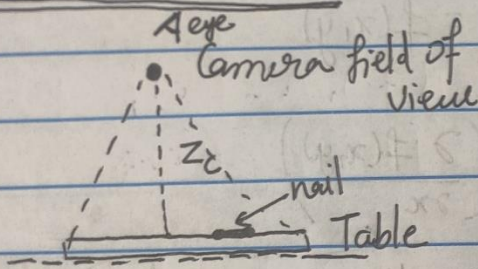
$$BA = \begin{bmatrix} b_{00} & b_{01} & b_{02} \\ b_{10} & b_{11} & b_{12} \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} a_{00} & a_{01} & a_{02} \\ a_{10} & a_{11} & a_{12} \\ 0 & 0 & 1 \end{bmatrix}$$

$$BA = \begin{bmatrix} b_{00}a_{00} + b_{01}a_{10} & b_{00}a_{01} + b_{01}a_{11} & b_{00}a_{02} + b_{01}a_{12} + b_{02} \\ b_{10}a_{00} + b_{11}a_{10} & b_{10}a_{01} + b_{11}a_{11} & b_{10}a_{02} + b_{11}a_{12} + b_{12} \\ 0 & 0 & 1 \end{bmatrix}$$

$$BA = \begin{bmatrix} c_{00} & c_{01} & c_{02} \\ c_{10} & c_{11} & c_{12} \\ 0 & 0 & 1 \end{bmatrix} \text{ where } c \text{ represents a constant.}$$

∴ BA is also an affine transformation

Problem 3) Solution:



$$\text{length of the nail (distance formula)} = l = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$$

Considering ideal perspective projection, we can compute image positions of (x_1, y_1) as (x'_1, y'_1) & (x_2, y_2) as (x'_2, y'_2) .

$$\begin{bmatrix} x'_1 \\ y'_1 \end{bmatrix} = \frac{f}{z_c} \begin{bmatrix} x_1 \\ y_1 \end{bmatrix} \quad \& \quad \begin{bmatrix} x'_2 \\ y'_2 \end{bmatrix} = \frac{f}{z_c} \begin{bmatrix} x_2 \\ y_2 \end{bmatrix}$$

$$\text{length of nail in the image} = l' = \sqrt{\left(\frac{f}{z_c}\right)^2 (x_1 - x_2)^2 + \left(\frac{f}{z_c}\right)^2 (y_1 - y_2)^2}$$

$$l' = \sqrt{\left(\frac{f}{z_c}\right)^2 [(x_1 - x_2)^2 + (y_1 - y_2)^2]}$$

$$l' = \frac{f}{z_c} \times l$$

$\therefore l'$ is only dependent on f , z_c & l , and not dependent on nail's position or orientation.

$\therefore l'$ will remain constant irrespective of changes in position of nail or orientation in case of ideal perspective projection.

Problem 4) Solution: Let I be an image. $I = f(x, y)$

We can write
$$\frac{\partial^2 I}{\partial x^2} = \frac{\partial}{\partial x} \left(\frac{\partial I}{\partial x} \right) = \frac{\partial}{\partial x} \left(\frac{\partial f(x, y)}{\partial x} \right)$$

Using Backward Diff. Formula of derivative in x-direction

$$\frac{\partial^2 I}{\partial x^2} = \frac{\partial}{\partial x} \left(\lim_{h \rightarrow 0} \frac{f(x, y) - f(x-h, y)}{h} \right)$$

For images that have discrete pixel values, we have to consider the smallest difference as $h=1$

$$\frac{\partial^2 I}{\partial x^2} = \frac{\partial}{\partial x} \left(\frac{f(x, y) - f(x-1, y)}{1} \right)$$

$$\frac{\partial^2 I}{\partial x^2} = \frac{f'(x, y) - f'(x-1, y)}{1}$$

$$\left[f'(x, y) = \frac{\partial}{\partial x} (f(x, y)) \right]$$

$$\left[f'(x-1, y) = \frac{\partial}{\partial x} (f(x-1, y)) \right]$$

Using forward difference formula above:

$$\frac{\partial^2 I}{\partial x^2} = \left[\frac{f(x+1, y) - f(x, y)}{1} \right] - \left[\frac{f(x, y) - f(x-1, y)}{1} \right]$$

$$\frac{\partial^2 I}{\partial x^2} = f(x+1, y) - 2f(x, y) + f(x-1, y)$$

We can take the coefficients of eqn. above to create a convolutional filter in x-direction:

$$\Rightarrow \begin{bmatrix} 1 & -2 & 1 \end{bmatrix}$$

$\swarrow \quad \downarrow \quad \searrow$
 $f(x-1, y) \quad f(x, y) \quad f(x+1, y)$

∴ $\frac{\partial^2 I}{\partial x^2}$ is approximated using $\begin{bmatrix} 1 & -2 & 1 \end{bmatrix}$ kernel