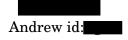
# Computer Vision - 16720 Homework 3



Start date: Feb 24th Due date: Mar 9th

#### Q1.1:

Our goal is to find the  $\Delta p = (u, v)^T$  that minimize the equation:

$$\begin{split} \sum_{(x,y)\in R^t} (I_{t+1}(x+u,y+v) - I_t(x,y))^2 \\ &\approx \sum_{(x,y)\in R^t} (I_{t+1}(x,y) + u(I_{t+1})_x(x,y) + v(I_{t+1})_y(x,y) - I_t(x,y))^2 \\ &= \sum_{(x,y)\in R^t} (\left[ (I_{t+1})_x(x,y) - (I_{t+1})_y(x,y) \right] \begin{bmatrix} u \\ v \end{bmatrix} - (I_t(x,y) - I_{t+1}(x,y)))^2 \\ &= \sum_{(x,y)\in R^t} (A\Delta p - b)^2 \end{split}$$

We can take a derivative with respect to  $\Delta p$ 

$$\frac{\partial}{\partial \Delta p} \sum_{(x,y) \in R^t} (\mathbf{A} \Delta \mathbf{p} - b)^2 = \sum_{(x,y) \in R^t} 2\mathbf{A}^T (\mathbf{A} \Delta \mathbf{p} - b)$$

And set it to zero we could get:

$$= \sum_{(x,y)\in R^t} A^T A \Delta p = \sum_{(x,y)\in R^t} A^T b$$

From above we can see  $A^T A =$ 

$$\begin{bmatrix} (I_{t+1})_x^2(x,y) & I_{t+1})_x(x,y)(I_{t+1})_y(x,y) \\ (I_{t+1})_x(x,y)(I_{t+1})_y(x,y) & (I_{t+1})_y^2(x,y) \end{bmatrix}$$

Which is the Gauss-Newton approximation of Hessian matrix (No second derivative).

To solve  $\Delta p$ ,  $A^T A$  should be invertible and the determinant of  $A^T A$  should not equal to zero, i.e,  $det(A^T A) \neq 0$ 

### Q1.2: Lucas Kanade Inverse Compositional Implementation

Please see the code submitted on blackboard.

#### Q1.3: Test car sequence and Test ultrasound sequence

The output of Lucas-Kanade Tracking with One Single Template for the car sequence was as below.



Figure 1: L-K Tracking with One Single Template for the car sequence

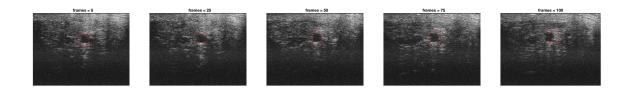


Figure 2: L-K Tracking with One Single Template for the ultrasound sequence

## Q1.4: Extra credits

Please see the code submitted on blackboard.



Figure 3: Lucas-Kanade Tracking with Template Correction for the car sequence

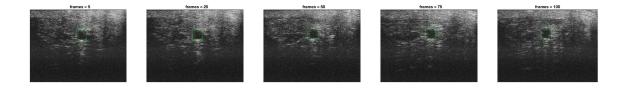


Figure 4: Lucas-Kanade Tracking with Template Correction for the ultrasound sequence

#### **Q2.1: Appearance Basis**

From the question we can know that  $B_c's$  are bases and they're orthogonal to each other. It means that the mutually inner product (dot product) of  $B_cs$  are zero and the inner product with itself is a constant. Since we have :

$$I_{t+1} = I_t + \sum_{c=1}^k w_c B_c$$

It's equivalent to:

$$I_{t+1} - I_t = \sum_{c=1}^{k} w_c B_c$$

For a certain parameter  $w_i$  where  $i \in [1,k]$ , we could multiply the corresponding basis  $B_i$  in both side of the equation above then derive:

$$\begin{split} B_i \cdot (I_{t+1} - I_t) &= B_i \cdot \sum_{c=1}^k w_c B_c \\ &= B_i \cdot (w_1 B_1 + \dots + w_i B_i + \dots + w_k B_k) \\ &= w_1 B_1 \cdot B_i + \dots + w_i B_i \cdot B_i + \dots + w_k B_k \cdot B_i \end{split}$$

From above we could know that except  $B_i \cdot B_i$ , all other dot product  $B_1 \cdot B_i ... B_k \cdot B_i$  are zero. So the equation above is equivalent to :

$$\begin{split} w_1 B_1 \cdot B_i + \dots + w_i B_i \cdot B_i + \dots + w_k B_k \cdot B_i \\ &= 0 + \dots + w_i B_i \cdot B_i + \dots + 0 \\ &= w_i ||B_i||^2 = B_i \cdot (I_{t+1} - I_t) \end{split}$$

So for a certain  $w_i$ ,

$$w_i = \frac{B_i \cdot (I_{t+1} - I_t)}{||B_i||^2}$$

So for c = 1, 2, ..., k

$$w_c = \frac{B_c \cdot (I_{t+1} - I_t)}{||B_c||^2}$$

## Q2.2: Tracking

Please see the code submitted on blackboard.

## **Q2.3: Lucas-Kanade Tracking with Appearance Basis**











Figure 5: Lucas-Kanade Tracking with Appearance Basis

### **Q3.1: Dominant Motion Estimation**

### **Q3.2: Moving Object Detection**

### **Q3.3: Moving Object Detection**

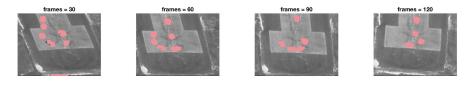


Figure 6: Lucas-Kanade Tracking of affine motion

From the images above we can see the moving objects has been detected.