Computer Vision - 16720A

[redacted]

Carnegie Mellon University

[redacted]

1. Lucas-Kanade Tracking

1.1.

1. What is $\frac{\partial W(x;p)}{\partial p^T}$?

$$W(x;p) = x + p \tag{1}$$

$$\frac{\partial W(x;p)}{\partial p^T} = \frac{\partial (x+p)}{\partial p^T} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \tag{2}$$

2. What is A and b?

$$A = \begin{bmatrix} \frac{\partial I_{t+1}(x'_1)}{\partial x_1'^T} & \cdots & 0^T \\ \vdots & \ddots & \vdots \\ 0^T & \cdots & \frac{\partial I_{t+1}(x'_N)}{\partial x_N'^T} \end{bmatrix} \begin{bmatrix} \frac{\partial W(x_1;p)}{\partial p^T} \\ \frac{\partial W(x_2;p)}{\partial p^T} \\ \vdots \\ \frac{\partial W(x_N;p)}{\partial p^T} \end{bmatrix} \tag{3}$$

3. What conditions must $A^T A$ meet so that a unique solution to Δp can be found?
   $A^T A$ must be invertible - it should be non-singular, full rank and its determinant should not be 0

1.2.

1.3.

Figure 1: Lucas-Kanade Tracking with One Single Template

1.4.

Here the blue rectangles are created with the baseline tracker in Q1.3, the red ones with the tracker in Q1.4

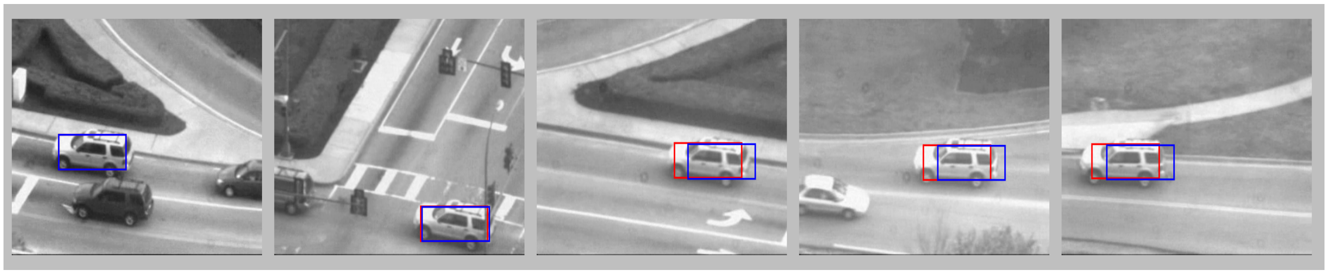

Figure 2: Lucas-Kanade Tracking with Template Correction

2. Affine Motion Subtraction

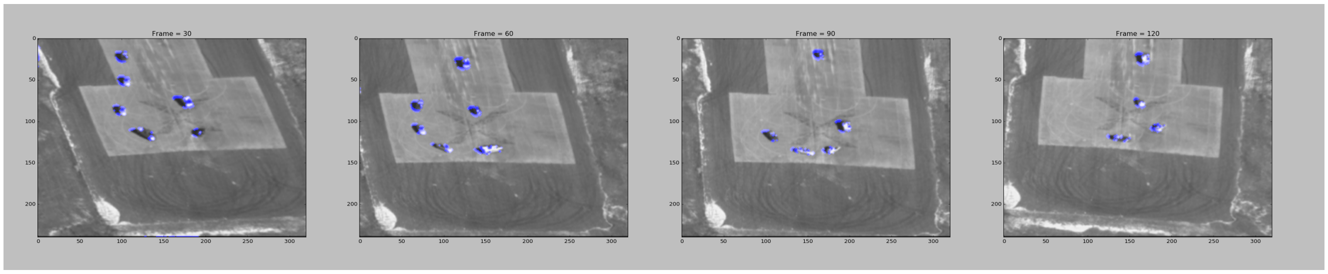

Figure 3: Lucas-Kanade Affine

3.

In the classical Lucas Kanade approach, inverse of Hessian has to be calculated and it must be multiplied by the result of the gradient descent parameter at every time instant in the iteration. This is highly computationally inefficient. $(O(n^3) + O(n^2))$. But in the inverse composition affine approach, at every time step, the template is warped. Hessian becomes constant and has to be calculated just once as well the Jacobian and steepest gradient descent parameter. The latter method thus saves a lot of time.