

A pure translation

$$W(x; p) = x + p.$$

Starting from a rectangular neighborhood of pixels $N \in \{x_d\}_{d=1}^D$ on frame I_t , the Lk tracker aims to move it by an offset $p = [p_x, p_y]^T$ to obtain another rectangle on the next frame I_{t+1} . To minimize the pixel square difference:

$$p^* = \underset{p}{\operatorname{argmin}} = \sum_{x \in N} \|I_{t+1}(x+p) - I_t(x)\|^2$$

Starting with an initial guess of p ($p = [0, 0]^T$), we can compute the optimal p^* iteratively.

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

where $\Delta p = [\Delta p_x, \Delta p_y]^T$ is the change in template offset.

$x' = W(x; p) = x + p$. and $\frac{\partial I(x')}{\partial x'^T}$ is a vector of x - and y -image gradients at pixel coordinate x' . Incorporate:

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

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

$$\frac{\partial W(x; p)}{\partial p^T} = \begin{bmatrix} \frac{\partial W_x}{\partial p_1} & \dots & \frac{\partial W_x}{\partial p_n} \\ \frac{\partial W_y}{\partial p_1} & \dots & \frac{\partial W_y}{\partial p_n} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$\textcircled{2} \quad p^* = \sum_{x \in N} \| \mathcal{I}_{t+1}(x' + \Delta p) - \mathcal{I}_t(x) \|_2^2$$

$$= \sum_{x \in N} \left\| \frac{\partial \mathcal{I}_{t+1}(x')}{\partial x'^T} \frac{\cancel{\frac{\partial W(x; p)}{\partial p^T}}}{\cancel{\Delta p}} \Delta p - (\mathcal{I}_t(x) - \mathcal{I}_{t+1}(x')) \right\|_2^2$$

Identity Matrix

so: $A = \begin{bmatrix} \frac{\partial \mathcal{I}_{t+1}(x'_1)}{\partial x'^T} \\ \vdots \\ \frac{\partial \mathcal{I}_{t+1}(x'_D)}{\partial x'^T} \end{bmatrix}$

$b = \begin{bmatrix} \mathcal{I}_t(x_1) - \mathcal{I}_{t+1}(x'_1) \\ \vdots \\ \mathcal{I}_t(x_D) - \mathcal{I}_{t+1}(x'_D) \end{bmatrix}$

$$\textcircled{3} \quad \underset{\Delta p}{\operatorname{arg \min}} \| A \Delta p - b \|_2^2 \Rightarrow \Delta p = (A^T A)^{-1} A^T b$$

↑
Hessian Matrix

Affine

$$\Delta P = [P_1, \dots, P_b]^T$$

$$x' = W(x; p) = \begin{bmatrix} 1+p_1 & p_2 \\ p_4 & 1+p_5 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} p_3 \\ p_6 \end{bmatrix}$$

Then we can represent this affine warp in homogenous coordinates as:

$$x' = Mx$$

where $M = \begin{bmatrix} 1+p_1 & p_2 & p_3 \\ p_4 & 1+p_5 & p_6 \\ 0 & 0 & 1 \end{bmatrix}$

M will differ between successive image pairs

$$P^* = \sum_{t \in N} \| I_{t+1}(x' + \Delta P) - I_t(x) \|_2^2$$

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

$$W(x; p) = \begin{bmatrix} 1+p_1 & p_2 & p_3 \\ p_4 & 1+p_5 & p_6 \\ 0 & 0 & 1 \end{bmatrix} \quad \frac{\partial W(x; p)}{\partial p^T} = \begin{bmatrix} \frac{\partial W(x; p)}{\partial p_1} & \dots & \frac{\partial W(x; p)}{\partial p_b} \\ \frac{\partial W(x; p)}{\partial p_{b+1}} & \dots & \frac{\partial W(x; p)}{\partial p_m} \\ \vdots & & \vdots \end{bmatrix}$$

$$= \begin{bmatrix} x & y & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & x & y & 1 \end{bmatrix}$$

Efficient tracking - Inverse Composition 2K

In each iteration, try to find the inverse warping $(W(x; op))^{-1}$ that best align our current tracking rectangle $T_{t+1}(W(x; p))$ in the next frame with the template in the current frame $I_t(x)$. This is equivalent to finding the warping on the template $I_t(W(x; op))$ that best aligns it with $I_{t+1}(W(x; p))$.

$$p^* = \underset{p}{\operatorname{argmin}} n = \sum_{x \in N} \| I_t(W(x; op)) - I_{t+1}(W(x; p)) \|_2^2$$

where we linearize just around the current frame I_t as:

$$I_t(W(x; 0+op)) \approx I_t(x) + \frac{\partial I_t(x)}{\partial T} \frac{\partial W(x; 0)}{\partial T} op$$
$$\Rightarrow \underset{op}{\operatorname{argmin}} \| A' op - b' \|_2^2$$

$$\text{Update: } W(x; p) \leftarrow W(W(x; op)^{-1}, p)$$

using affine warp where $p \in M$ and $op \in \Delta M$, results in $M \leftarrow M (\Delta M)^{-1}$.

Then Hessian Matrix is :

$$H = A^T \cdot A' \sum_{x \in N} \left[\nabla T \frac{\partial W}{\partial p} \right]^T \left[\nabla T \frac{\partial W}{\partial p} \right]$$

The Jacobian $\frac{\partial W}{\partial p}$ is evaluated at $(x; 0)$, so H can be pre-computed.