

LUCAS KANADE HOMEWORK 3

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1.1 a)

$$W(x; p) = \begin{bmatrix} 1 & 0 & p_1 \\ 0 & 1 & p_2 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

$$\Rightarrow \begin{bmatrix} W_x(x; p) \\ W_y(x; p) \end{bmatrix} = \begin{bmatrix} x + p_1 \\ y + p_2 \end{bmatrix}$$

Taking derivative w.r.t p:

$$\frac{\partial W(x; p)}{\partial p^T} = \begin{bmatrix} \frac{\partial(x + p_1)}{\partial p_1} & \frac{\partial(x + p_1)}{\partial p_2} \\ \frac{\partial(y + p_2)}{\partial p_1} & \frac{\partial(y + p_2)}{\partial p_2} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

1.1 b)

$$A = \sum_{x \in N} \frac{\partial I_{t+1}(x')}{\partial x'^T} \frac{\partial W(x; p)}{\partial p^T}$$

A is the steepest gradient of the images

$$b = \sum_{x \in N} I_t(x) - I_{t+1}(x')$$

b is the error image

1.1 c)

To minimize Δp :

$$\operatorname{argmin}_{\Delta p} \|A\Delta p - b\|_2^2$$

$$\sum_{x \in N} A^T (A\Delta p - b) = 0$$

$$\sum_{x \in N} A^T A \Delta p = \sum_{x \in N} A^T b$$

$$\Delta p = \sum_{x \in N} A^T A (A^T b)$$

for Δp to have a unique solution $A^T A$ must be invertible and non singular.

1.2

```
❷ LucasKanade.py > ...
1  import numpy as np
2  from scipy.interpolate import RectBivariateSpline
3
4  def LucasKanade(It, It1, rect, threshold, num_iters, p0=np.zeros(2)):
5      """
6          :param It: template image
7          :param It1: Current image
8          :param rect: Current position of the car (top left, bot right coordinates)
9          :param threshold: if the length of dp is smaller than the threshold, terminate the optimization
10         :param num_iters: number of iterations of the optimization
11         :param p0: Initial movement vector [dp_x0, dp_y0]
12         :return: p: movement vector [dp_x, dp_y]
13     """
14     p = p0
15     # Adding a threshold value below which delta p should be
16     # Put your implementation here
17     h1 = It.shape[0]
18     w1 = It.shape[1]
19     h2 = It1.shape[0]
20     w2 = It1.shape[1]
21
22     x0 = rect[0]
23     y0 = rect[1]
24
25     x1 = rect[2]
26     y1 = rect[3]
27
28     interp_It = RectBivariateSpline(np.arange(h1),np.arange(w1),It)
29     interp_It1 = RectBivariateSpline(np.arange(h2),np.arange(w2),It1)
30
31     columns,rows = np.meshgrid(np.linspace(x0,x1,87),np.linspace(y0,y1,36))
32
33     var1 = int((y1-y0)+1)
34     var2 = int((x1-x0)+1)
35
36     pixel = interp_It.ev(rows,columns)
37     for i in range(int(num_iters)):
38
39         warped_rows = np.linspace(p[1]+y0,p[1]+y1, 36)
40         warped_col = np.linspace(p[0]+x0,p[0]+x1, 87)
41         grad_col, grad_row = np.meshgrid(warped_col,warped_rows)
42
43         dx = interp_It1.ev(grad_row,grad_col,dx=1,dy=0)
44         dy = interp_It1.ev(grad_row,grad_col,dx=0,dy=1)
45
46         A = np.vstack((dy.flatten(),dx.flatten())).T
47
48         pixel_warped = interp_It1.ev(grad_row,grad_col)
49         b = (pixel.flatten()-pixel_warped.flatten())
50
51         del_p = np.linalg.pinv(A.T @ A) @ A.T @ b
52         p += del_p
53         if np.linalg.norm(del_p) < threshold:
54             break
55
56     return p
```

1.3

testCarSequence.py Results:



Frame 1



Frame 100



Frame 200



Frame 300



Frame 400

testGirlSequence.py Results:



Frame 1



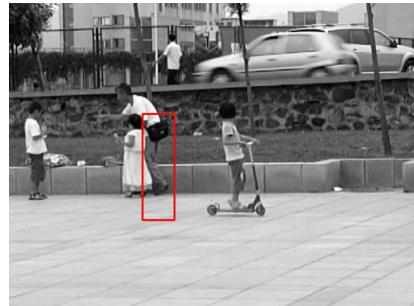
Frame 20



Frame 40



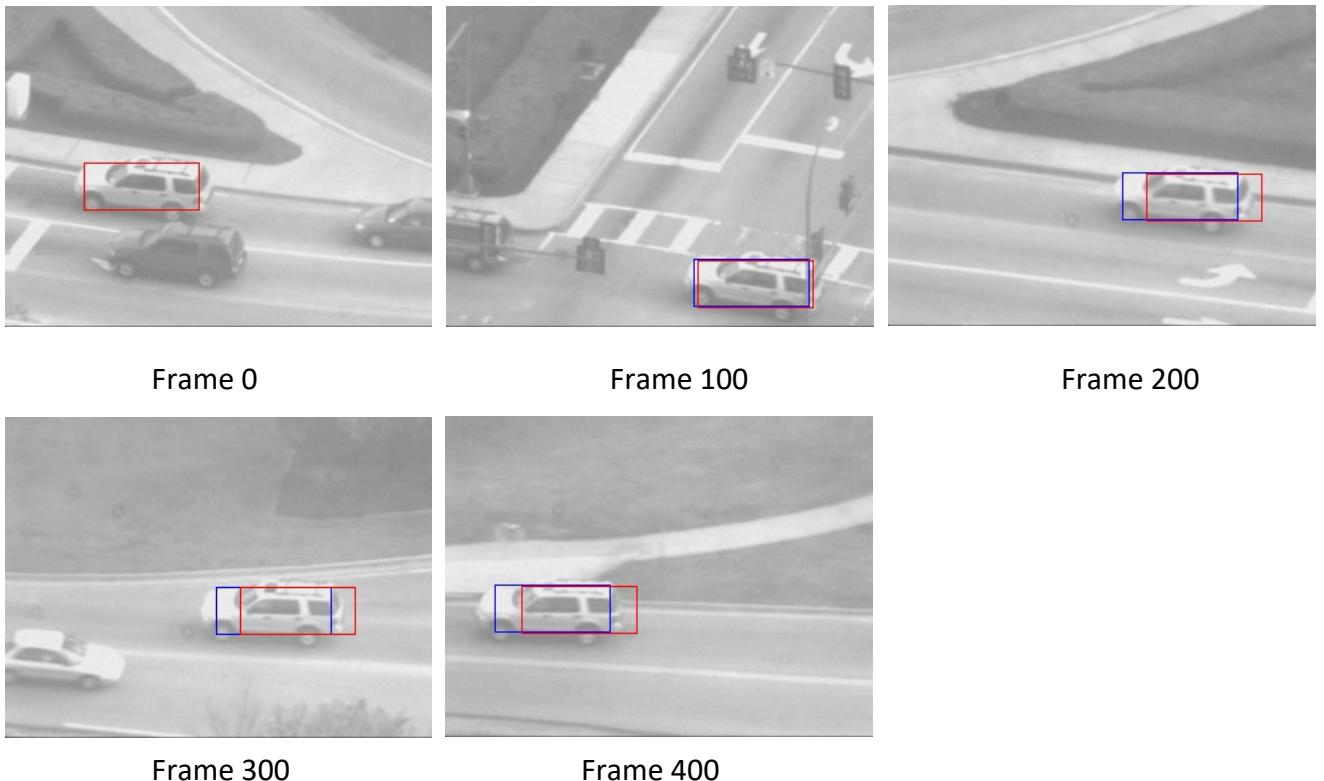
Frame 60



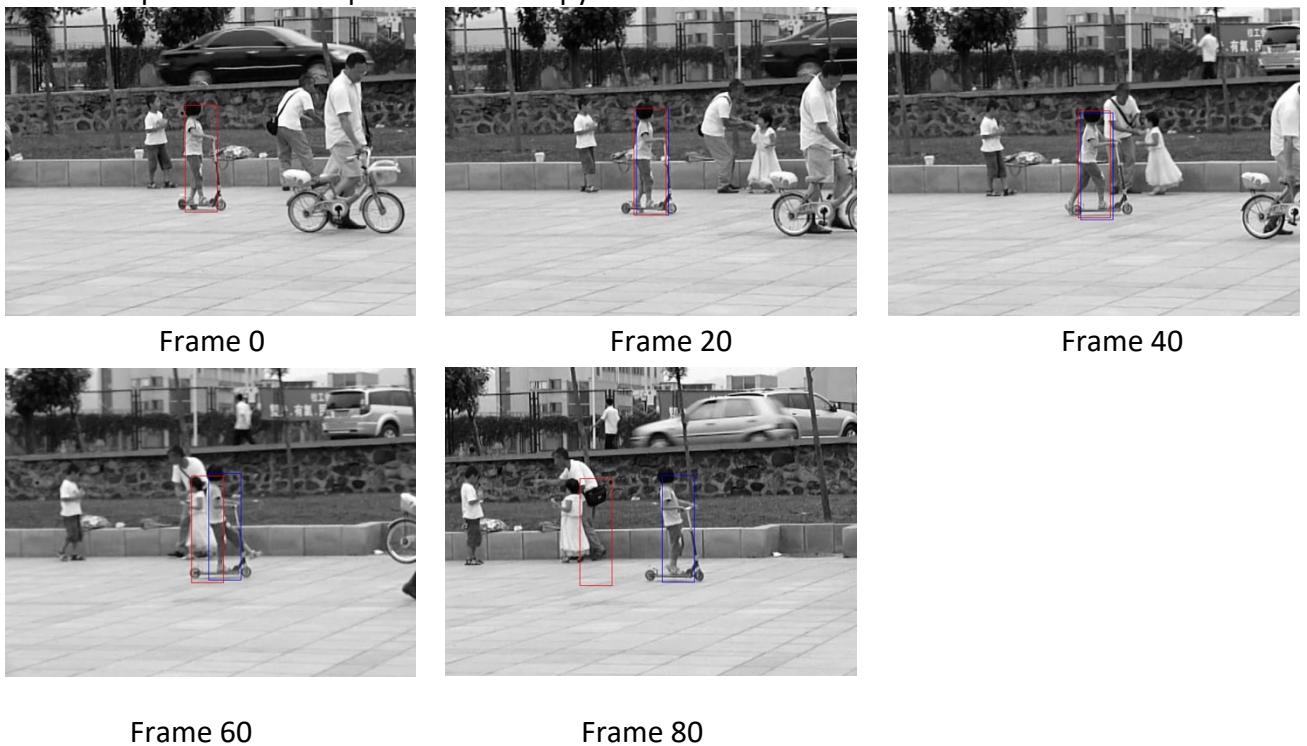
Frame 80

1.4

testCarSequenceWithTemplateCorrection.py



testGirlSequenceWithTemplateCorrection.py



2.1

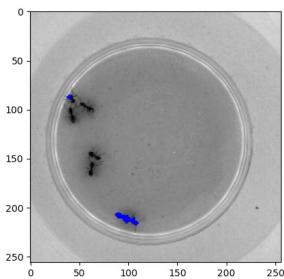
```
↳ LucasKanadeAffine.py > ⚙ LucasKanadeAffine
 1 import numpy as np
 2 from scipy.interpolate import RectBivariateSpline
 3 from scipy.ndimage import affine_transform, sobel
 4
 5 def LucasKanadeAffine(It, It1, threshold, num_iters):
 6     """
 7         :param It: template image
 8         :param It1: Current image
 9         :param threshold: if the length of dp is smaller than the threshold, terminate the optimization
10         :param num_iters: number of iterations of the optimization
11         :return: M: the Affine warp matrix [2x3 numpy array] put your implementation here
12     """
13     # put your implementation here
14     M = np.array([[1.0, 0.0, 0.0], [0.0, 1.0, 0.0]])
15     p = np.zeros([6])
16
17     h1 = It.shape[0]
18     w1 = It.shape[1]
19     h2 = It1.shape[0]
20     w2 = It1.shape[1]
21     interp_It = RectBivariateSpline(np.arange(h1), np.arange(w1), It)
22     interp_It1 = RectBivariateSpline(np.arange(h2), np.arange(w2), It1)
23
24     for i in range(int(num_iters)):
25         #Computing b
26         It_warp = affine_transform(It, M)
27
28         #Computing A
29         grad_col, grad_row = np.meshgrid(np.linspace(0,w1-1,w1),np.linspace(0,h1-1,h1))
30
31         grad_col = grad_col.flatten()
32         grad_row = grad_row.flatten()
33
34         dx = affine_transform(sobel(It1,1),M)
35         dy = affine_transform(sobel(It1,0),M)
36
37         dx = dx.flatten().T
38         dy = dy.flatten().T
39
40         A = np.array([dx * grad_col, dx * grad_row, dx,
41                     | | | | dy * grad_col, dy * grad_row, dy]).T
42         b = (It-It_warp).flatten()
43         del_p = np.linalg.pinv(A.T @ A) @ A.T @ b
44         p += del_p
45         M[0,0] = 1+p[0]
46         M[0,1] = p[1]
47         M[0,2] = p[2]
48         M[1,0] = p[3]
49         M[1,1] = 1+p[4]
50         M[1,2] = p[5]
51         if np.linalg.norm(del_p) < threshold:
52             | break
53     return M
```

2.2

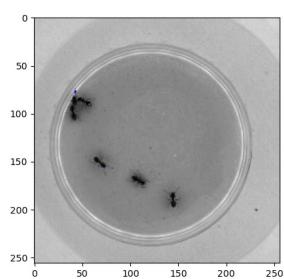
```
SubtractDominantMotion.py > SubtractDominantMotion
1 import numpy as np
2 from scipy.ndimage.morphology import binary_erosion, binary_dilation
3 from scipy.ndimage import affine_transform
4 from LucasKanadeAffine import LucasKanadeAffine
5 from InverseCompositionAffine import InverseCompositionAffine
6
7 def SubtractDominantMotion(image1, image2, threshold, num_iters, tolerance):
8     """
9         :param image1: Images at time t
10        :param image2: Images at time t+1
11        :param threshold: used for LucasKanadeAffine
12        :param num_iters: used for LucasKanadeAffine
13        :param tolerance: binary threshold of intensity difference when computing the mask
14        :return: mask: [nxm]
15    """
16
17    # put your implementation here
18    mask = np.ones(image1.shape, dtype=bool)
19    # M = LucasKanadeAffine(image1, image2, threshold, num_iters)
20    M = InverseCompositionAffine(image1, image2, threshold, num_iters)
21
22    It_warp = affine_transform(image1, M)
23    err = np.absolute(It_warp - image2)
24    mask = err > tolerance
25    mask = binary_dilation(mask, iterations = 5)
26    mask = binary_erosion(mask, iterations = 4)
27
28    return mask
29
```

2.3

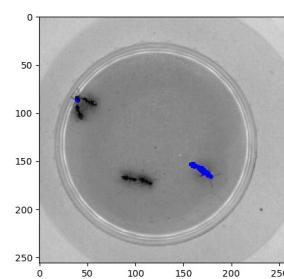
testAntSequence.py



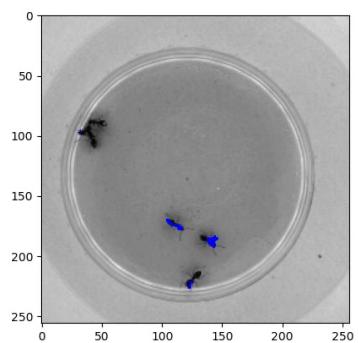
Frame 30



Frame 60

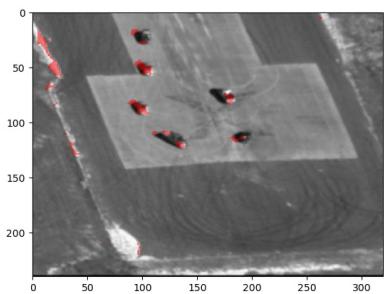


Frame 90

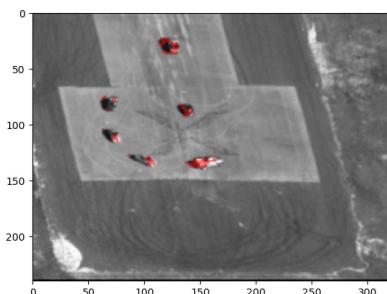


Frame 120

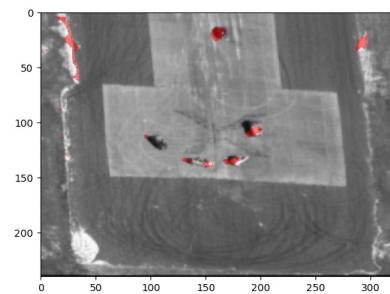
testAerialSequence.py



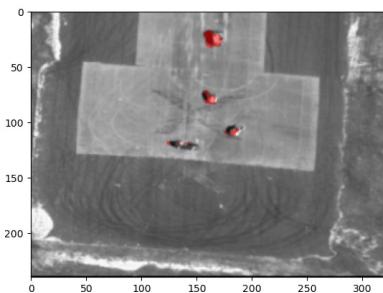
Frame 30



Frame 60



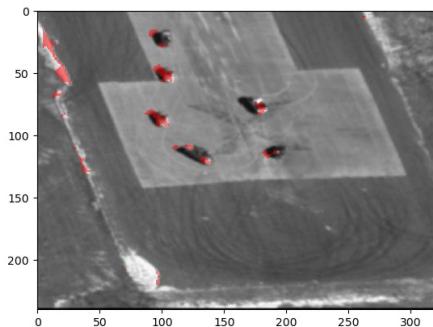
Frame 90



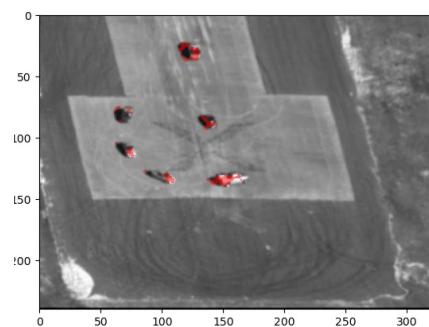
Frame 120

3.1

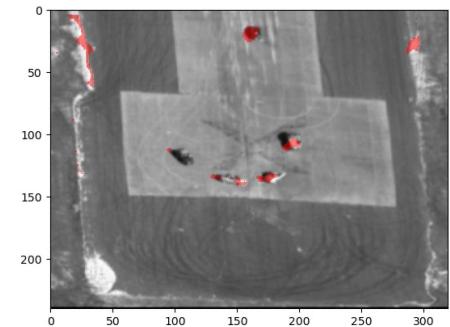
testAerialSequence.py (Inverse Composition)



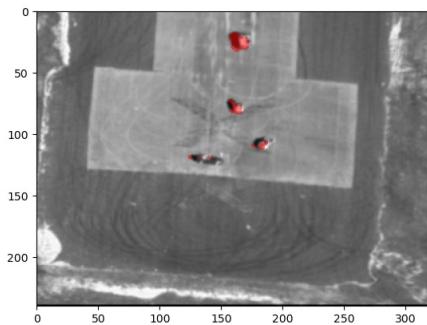
Frame 30



Frame 60

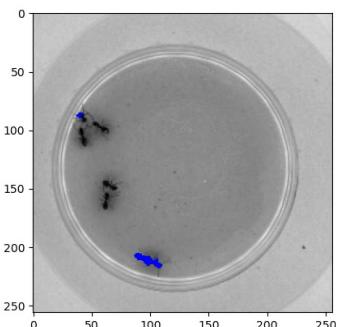


Frame 90

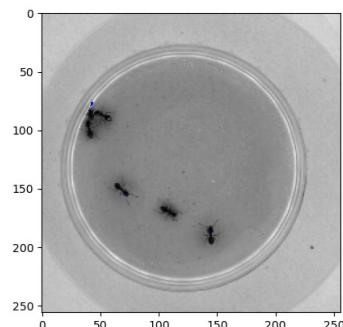


Frame 120

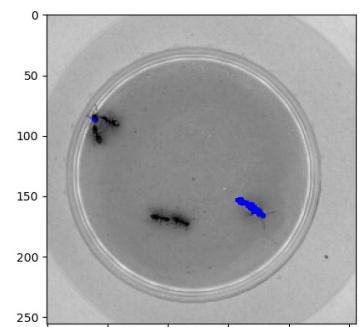
testAntSequence.py



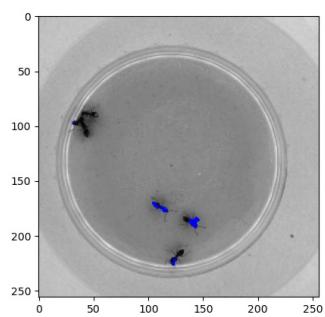
Frame 30



Frame 60



Frame 90



Frame 120

ACKNOWLEDGEMENTS:

- 1) My research lab mate Bassam Bikdash helped with Lucas Kanade Affine warp calculation for A matrix
- 2) Resources for Plotting image on image:
 - a. https://matplotlib.org/3.5.1/api/_as_gen/matplotlib.pyplot.imshow.html
 - b. https://matplotlib.org/stable/api/_as_gen/matplotlib.pyplot.plot.html
 - c. My research lab mate Bassam Bikdash

ADDITIONAL HAND CALCS FOR REFERENCE:

Q1(a) what is $\frac{\partial \omega(x; p)}{\partial p^T}$

$$\omega(x; p) = \begin{bmatrix} 1 & 0 & p_1 \\ 0 & 1 & p_2 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

$$\Rightarrow \begin{bmatrix} x + p_1 \\ y + p_2 \\ 1 \end{bmatrix} = \begin{bmatrix} \omega_x(x; p) \\ \omega_y(x; p) \end{bmatrix}$$

Taking derivative w.r.t p ,

$$\begin{bmatrix} \frac{\partial \omega_x(x; p)}{\partial p_1} & \frac{\partial \omega_x(x; p)}{\partial p_2} \\ \frac{\partial \omega_y(x; p)}{\partial p_1} & \frac{\partial \omega_y(x; p)}{\partial p_2} \end{bmatrix} = \begin{bmatrix} \frac{\partial(x + p_1)}{\partial p_1} & \frac{\partial(x + p_1)}{\partial p_2} \\ \frac{\partial(y + p_2)}{\partial p_1} & \frac{\partial(y + p_2)}{\partial p_2} \end{bmatrix}$$

$$\Rightarrow \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

Q1 b) what is A and what is b?

$$\arg \min_{\Delta p} \sum_{x \in N} \| I_{t+1}(x' + \Delta p) - I_t(x) \|_2^2$$

$$\Rightarrow I_{t+1}(x' + \Delta p) \approx I_{t+1}(x') + \frac{\partial I_{t+1}(x')}{\partial x'^T} \frac{\partial \omega(x'; p)}{\partial p^T} \Delta p$$

$$\therefore \arg \min_{\Delta p} \sum_{x \in N} \left\| I_{t+1}(x') + \frac{\partial I_{t+1}(x')}{\partial x'^T} \frac{\partial \omega(x'; p)}{\partial p^T} \Delta p - I_t(x) \right\|_2^2$$

$$\Rightarrow \arg \min_{\Delta p} \sum_{x \in N} \left\| \frac{\partial I_{t+1}(x')}{\partial x'^T} \frac{\partial \omega(x'; p)}{\partial p^T} \Delta p + I_{t+1}(x') - I_t(x) \right\|_2^2$$

$$\therefore A = \sum_{x \in N} \frac{\partial I_{t+1}(x')}{\partial x'^T} \frac{\partial \omega(x'; p)}{\partial p^T} \quad \text{since } \arg \min_{\Delta p} \| A \Delta p + b \|_2^2$$

$$b = \sum_{x \in N} -I_{t+1}(x') + I_t(x)$$

(Q1 c)

$$\underset{\Delta p}{\operatorname{argmin}} \sum_{x \in N} \left\| \underbrace{\frac{\partial I_{t+1}(x')}{\partial x'^T} \frac{\partial l(x; p)}{\partial p^T}}_A \Delta p + \underbrace{I_{t+1}(x') - I_t(x)}_b \right\|_2^2$$

$$\Rightarrow \underset{\Delta p}{\operatorname{argmin}} \| A \Delta p - b \|$$

To minimize the above equation:

$$\sum_{x \in N} A^T (A \Delta p - b) = 0$$

$$\Rightarrow \sum_{x \in N} A^T A \Delta p - A^T b = 0$$

$$\Rightarrow \sum_{x \in N} A^T A \Delta p = \sum_{x \in N} A^T b$$

$$\Rightarrow \Delta p = \sum_{x \in N} (A^T A)^{-1} A^T b$$

$\therefore A^T A$ needs to be invertible