

Image Motion





Brightness Constancy Equation

Image intensity at Time = t , $I(x, y, t)$

Image intensity at Time = $t + dt$, $I(x + dx, y + dy, t + dt)$

Assuming $I(x, y, t) = I(x + dx, y + dy, t + dt)$

Taylor Series expansion

$$I(x + dx, y + dy, t + dt) \approx I(x, y, t) + \frac{\partial I}{\partial x} dx + \frac{\partial I}{\partial y} dy + \frac{\partial I}{\partial t} dt$$

Therefore,

$$I(x, y, t) = I(x, y, t) + \frac{\partial I}{\partial x} dx + \frac{\partial I}{\partial y} dy + \frac{\partial I}{\partial t} dt$$

$$\frac{\partial I}{\partial x} dx + \frac{\partial I}{\partial y} dy + \frac{\partial I}{\partial t} dt = 0$$

Brightness Constancy Equation

$$\frac{\partial I}{\partial x} dx + \frac{\partial I}{\partial y} dy + \frac{\partial I}{\partial t} dt = 0$$

Taking derivative wrt time:

$$\frac{\partial I}{\partial x} \frac{dx}{dt} + \frac{\partial I}{\partial y} \frac{dy}{dt} + \frac{\partial I}{\partial t} = 0$$

Let

$$\nabla I = \begin{bmatrix} \frac{\partial I}{\partial x} \\ \frac{\partial I}{\partial y} \end{bmatrix}$$

(Frame spatial
gradient)

$$d = \begin{bmatrix} \frac{dx}{dt} \\ \frac{dy}{dt} \end{bmatrix}$$

(optical flow)

$$I_t = \frac{\partial I}{\partial t}$$

(derivative across
frames)

Brightness Constancy Equation

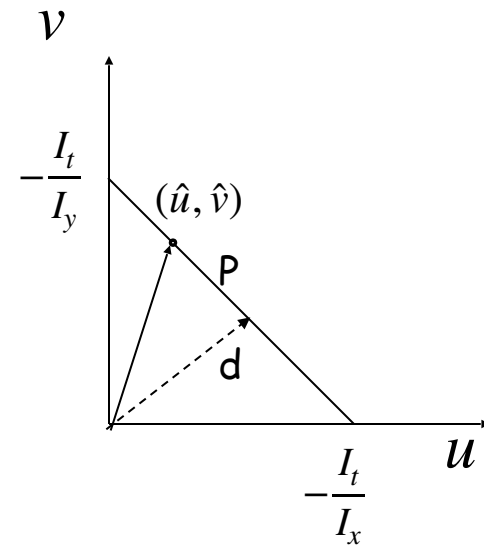
$$\frac{\partial I}{\partial x} \frac{dx}{dt} + \frac{\partial I}{\partial y} \frac{dy}{dt} + \frac{\partial I}{\partial t} = 0$$

Becomes:

$$I_x u + I_y v + I_t = 0$$

where, $u = \frac{dx}{dt}; v = \frac{dy}{dt}$

Line equation $v = -\frac{I_x}{I_y}u - \frac{I_t}{I_y}$



The OF is **CONSTRAINED** to be on a line !

$$d = \frac{f_t}{\sqrt{f_x^2 + f_y^2}}$$

Brightness Constancy Equation

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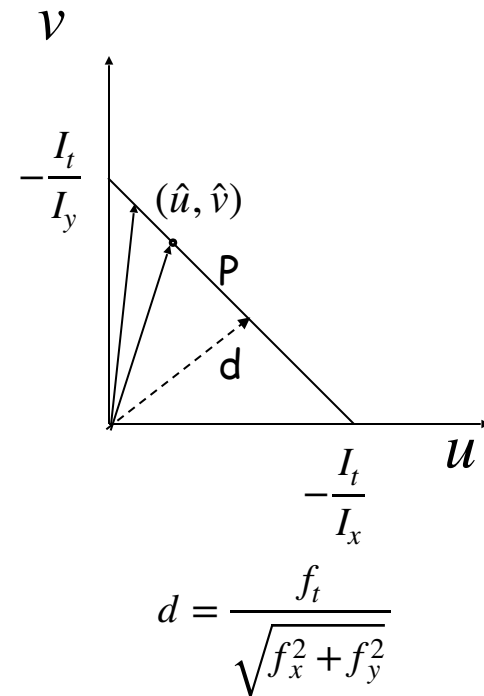
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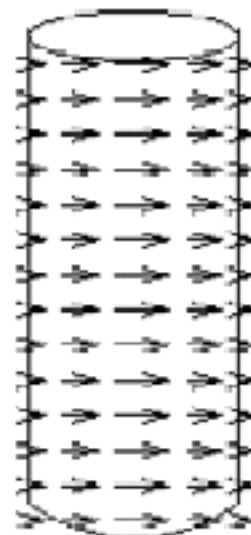
Aperture Problem in Real Life

Aperture Problem

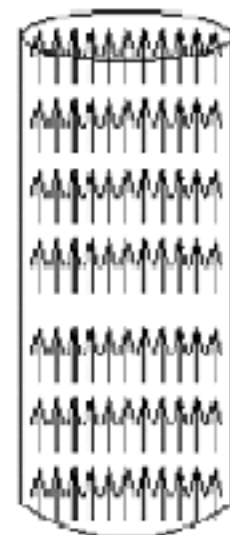
Barber pole illusion



Barber's pole



actual motion



perceived motion

Solving the aperture problem

- How to get more equations for a pixel?
 - Basic idea: impose additional constraints
 - most common is to assume that the flow field is smooth locally
 - one method: pretend the pixel's neighbors have the same (u,v)
 - If we use a 5x5 window, that gives us 25 equations per pixel!

$$0 = I_t(\mathbf{p}_i) + \nabla I(\mathbf{p}_i) \cdot [u \ v]$$

$$\begin{bmatrix} I_x(\mathbf{p}_1) & I_y(\mathbf{p}_1) \\ I_x(\mathbf{p}_2) & I_y(\mathbf{p}_2) \\ \vdots & \vdots \\ I_x(\mathbf{p}_{25}) & I_y(\mathbf{p}_{25}) \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = - \begin{bmatrix} I_t(\mathbf{p}_1) \\ I_t(\mathbf{p}_2) \\ \vdots \\ I_t(\mathbf{p}_{25}) \end{bmatrix}$$

$$\begin{matrix} \mathbf{A} \\ 25 \times 2 \end{matrix}$$

$$\begin{matrix} \mathbf{d} \\ 2 \times 1 \end{matrix}$$

$$\begin{matrix} \mathbf{b} \\ 25 \times 1 \end{matrix}$$

Lukas-Kanade flow

- Prob: we have more equations than unknowns

$$\begin{array}{ccc} A & d = & b \\ 25 \times 2 & 2 \times 1 & 25 \times 1 \end{array} \longrightarrow \text{minimize } \|Ad - b\|^2$$

- Solution: solve least squares problem
 - minimum least squares solution given by solution (in d)

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

$$\begin{array}{ccc} & 2 \times 2 & 2 \times 1 & 2 \times 1 \end{array}$$

$$\begin{array}{c} \left[\begin{array}{cc} \sum I_x I_x & \sum I_x I_y \\ \sum I_x I_y & \sum I_y I_y \end{array} \right] \begin{array}{c} \left[\begin{array}{c} u \\ v \end{array} \right] = - \left[\begin{array}{c} \sum I_x I_t \\ \sum I_y I_t \end{array} \right] \\ A^T A \qquad \qquad \qquad A^T b \end{array}$$

- The summations are over all pixels in the K x K window
- This technique was first proposed by Lukas & Kanade (1981)

Taking a closer look at $(A^T A)$

$$A = \begin{bmatrix} I_x(p_1) & I_y(p_1) \\ I_x(p_2) & I_y(p_2) \\ \dots & \dots \\ I_x(p_{N^2}) & I_y(p_{N^2}) \end{bmatrix}$$

$$A^T = \begin{bmatrix} I_x(p_1) & I_x(p_2) & \dots & I_x(p_{N^2}) \\ I_y(p_1) & I_y(p_2) & \dots & I_y(p_{N^2}) \end{bmatrix}$$

$$A^T A = \begin{bmatrix} \sum I_x^2 & \sum I_x I_y \\ \sum I_x I_y & \sum I_y^2 \end{bmatrix}$$

This is the same matrix we used for corner detection!

Taking a closer look at $(A^T A)$

The matrix for corner detection:

$$A^T A = \begin{bmatrix} \sum I_x^2 & \sum I_x I_y \\ \sum I_x I_y & \sum I_y^2 \end{bmatrix}$$

is singular (not invertible) when $\det(A^T A) = 0$

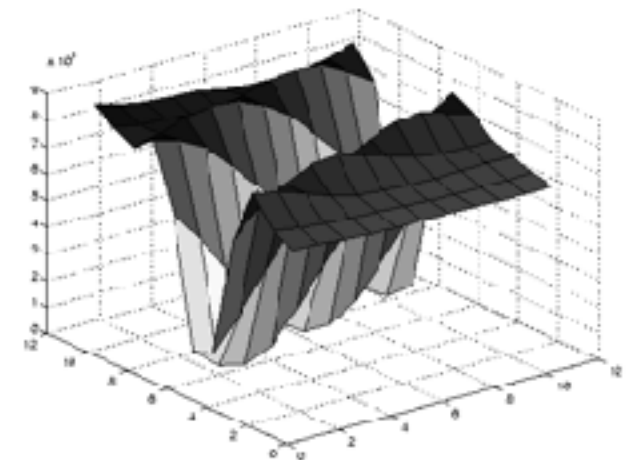
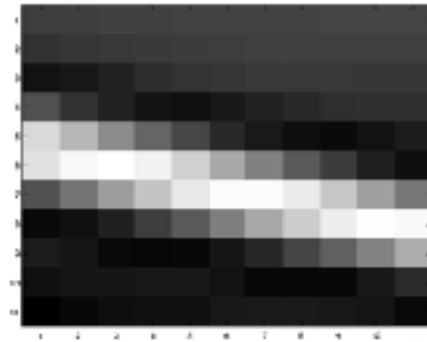
But $\det(A^T A) = \prod \lambda_i = 0 \rightarrow$ one or both e.v. are 0

One e.v. = 0 \rightarrow no corner, just an edge

Two e.v. = 0 \rightarrow no corner, homogeneous region

} Aperture

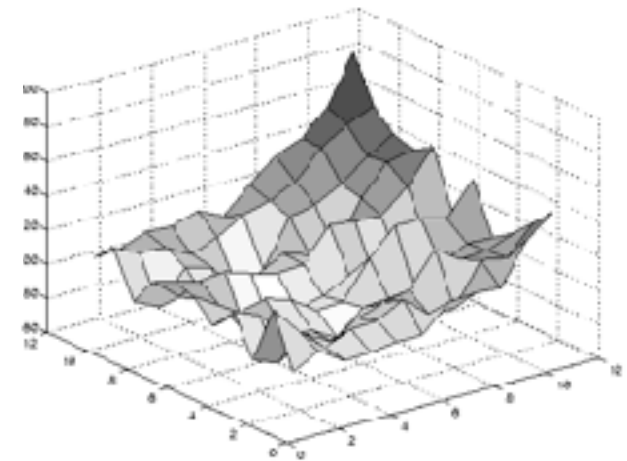
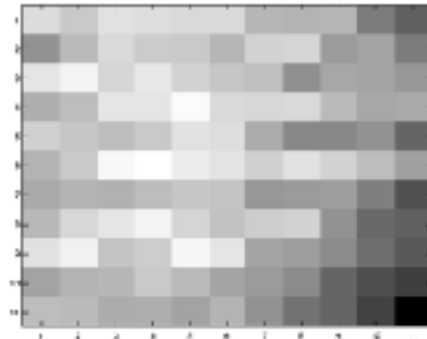
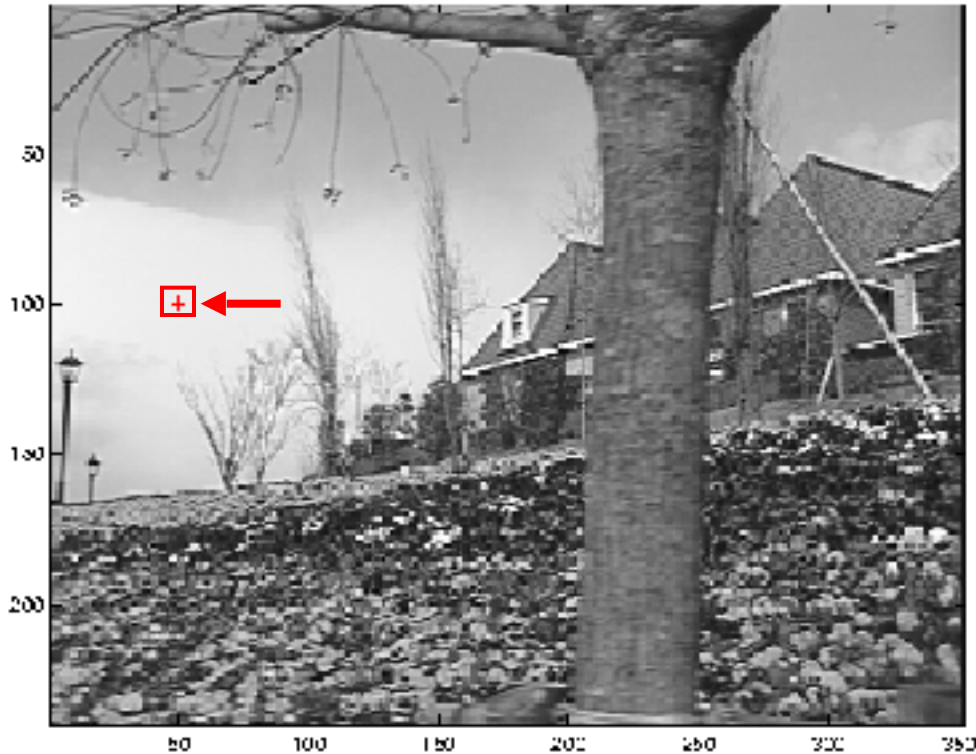
} Problem !



$$\sum \nabla I (\nabla I)^T$$

- large gradients, all the same
- large λ_1 , small λ_2

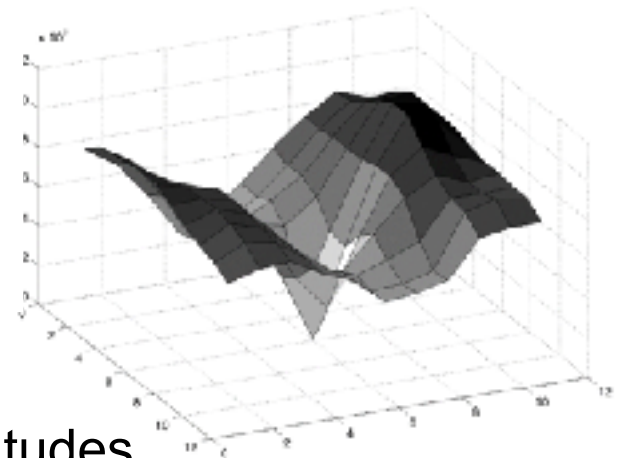
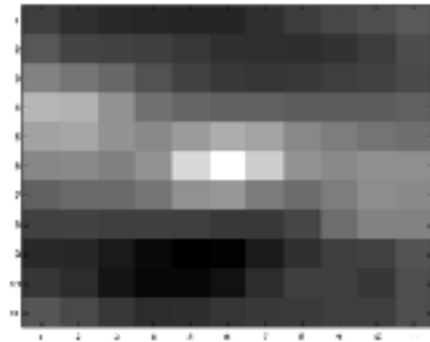
Low texture region



$$\sum \nabla I (\nabla I)^T$$

- gradients have small magnitude
- small λ_1 , small λ_2

High textured region

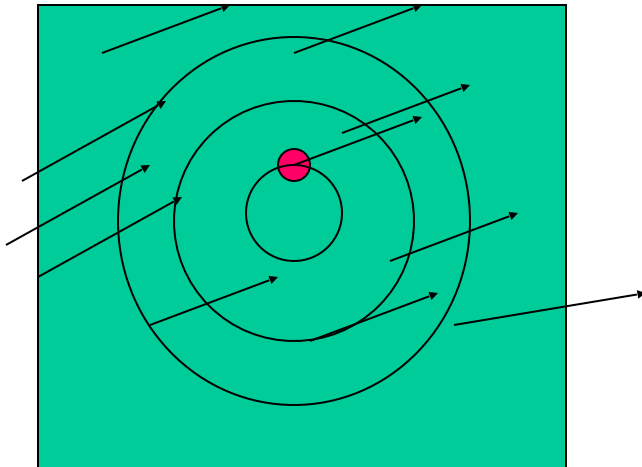


$$\sum \nabla I (\nabla I)^T$$

- gradients are different, large magnitudes
- large λ_1 , large λ_2

An improvement ...

- NOTE:
 - The assumption of constant OF is more likely to be wrong as we move away from the point of interest (the center point of Q)



Use weights to control the influence of the points: the farther from p , the less weight

Solving for v with weights:

- Let W be a diagonal matrix with weights
- Multiply both sides of $Av = b$ by W :

$$W A v = W b$$

- Multiply both sides of $WAv = Wb$ by $(WA)^T$:

$$A^T W W A v = A^T W W b$$

- $A^T W^2 A$ is square (2×2):
 - $(A^T W^2 A)^{-1}$ exists if $\det(A^T W^2 A) \neq 0$

- Assuming that $(A^T W^2 A)^{-1}$ does exist:

$$(A^T W^2 A)^{-1} (A^T W^2 A) v = (A^T W^2 A)^{-1} A^T W^2 b$$

$$v = (A^T W^2 A)^{-1} A^T W^2 b$$

Observation

- This is a problem involving two images BUT
 - Can measure sensitivity by just looking at one of the images!
 - This tells us which pixels are easy to track, which are hard
 - very useful later on when we do feature tracking...

Revisiting the small motion assumption

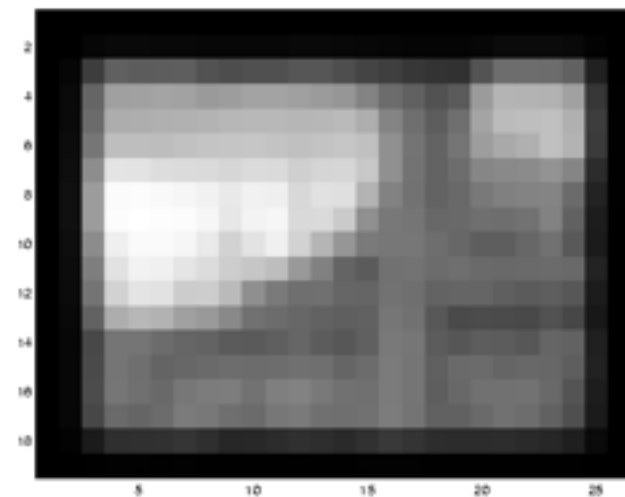
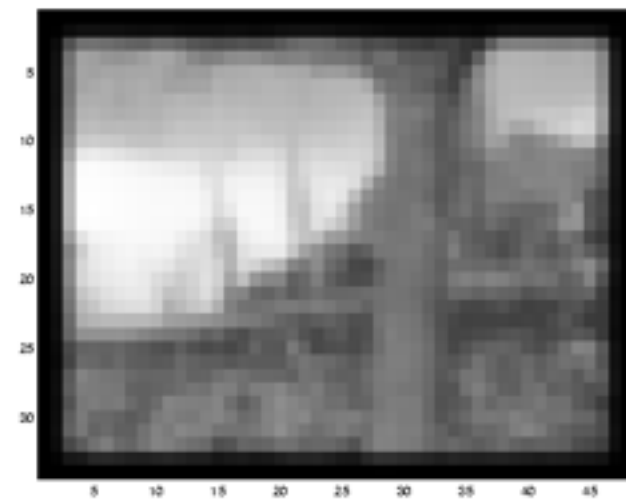


- Is this motion small enough?
 - Probably not—it's much larger than one pixel (2nd order terms dominate)
 - How might we solve this problem?

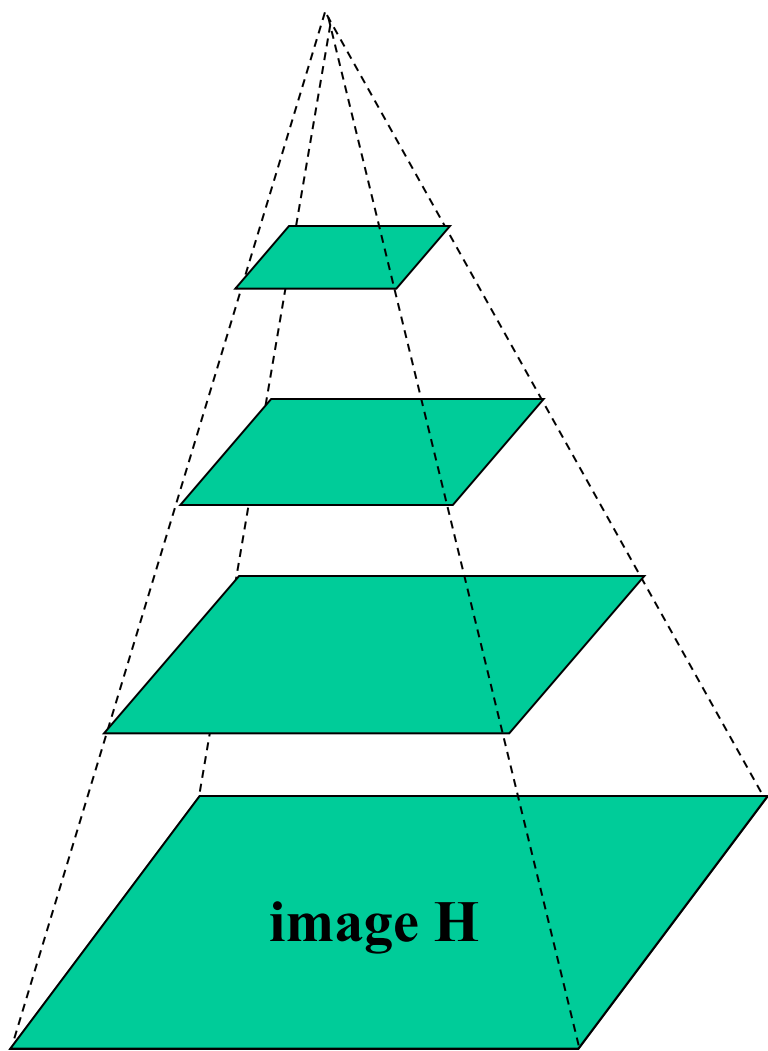
Iterative Refinement

- Iterative Lukas-Kanade Algorithm
 1. Estimate velocity at each pixel by solving Lucas-Kanade equations
 2. Warp $I(t-1)$ towards $I(t)$ using the estimated flow field
 - *use image warping techniques*
 3. Repeat until convergence

Reduce the resolution!



Coarse-to-fine optical flow estimation



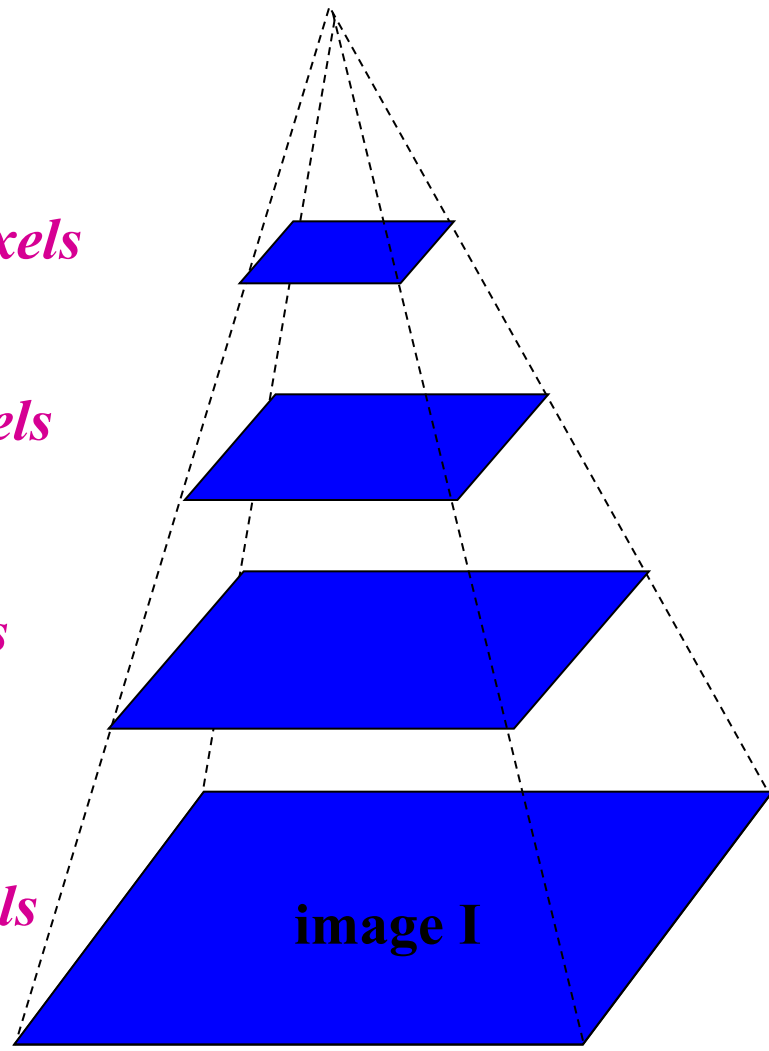
Gaussian pyramid of image I_{t-1}

$u=1.25$ pixels

$u=2.5$ pixels

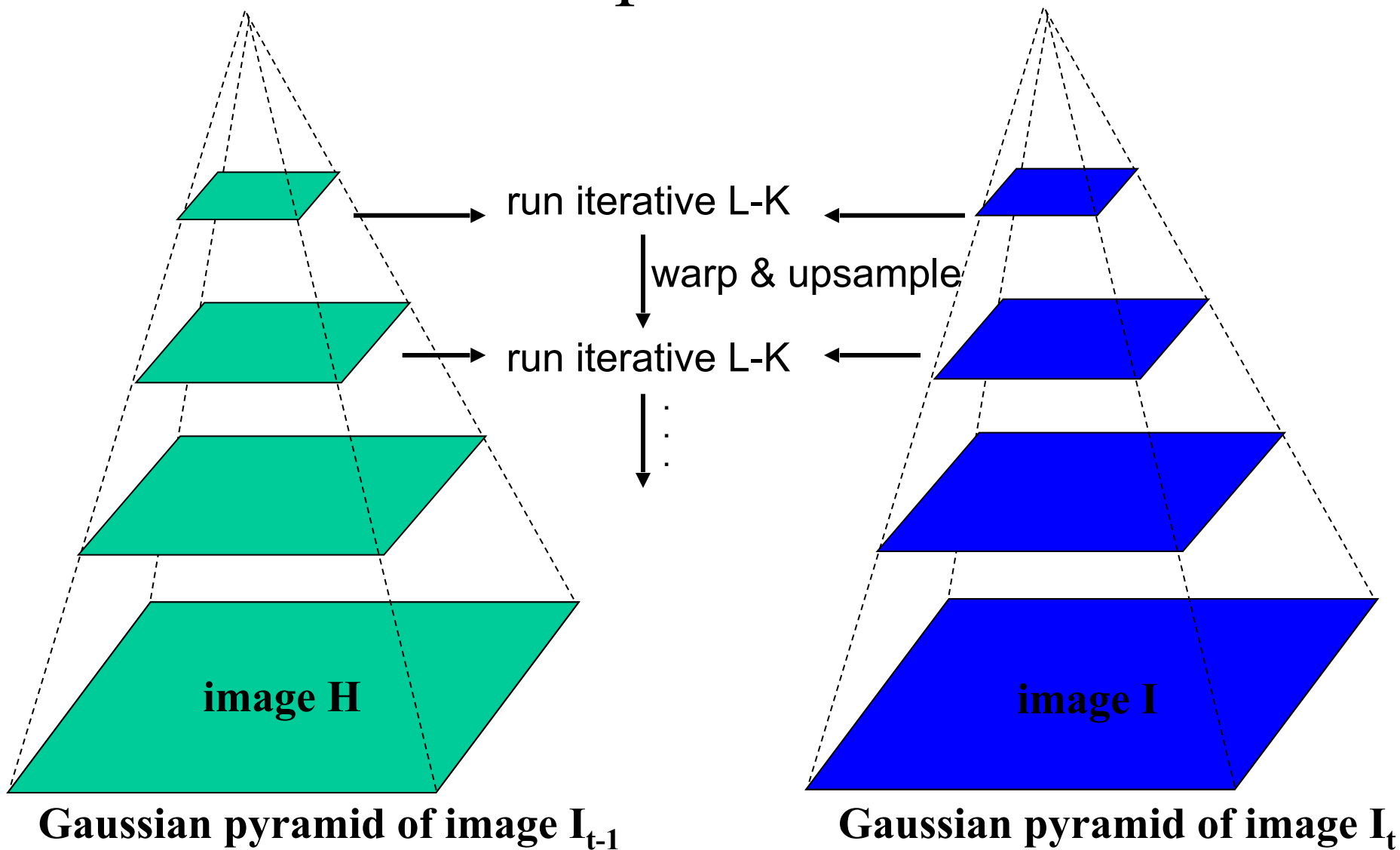
$u=5$ pixels

$u=10$ pixels

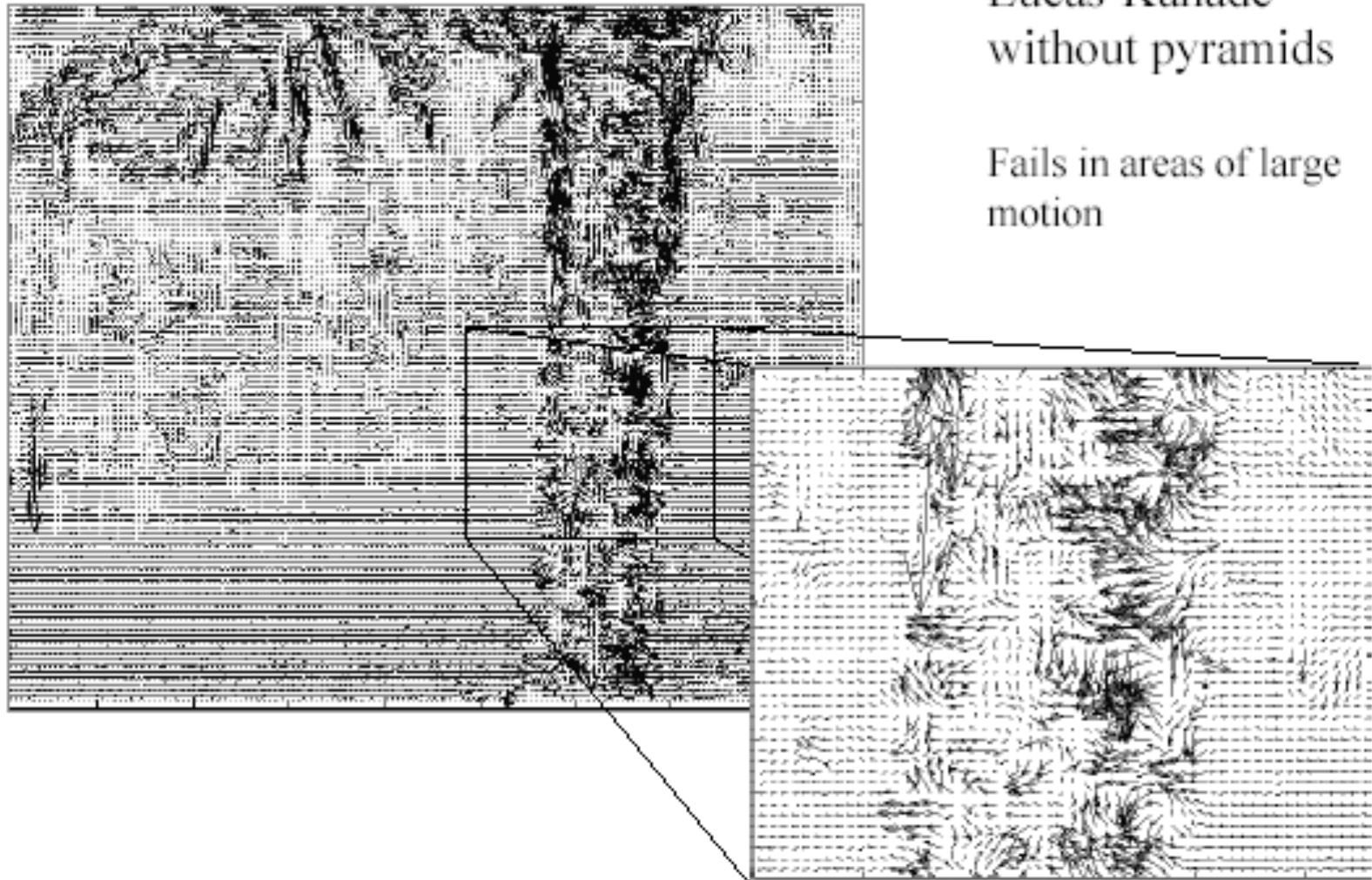


Gaussian pyramid of image I_t

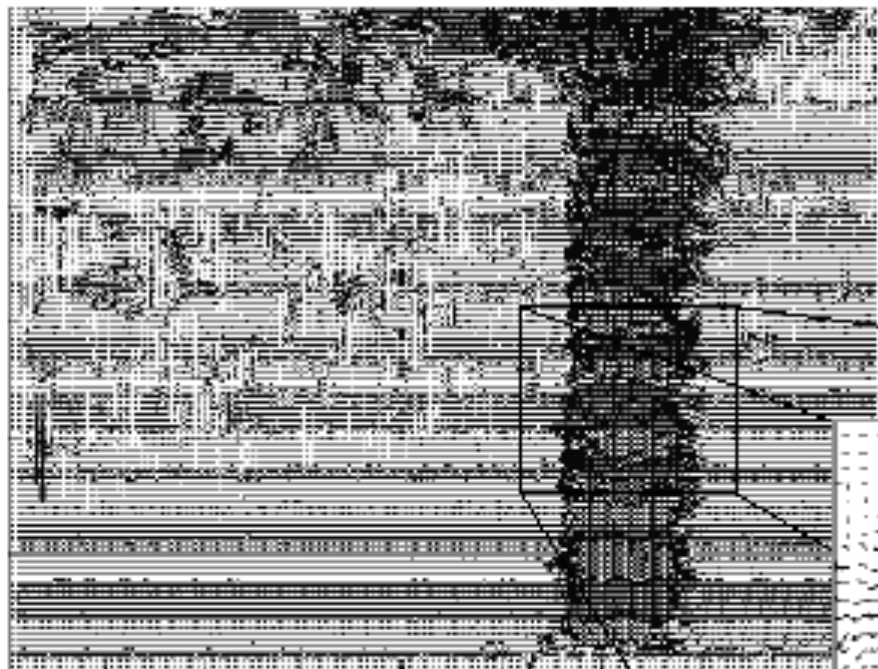
Coarse-to-fine optical flow estimation



Optical Flow Results



Optical Flow Results



Lucas-Kanade with Pyramids

