CS4495/6495
Introduction to Computer Vision

6B-L3 *Hierarchical LK*

Revisiting the small motion assumption

- Is this motion small enough?
  - Probably not – much larger than one pixel
  - How might we solve this problem?

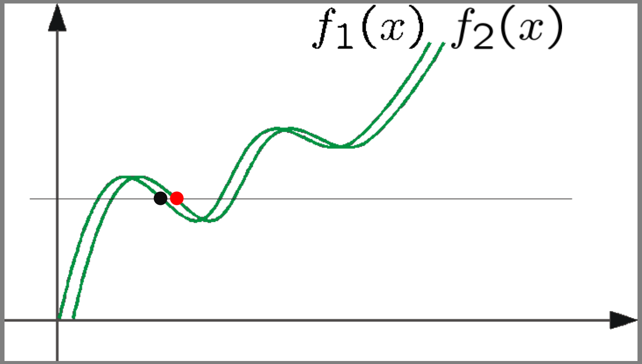
Garden image sequence #1

Revisiting the small motion assumption

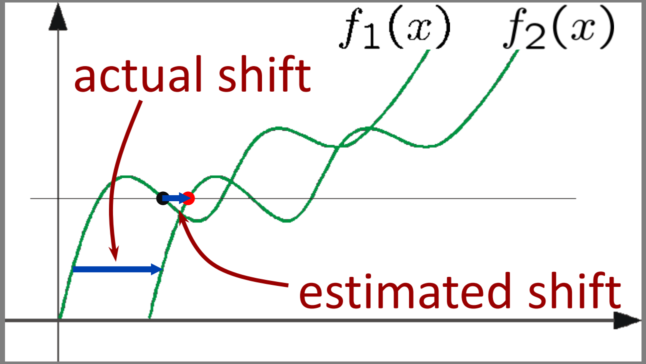
- Is this motion small enough?
  - Probably not – much larger than one pixel
  - How might we solve this problem?

Garden image sequence #2

Optical Flow: Aliasing



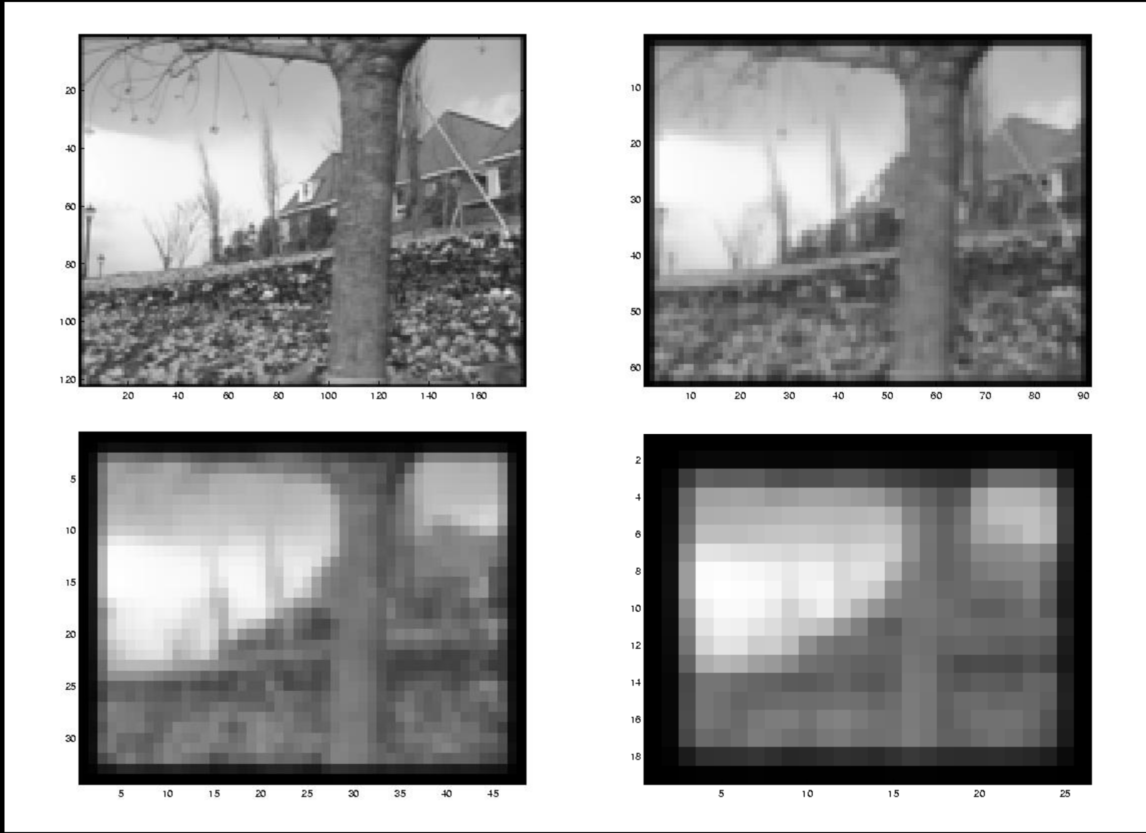
nearest match is correct (no aliasing)

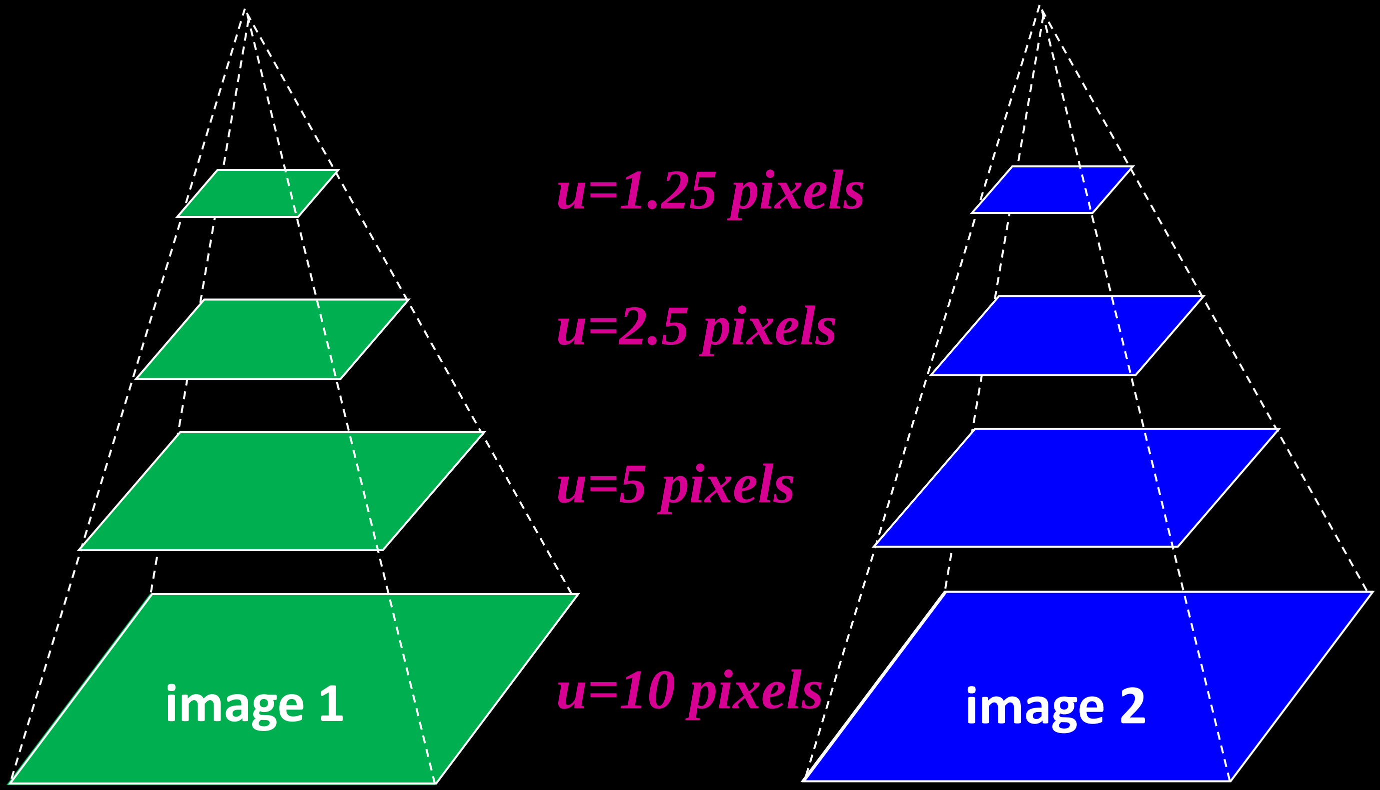


nearest match is incorrect (aliasing)

To overcome aliasing: coarse-to-fine estimation

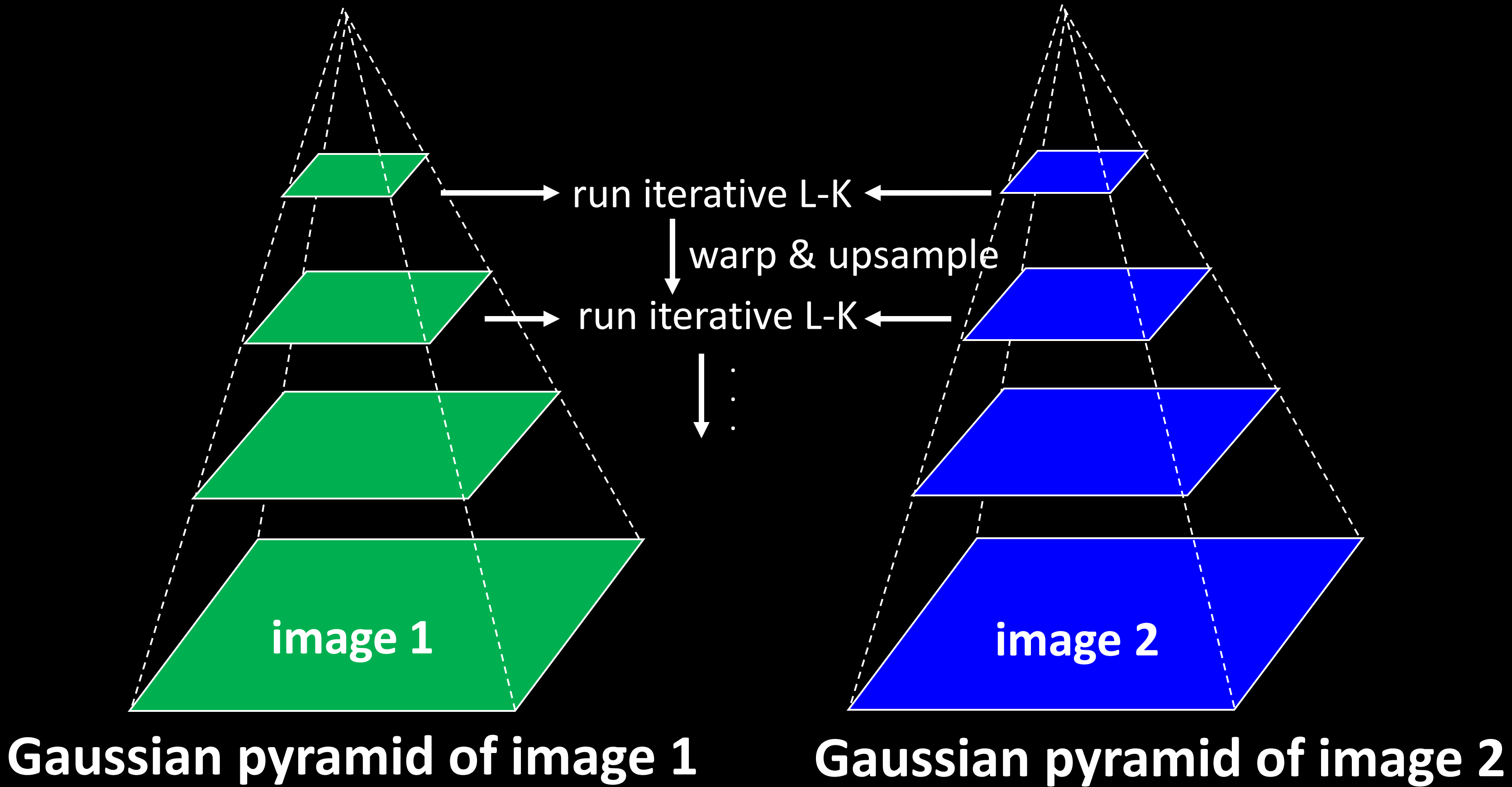
Reduce the resolution!



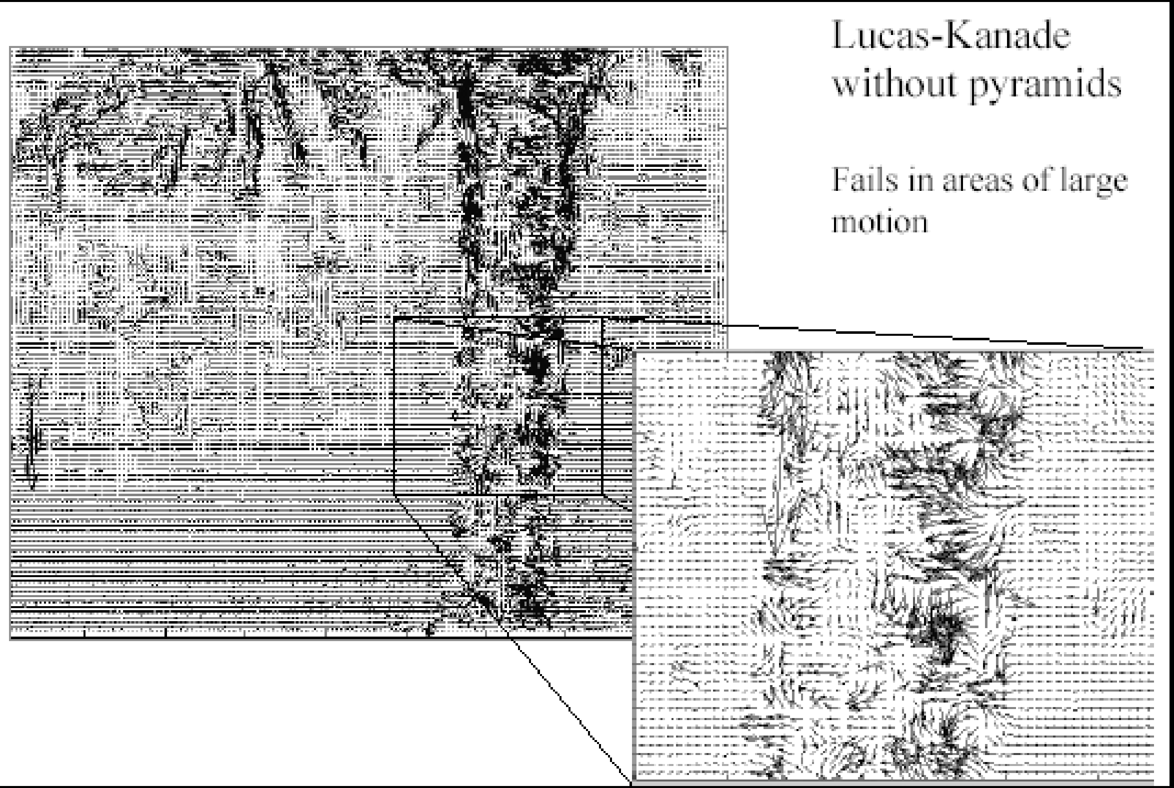


Gaussian pyramid of image 1

Gaussian pyramid of image 2

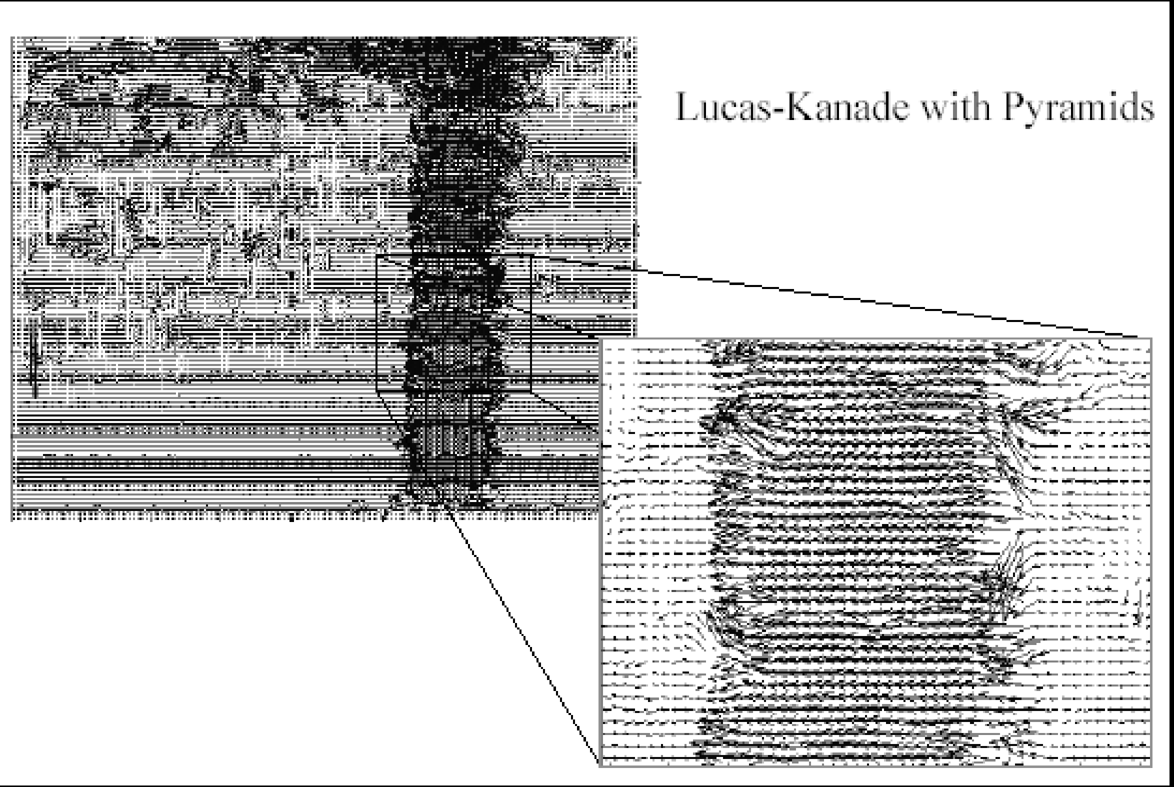

run iterative L-K
warp & upsample
run iterative L-K
image 1
image 2
Gaussian pyramid of image 1
Gaussian pyramid of image 2

Optical Flow Results



*From Khurram Hassan-Shafique CAP5415 Computer Vision 2003

Optical Flow Results



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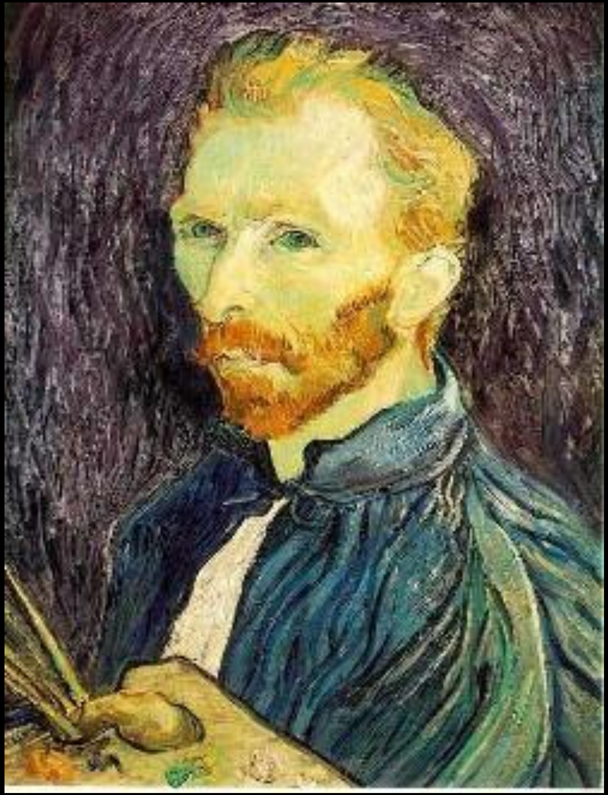
Detour: Multi-scale analysis, image pyramids



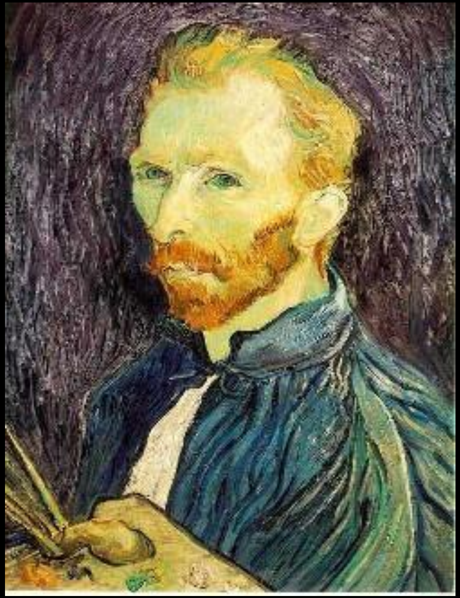
1/4

1/8

Throw away every other row and column to create a 1/2 size image: *image sub-sampling*

S. Seitz

Bad image sub-sampling



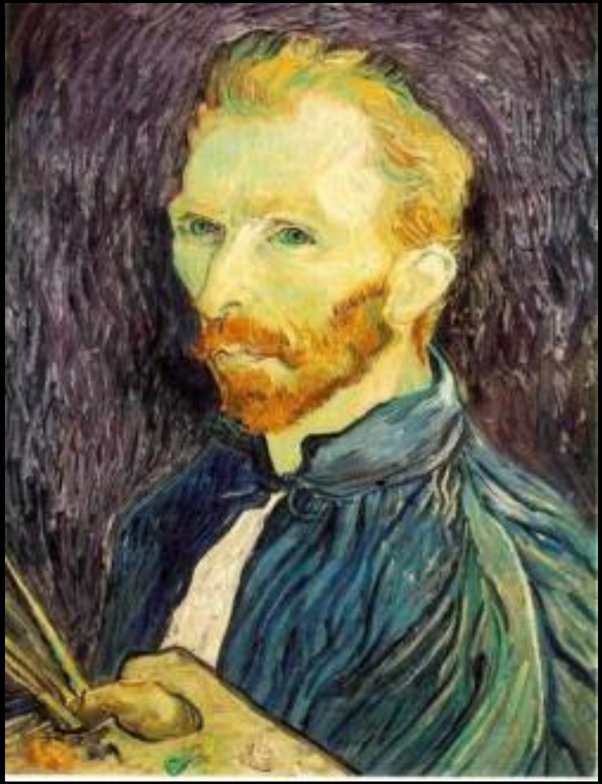
1/2

1/4 (2x zoom)

1/8 (4x zoom)

Aliasing! What do we do?

S. Seitz



Gaussian 1/2

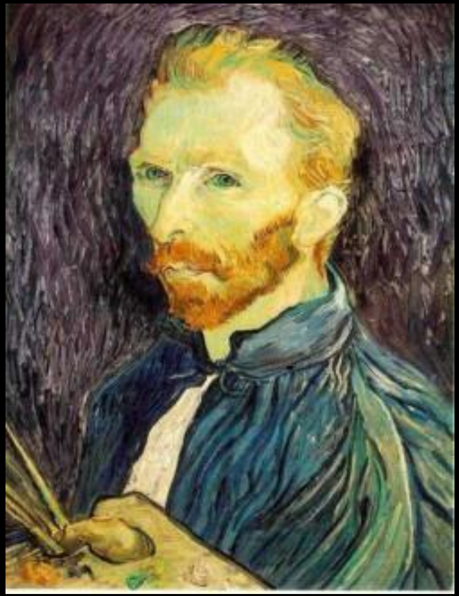
G 1/4

G 1/8

Solution: Filter the image, *then* subsample

S. Seitz

Subsampling with Gaussian pre-filtering



Gaussian 1/2

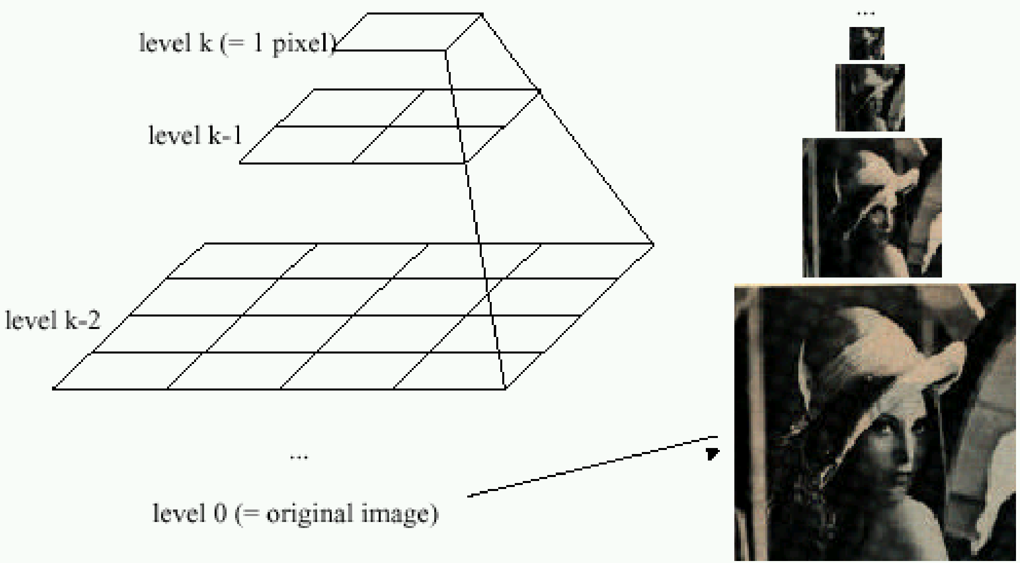
G 1/4

G 1/8

S. Seitz

Image Pyramids

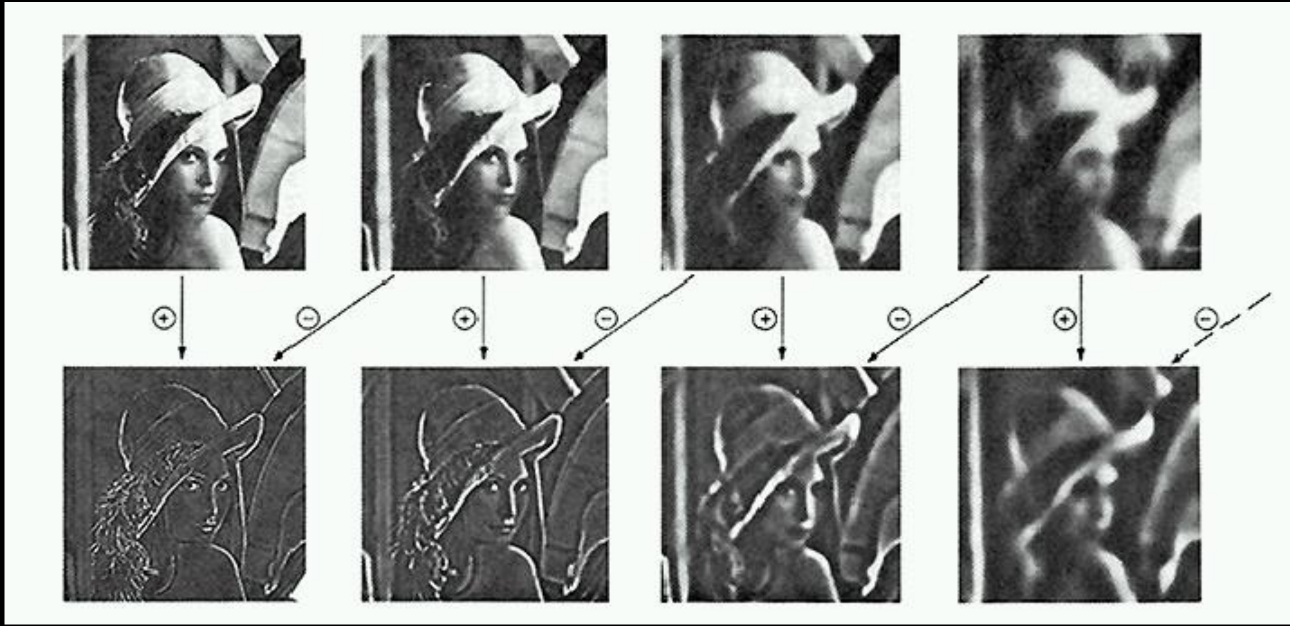
Idea: Represent NxN image as a "pyramid" of 1×1, 2×2, 4×4, ..., $2^k \times 2^k$ images (assuming $N=2^k$)



Known as a **Gaussian Pyramid** [Burt and Adelson, 1983]

“Band-pass” filtering

Gaussian Pyramid (low-pass images)

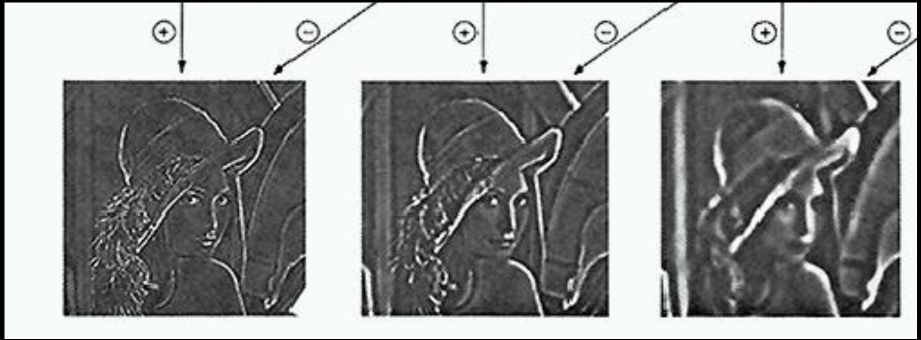


Laplacian Pyramid (subband images)

These are “bandpass” images (almost).

Laplacian Pyramid

Original image

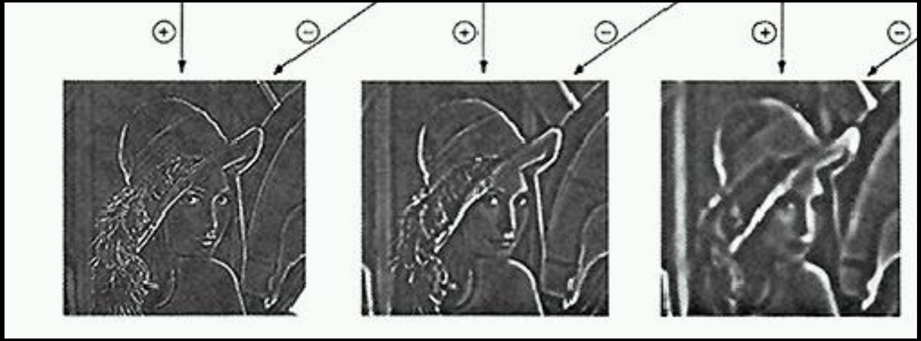


How can we reconstruct (collapse) this pyramid into the original image?

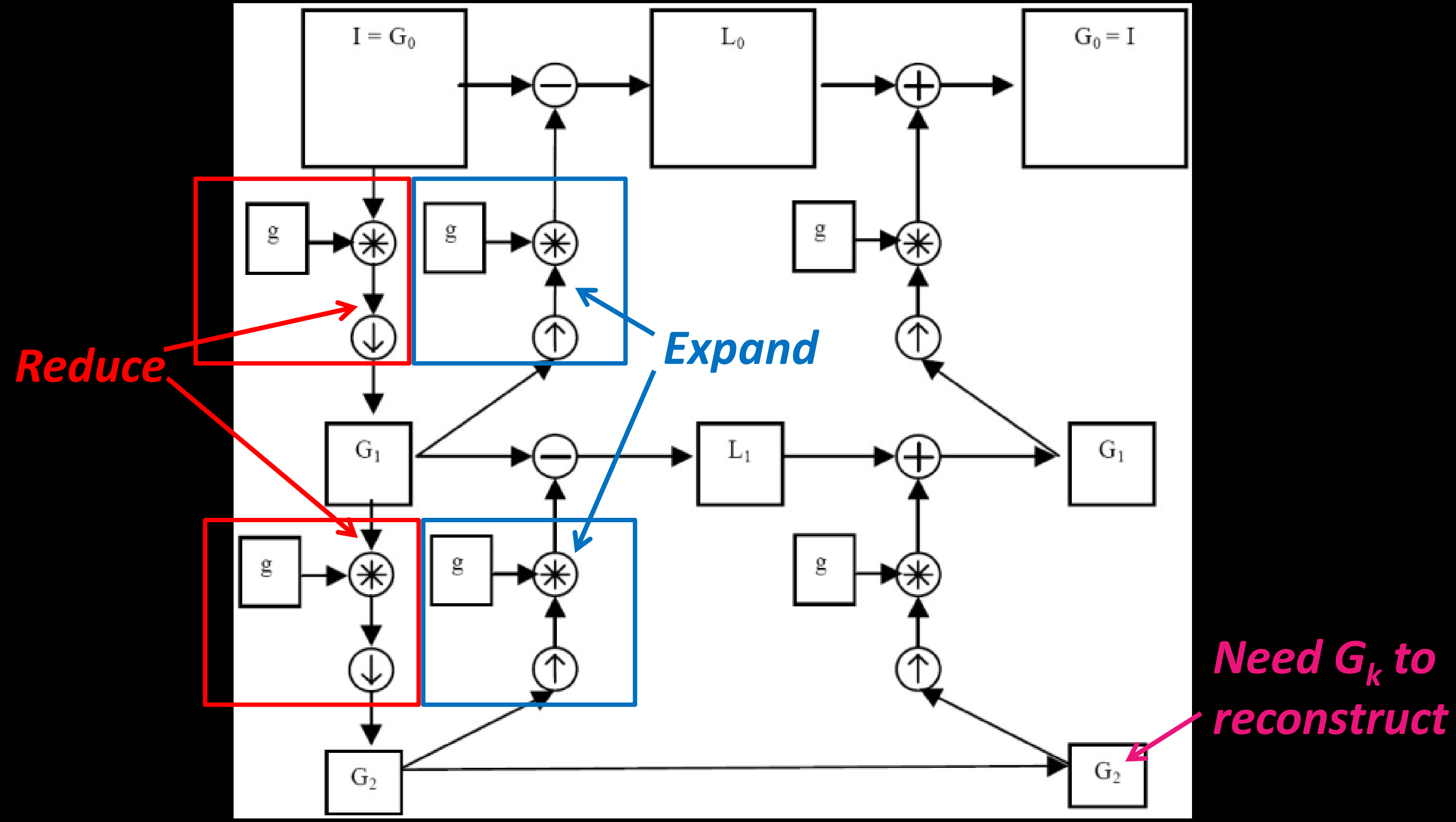
Laplacian Pyramid

Need this!

Original image

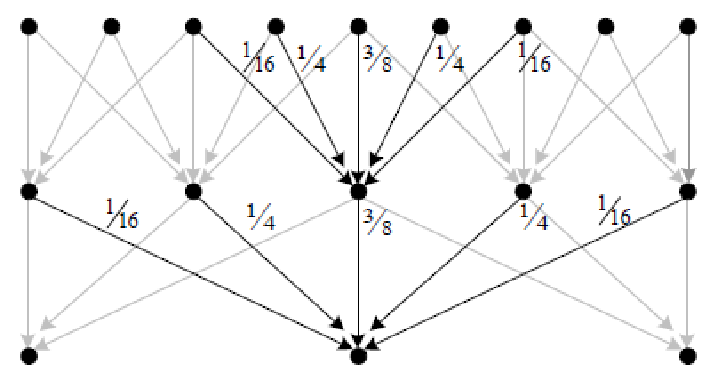


How can we reconstruct (collapse) this pyramid into the original image?



I = G0
L0
G0 = I
g
Reduce
Expand
G1
L1
G1
G2
G2
Need Gk to reconstruct

Reduce and Expand

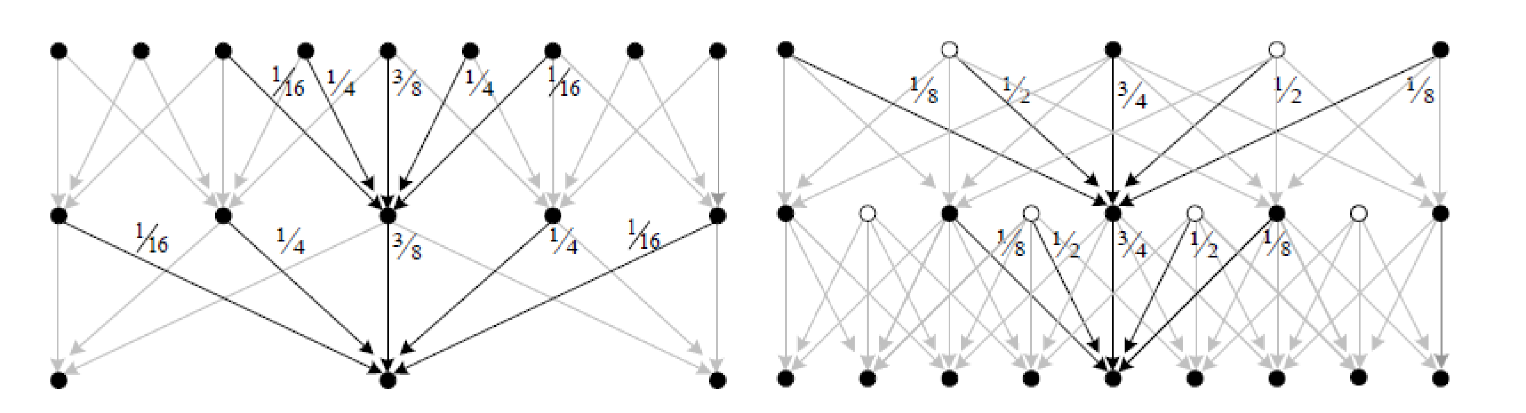


(a)

Reduce

Apply “5-tap” (1 4 6 4 1)/16 ***separable*** filter to make reduced image.

Reduce and Expand



(a) (b)

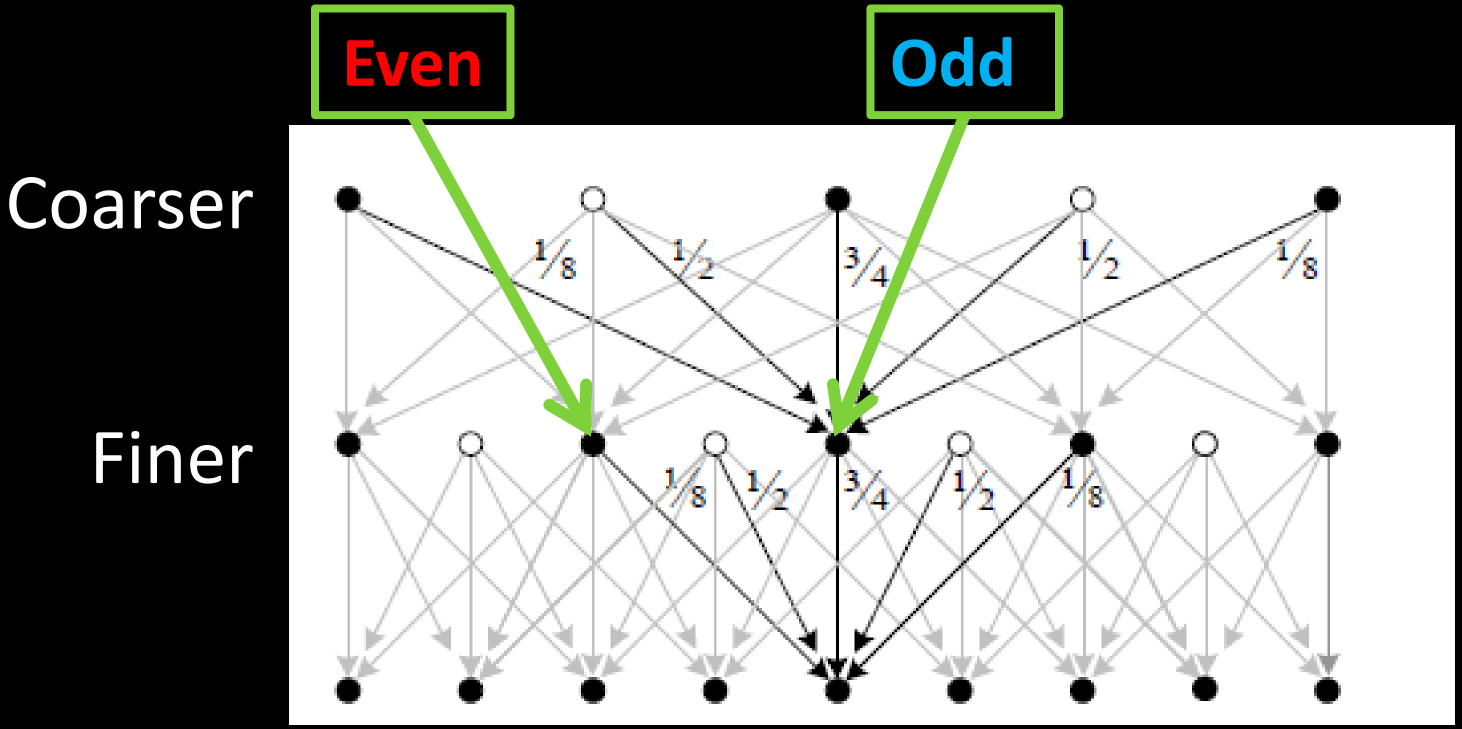
Reduce

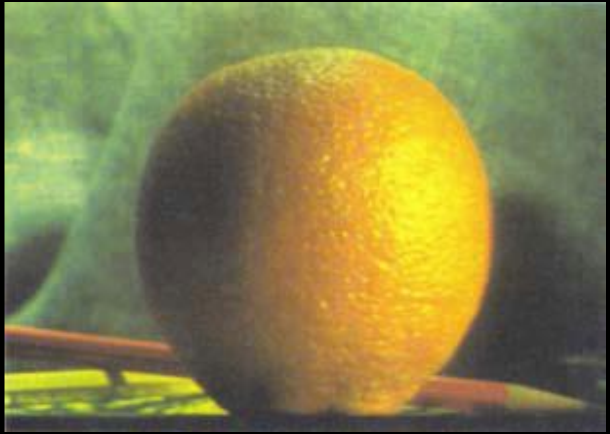
Apply “5-tap” (1 4 6 4 1)/16 ***separable*** filter to make reduced image.

Expand

Apply different “3-tap” separable filters for even and odd pixels to make expanded image...

Apply different “3-tap” separable filters for even and odd pixels to make expanded image.



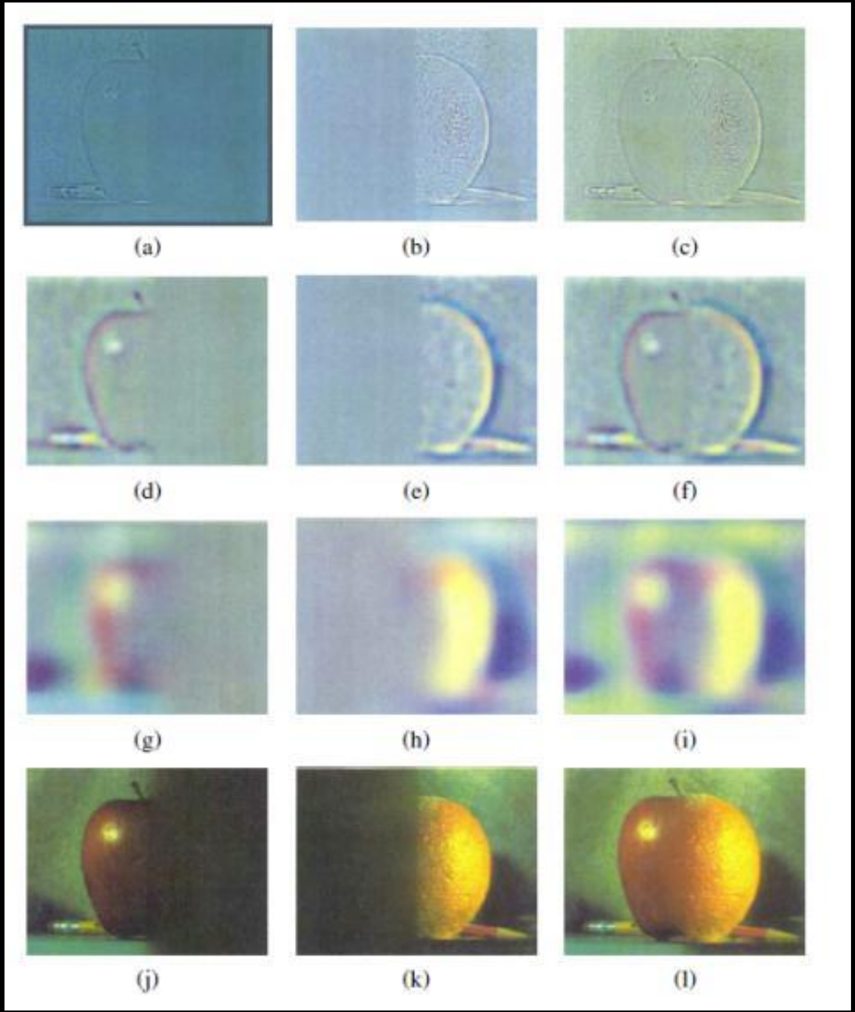


L_0

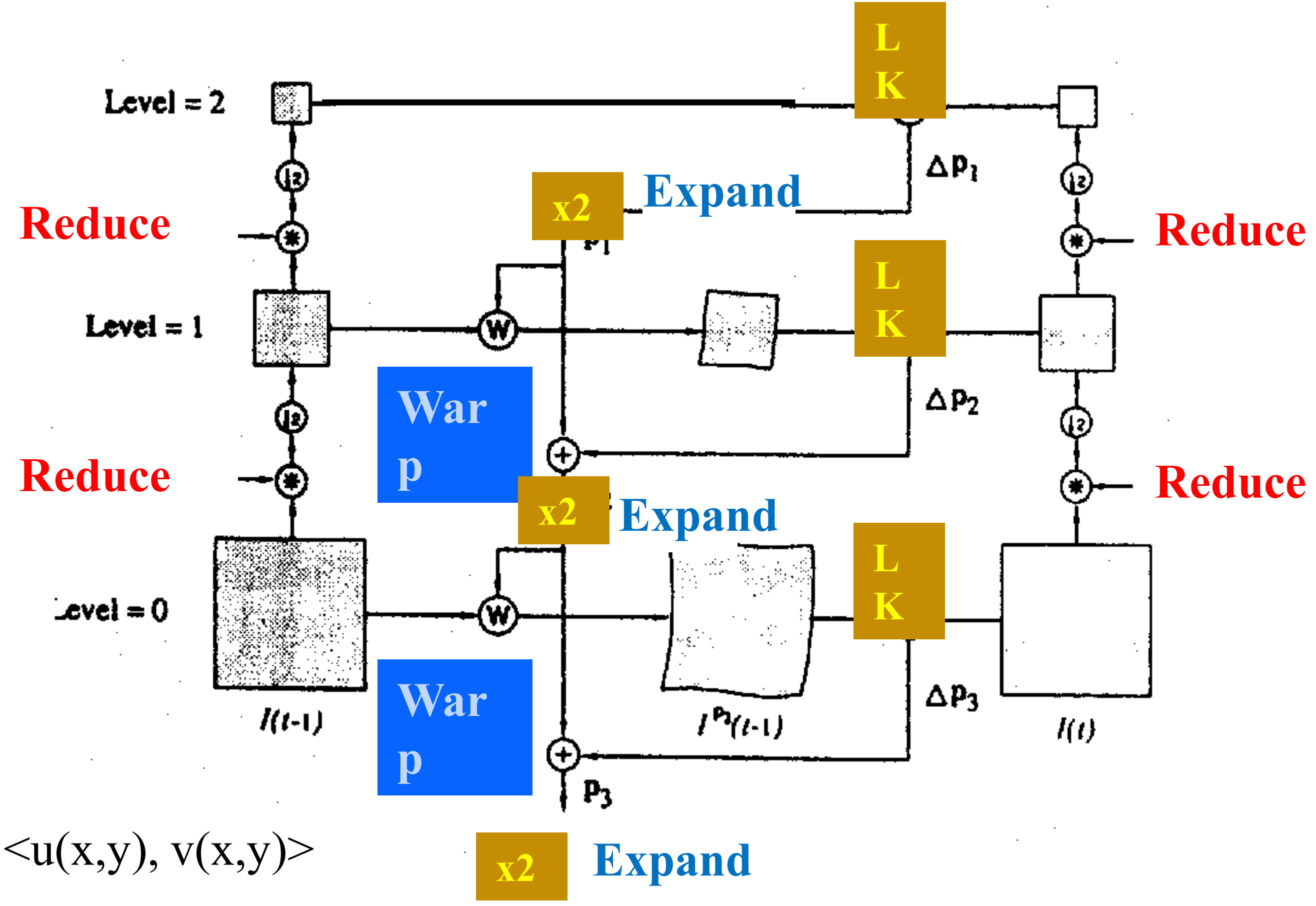
L_2

L_4

Reconstructed



Applying pyramids to LK



Final <u(x,y), v(x,y)>

Hierarchical LK

1. Compute Iterative LK at level K

2. Initialize $u_{K+1}, v_{K+1} = 0$ at size of level K+1

3. For Each Level *i* from *K* to 0

- Upsample (EXPAND) u_{i+1}, v_{i+1} to create u_i^p, v_i^p flow fields of now twice resolution as level *i+1*
- Multiply u_i^p, v_i^p by 2 to get predicted flow
- Warp level i Gaussian version of I_2 according to predicted flow to create I_2'

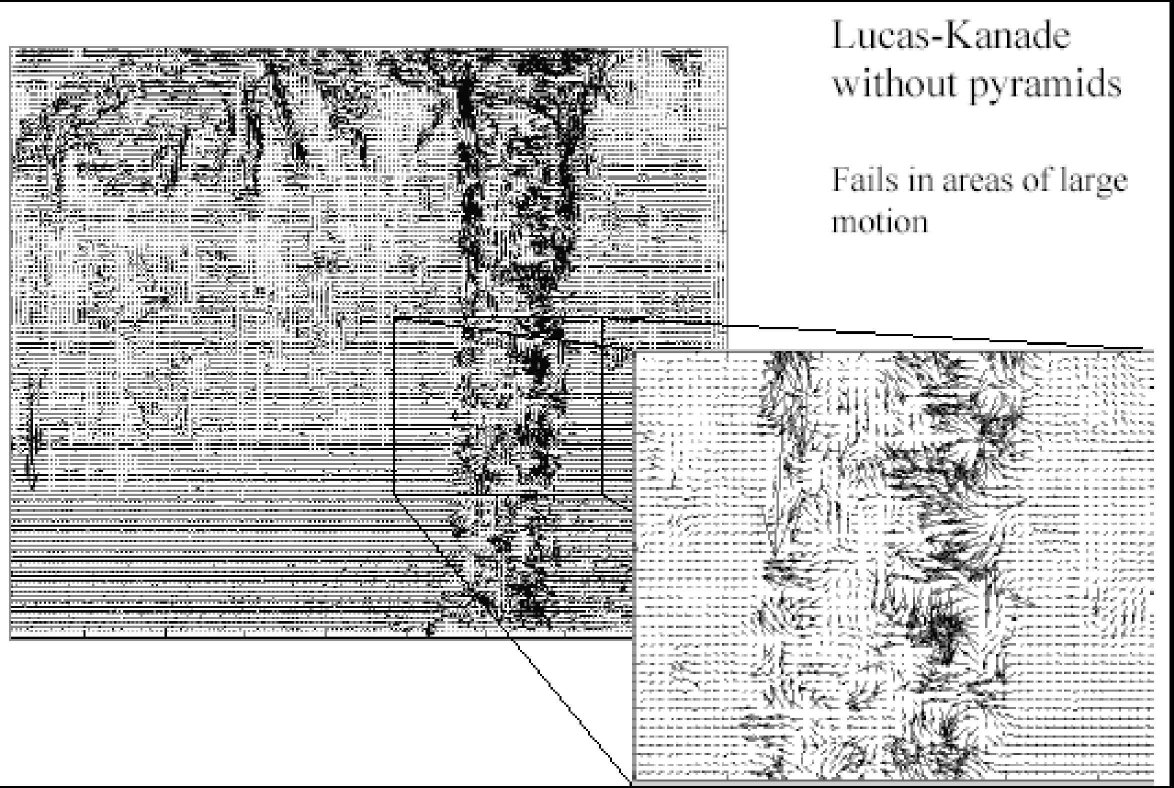
3. For Each Level i from K to 0

- Apply LK between $I_2{}'$ and level i Gaussian version of I_1 to get u_i^δ, v_i^δ (the correction in flow)

Add corrections to obtain the flow u_i, v_i at i th level, i.e.,

$$u_i = u_i^p + u_i^\delta$$
$$v_i = v_i^p + v_i^\delta$$

Optical Flow Results



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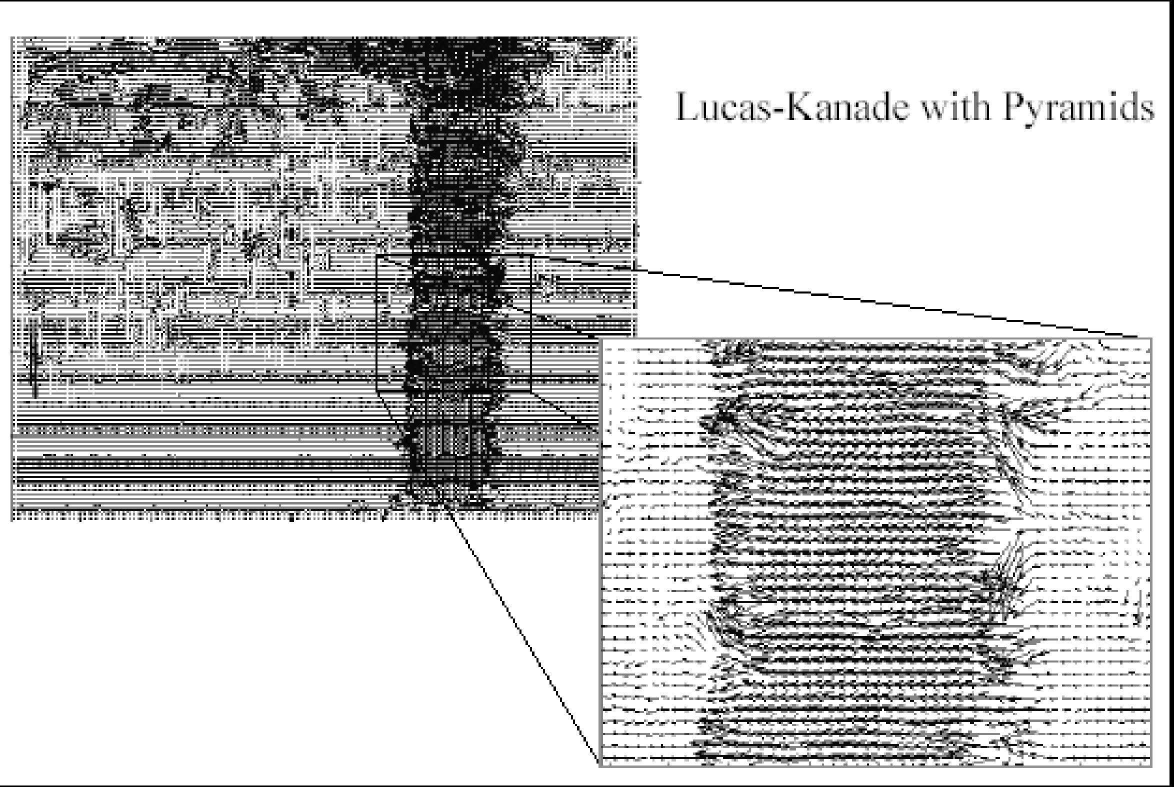
Optical Flow Results



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Sparse LK

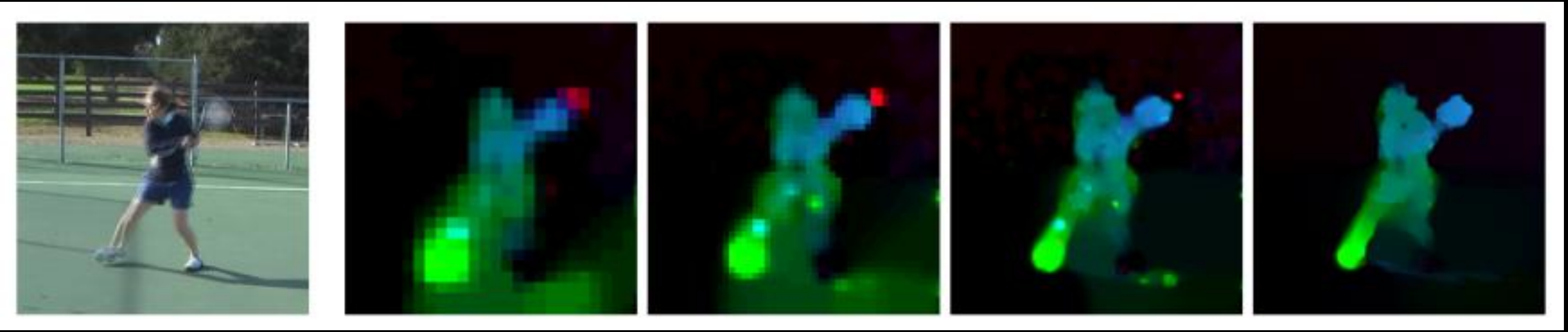
- The Lucas-Kanade algorithm described gives a dense field, (u, v) everywhere.
- But we said that we only want to solve LK where the eigenvalues are well behaved.

Sparse LK

- "Sparse LK" is basically just that: hierarchical applied to good feature locaitons.
- OpenCV LK used to be dense – then became sparse!

Start with something similar to Lucas-Kanade

+ gradient constancy
+ energy minimization with smoothing term
+ region matching
+ keypoint matching (long-range)



Large displacement optical flow Brox et al., CVPR 2009