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LUKAS KANADE

COMPUTER VISION

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# LUKAS KANADE

## 1.1 HESSIAN

Soln. 1.3

$$\min_{u,v} J(u,v) = \sum_{(x,y) \in R_t} (I_{t+1}(x+u, y+v) - I_t(x,y))^2 \rightarrow (1)$$

1) Brightness constancy constraint.

$$I_{t+1}(x+u, y+v) - I_t(x,y) = 0$$

2. Small motion. Taylor expansion of I

$$I_{t+1}(x+u, y+v) = I_{t+1}(x,y) + \frac{\partial I_{t+1}}{\partial x} u + \frac{\partial I_{t+1}}{\partial y} v \quad \left( \begin{array}{l} \text{taking} \\ \text{first} \\ \text{order} \\ \text{terms} \end{array} \right)$$

combining these 2

$$0 = I_{t+1}(x,y) + I_x u + I_y v - I_t(x,y) \quad \left\{ \begin{array}{l} \text{where } I_x = \frac{\partial I_{t+1}}{\partial x} \\ I_y = \frac{\partial I_{t+1}}{\partial y} \end{array} \right.$$

$$\Rightarrow [I_{t+1}(x,y) - I_t(x,y)] + I_x u + I_y v = 0$$

$$\Rightarrow I_t + \nabla I \cdot \langle u, v \rangle = 0$$

$$\text{or } -I_t = \nabla I \cdot \langle u, v \rangle$$

and it is of the form

$$\begin{bmatrix} I_x(p_1) & I_y(p_1) \\ I_x(p_2) & I_y(p_2) \\ \vdots & \vdots \\ I_x(p_n) & I_y(p_n) \end{bmatrix} \times \begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} I_t(p_1) \\ I_t(p_2) \\ \vdots \\ I_t(p_n) \end{bmatrix} \rightarrow (4)$$

$\begin{matrix} A \\ n \times 2 \end{matrix}$

$\begin{matrix} \Delta p \\ 2 \times 1 \end{matrix}$

$\begin{matrix} b \\ n \times 1 \end{matrix}$

$\Rightarrow$  we need to minimize ~~max~~  $\|A \Delta p - b\|^2$   
or  $\min_{\Delta p} (A \Delta p - b)^2$

multiplying eq (4)  $A \Delta p = b$  by  $A^T$  we get :-

$$(A^T A) d = A^T b$$

here :-  $A^T A = \begin{bmatrix} \sum I_{xx} & \sum I_{xy} \\ \sum I_{yx} & \sum I_{yy} \end{bmatrix}$

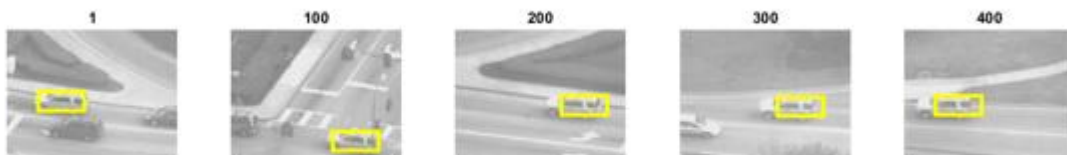
(b) conditions

(i)  $A^T A$  should be invertible

(ii)  $\underbrace{-\lambda_1 / \lambda_2}_{\text{eigen values}}$  should not be too large

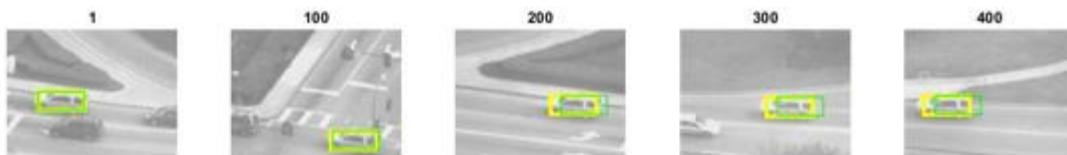
large  $\lambda_1$  &  $\lambda_2$  (both of them) relate to corner like in Harris corner detector).

### 1.3 LUKAS KANADE



### 1.4 LUKAS KANADE WITH TEMPLATE CORRECTION

It can be seen in the frames below that this is quite better than the previous case.



## 2.1 APPEARANCE BASIS

2.1

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

(Taken reference from Lukas Kanade 20 years <sup>section 3.4</sup> on paper)

=> Given where  $\{B_c\}_{c=1}^k$  is a set of  $k$  orthogonal image bases.

Here, the least square problem aims to minimize

$$\left\| I_{t+1} - I_t - \sum_{c=1}^k w_c B_c \right\|^2$$

Now  $I_t = T$  (template) (in the given quantity)  
the it becomes  $I_{t+1} = I(w; p)$

$$\sum_x \left[ I(w(x; p)) - T(x) - \sum_{c=1}^m w_c B_c(x) \right]^2$$

or

$$\left\| I(w(x; p)) - T(x) - \sum_{c=1}^m w_c B_c \right\|^2 \quad \left\{ \begin{array}{l} \text{|| is L2 norm} \\ \text{euclidean.} \end{array} \right.$$

Now a collection of  $B_c$  vectors are spanned by  $(B_c)$  & its orthogonal complement by  $\text{span}(B_c)^\perp$

$$=) \left\| I(w(x; p)) - T(x) - \sum_{c=1}^m w_c B_c \right\|_{\text{span}(B_c)}^2 + \left\| I(w(x; p)) - T(x) - \sum_{c=1}^m w_c B_c \right\|_{\text{span}(B_c)^\perp}^2$$

with norm 2, ~~orthogonal~~ orthogonal components in  $\uparrow$  all directions

$$\left\| I(w(x; p)) - T(x) - \sum_{c=1}^m w_c B_c \right\|_{\text{span}(B_c)}^2 + \left\| I(w(x; p)) - T(x) \right\|_{\text{span}(B_c)^\perp}^2$$

then minimize this  
w.r.t  $w$ .

does not depend on  $w$

first minimize w.r.t  $p$

**$B_c$  are orthonormal**

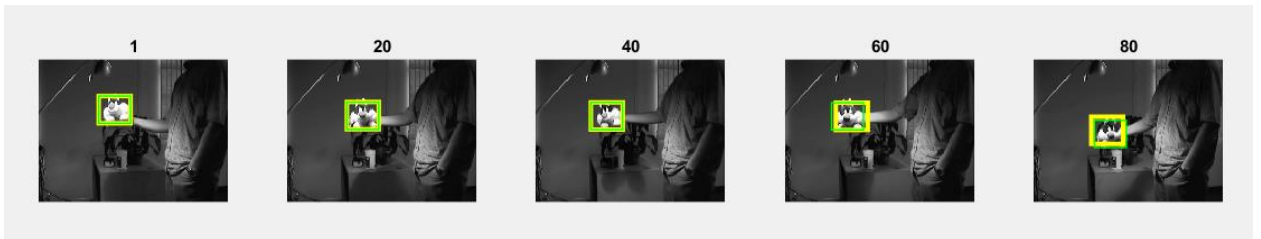
$$w_c = \sum_x B_c^T(x) \cdot [I_{t+1}(x) - I_t(x)]$$

## 2.3 LUKAS KANADE BASIS

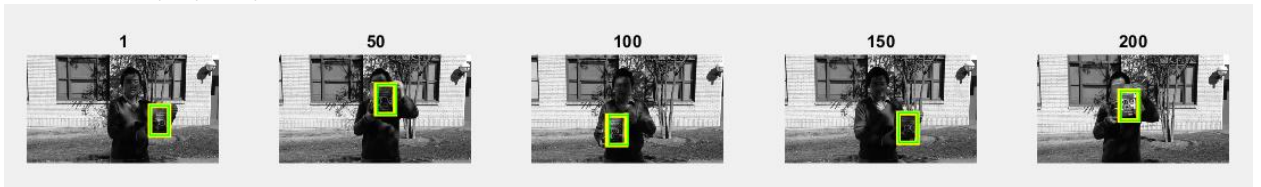


Yellow: Lukas Kanade  
Green: Lukas Kanade Basis  
Both are coming to the same location

Results when skipping 4 frames in between and output for frame number 1, 20, 40, 60 and 80.



Output for book:  
For Frames 1, 50, 100, 150 and 200



## 3.3 LUKAS KANADE AFFINE

