Motion and Optical Flow

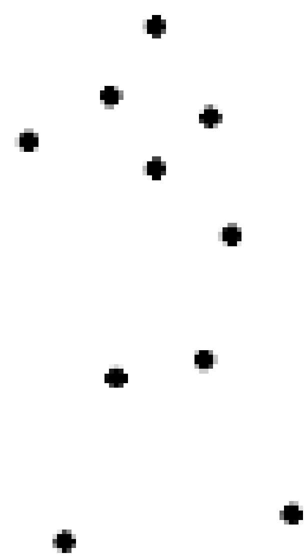
CSE 455
Linda Shapiro

We live in a moving world

- Perceiving, understanding and predicting motion is an important part of our daily lives

Motion and perceptual organization

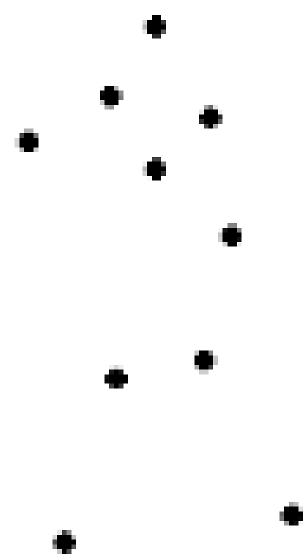
- Even "impoverished" motion data can evoke a strong percept



G. Johansson, "Visual Perception of Biological Motion and a Model For Its Analysis", *Perception and Psychophysics 14, 201-211, 1973.*

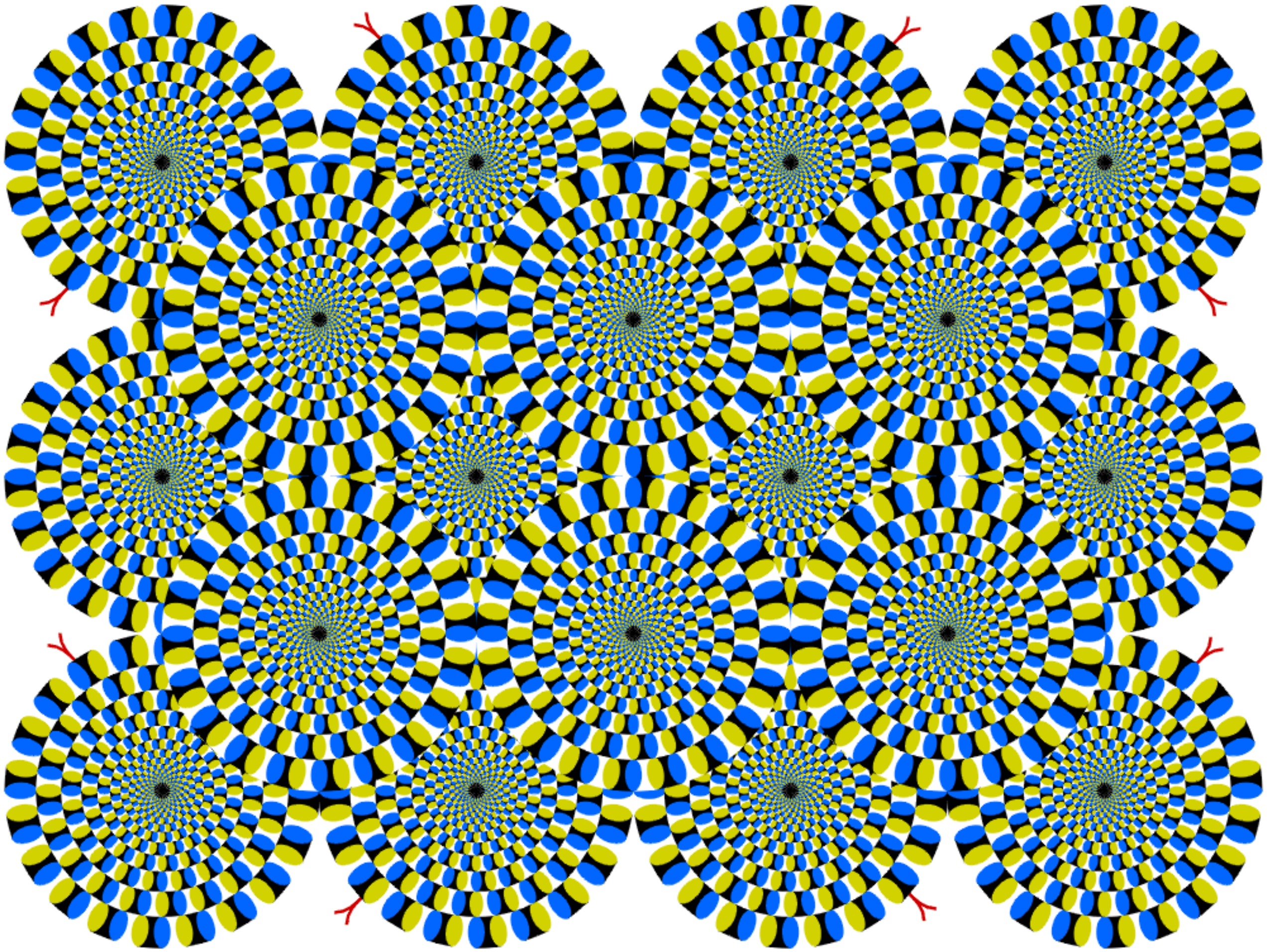
Motion and perceptual organization

- Even “impoverished” motion data can evoke a strong percept



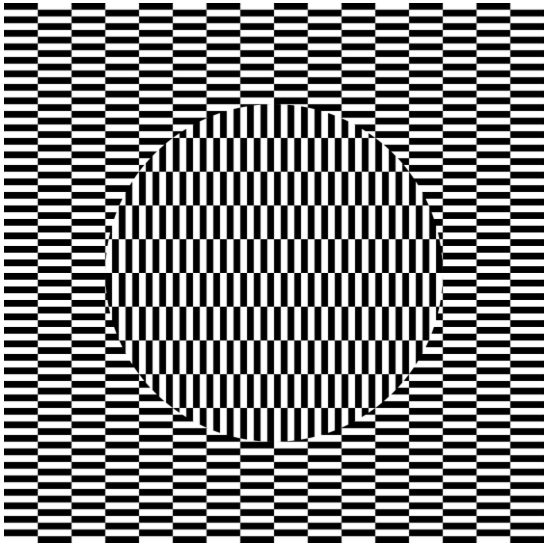
G. Johansson, “Visual Perception of Biological Motion and a Model For Its Analysis",
Perception and Psychophysics 14, 201-211, 1973.

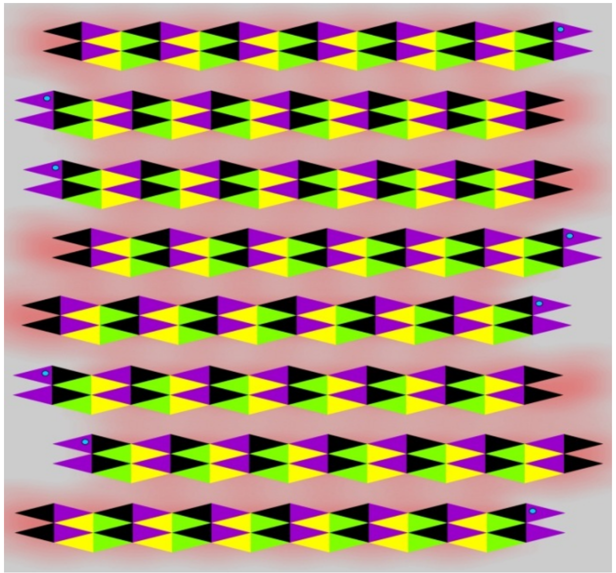
Seeing motion from a static picture?

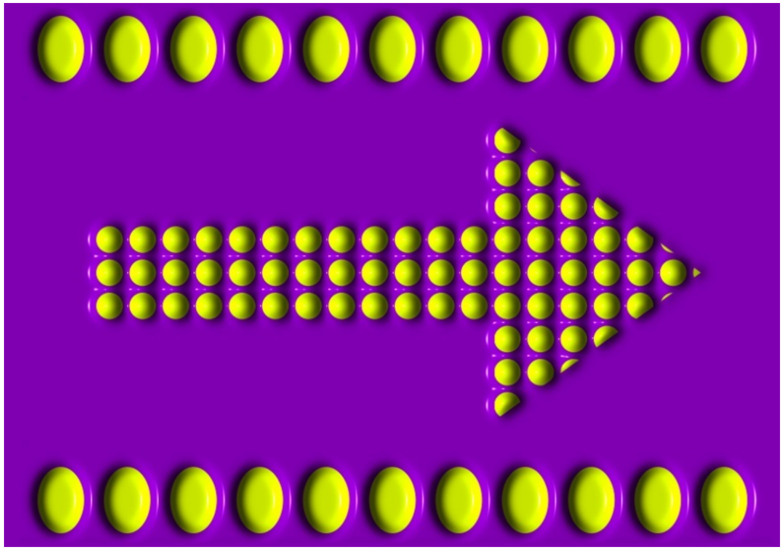


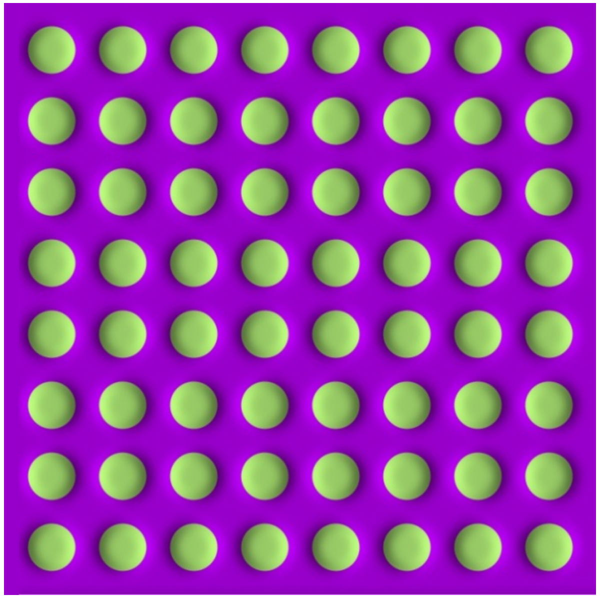
http://www.ritsumei.ac.jp/~akitaoka/index-e.html

More examples



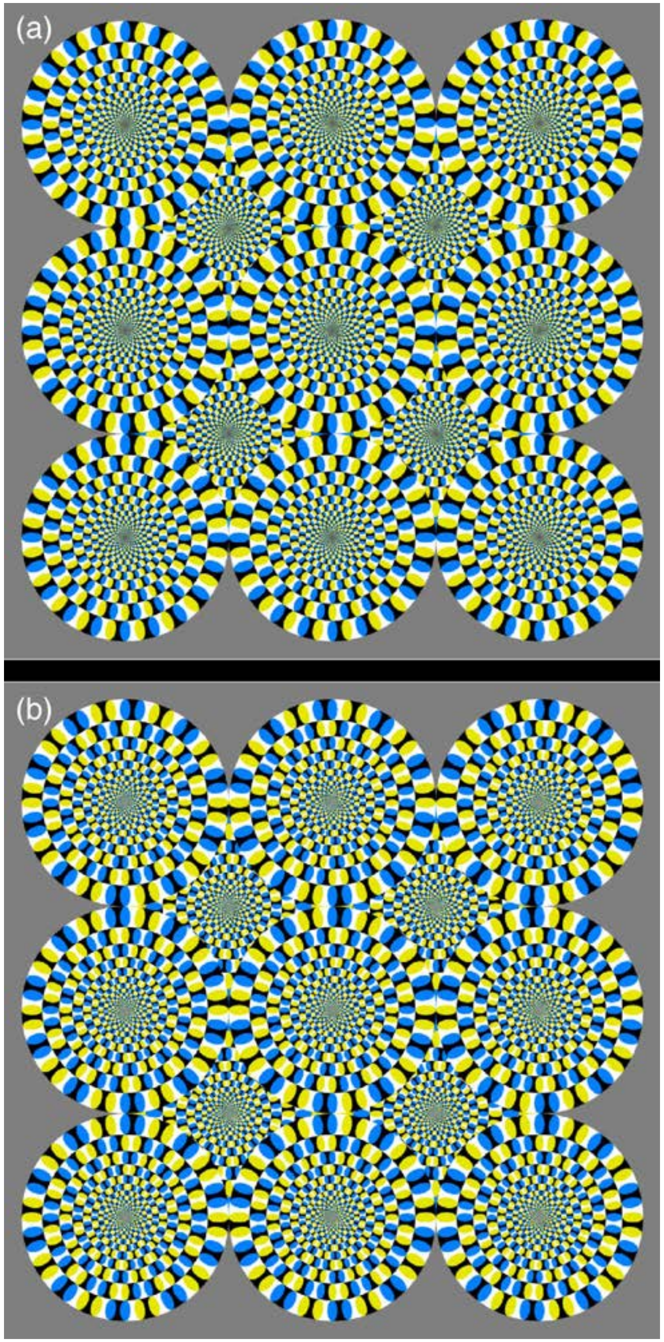






How is this possible?

- The true mechanism is yet to be revealed
- FMRI data suggest that illusion is related to some component of eye movements
- We don't expect computer vision to "see" motion from these stimuli, yet



The cause of motion

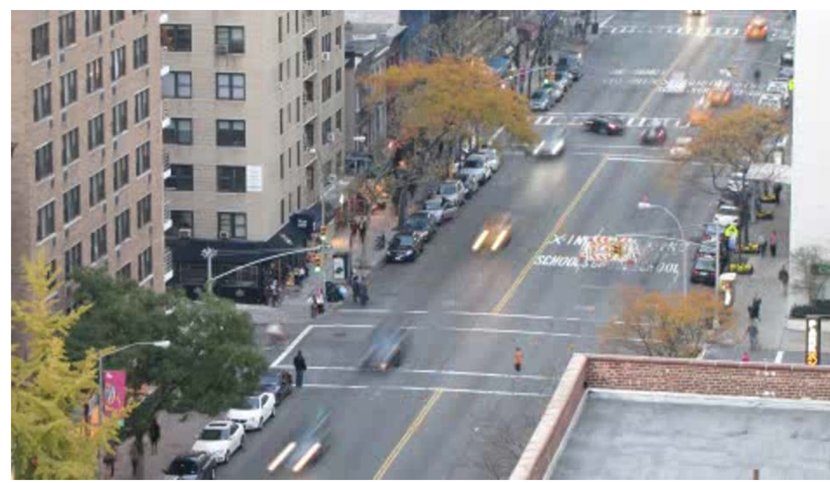
- Three factors in imaging process
  - Light
  - Object
  - Camera
- Varying either of them causes motion
  - Static camera, moving objects (surveillance)
  - Moving camera, static scene (3D capture)
  - Moving camera, moving scene (sports, movie)
  - Static camera, moving objects, moving light (time lapse)

Motion scenarios (priors)

Static camera, moving scene

Moving camera, static scene

Moving camera, moving scene



Static camera, moving scene, moving light

We still don’t touch these areas

How can we recover motion?

Recovering motion

- Feature-tracking
  - Extract visual features (corners, textured areas) and “track” them over multiple frames

- Optical flow
  - Recover image motion at each pixel from spatio-temporal image brightness variations (optical flow)

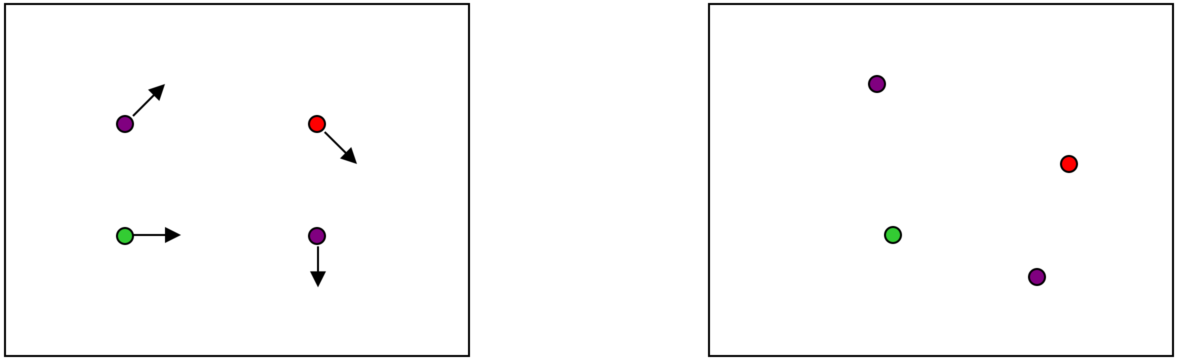
Two problems, one registration method

B. Lucas and T. Kanade. An iterative image registration technique with an application to stereo vision. In *Proceedings of the International Joint Conference on Artificial Intelligence*, pp. 674–679, 1981.

Feature tracking

- Challenges
  - Figure out which features can be tracked
  - Efficiently track across frames
  - Some points may change appearance over time (e.g., due to rotation, moving into shadows, etc.)
  - Drift: small errors can accumulate as appearance model is updated
  - Points may appear or disappear: need to be able to add/delete tracked points

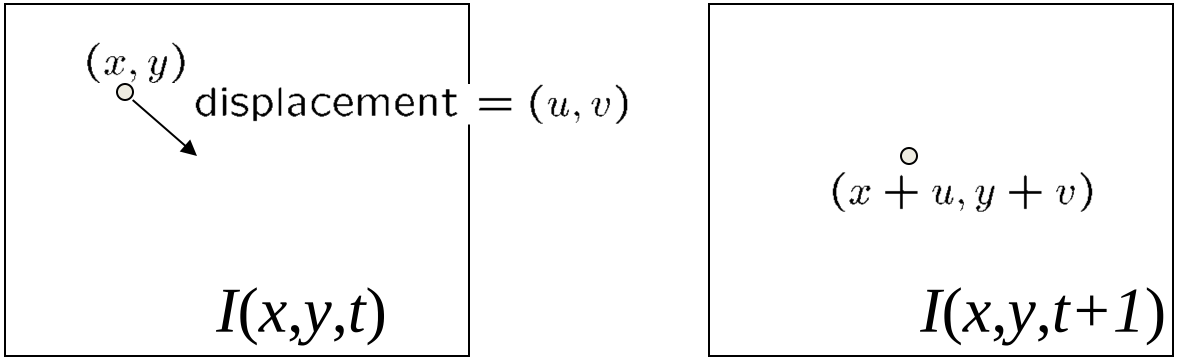
Feature tracking



$I(x,y,t)$ $I(x,y,t+1)$

- Given two subsequent frames, estimate the point translation
- Key assumptions of Lucas-Kanade Tracker
  - **Brightness constancy:** projection of the same point looks the same in every frame
  - **Small motion:** points do not move very far
  - **Spatial coherence:** points move like their neighbors

The brightness constancy constraint



- Brightness Constancy Equation:

$$I(x, y, t) = I(x+u, y+v, t+1)$$

Take Taylor expansion of *I(x+u, y+v, t+1)* at *(x,y,t)* to linearize the right side:

Image derivative along x   Difference over frames

$$I(x+u, y+v, t+1) \approx I(x, y, t) + I_x \cdot u + I_y \cdot v + I_t$$

$$I(x+u, y+v, t+1) - I(x, y, t) = +I_x \cdot u + I_y \cdot v + I_t$$

So: $I_x \cdot u + I_y \cdot v + I_t \approx 0 \quad \rightarrow \nabla \mathrm{I} \cdot [\mathrm{u} \;\; \mathrm{v}]^{\mathrm{T}} + \mathrm{I_t} = 0$

The brightness constancy constraint

Can we use this equation to recover image motion (u,v) at each pixel?

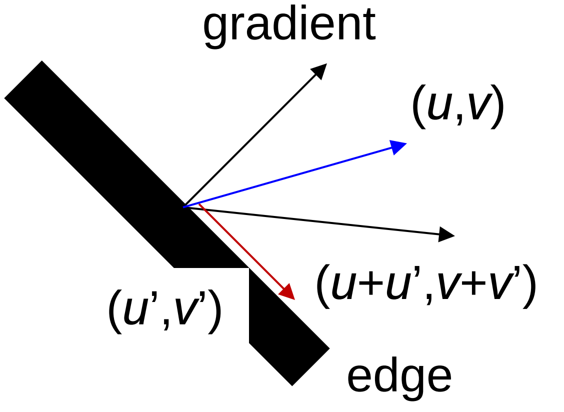
$$\nabla I \cdot [u \;\; v]^T + I_t = 0$$

- How many equations and unknowns per pixel?
  - One equation (this is a scalar equation!), two unknowns (u,v)

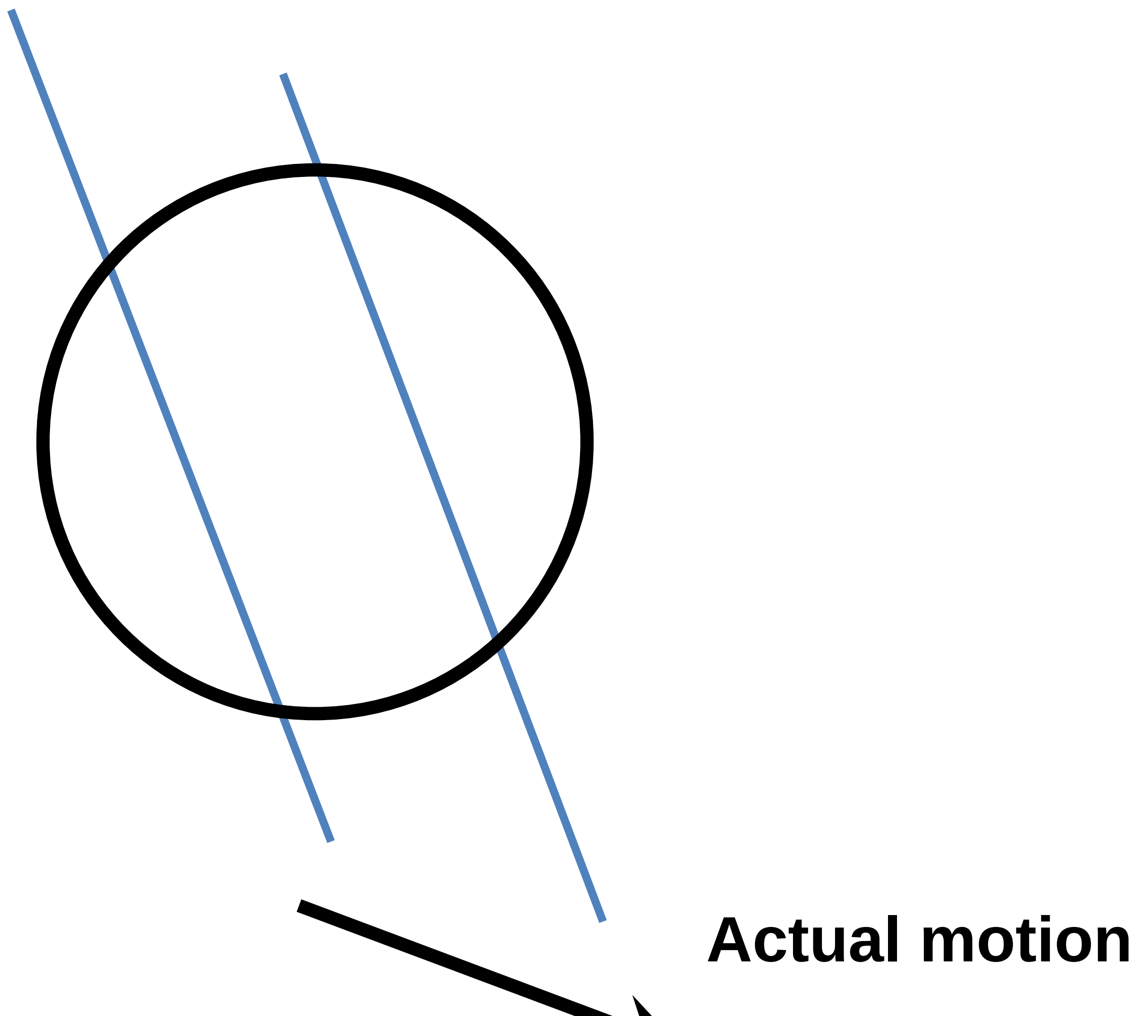
The component of the motion perpendicular to the gradient (i.e., parallel to the edge) cannot be measured

If (*u*, *v*) satisfies the equation, so does (*u+u'*, *v+v'*) if

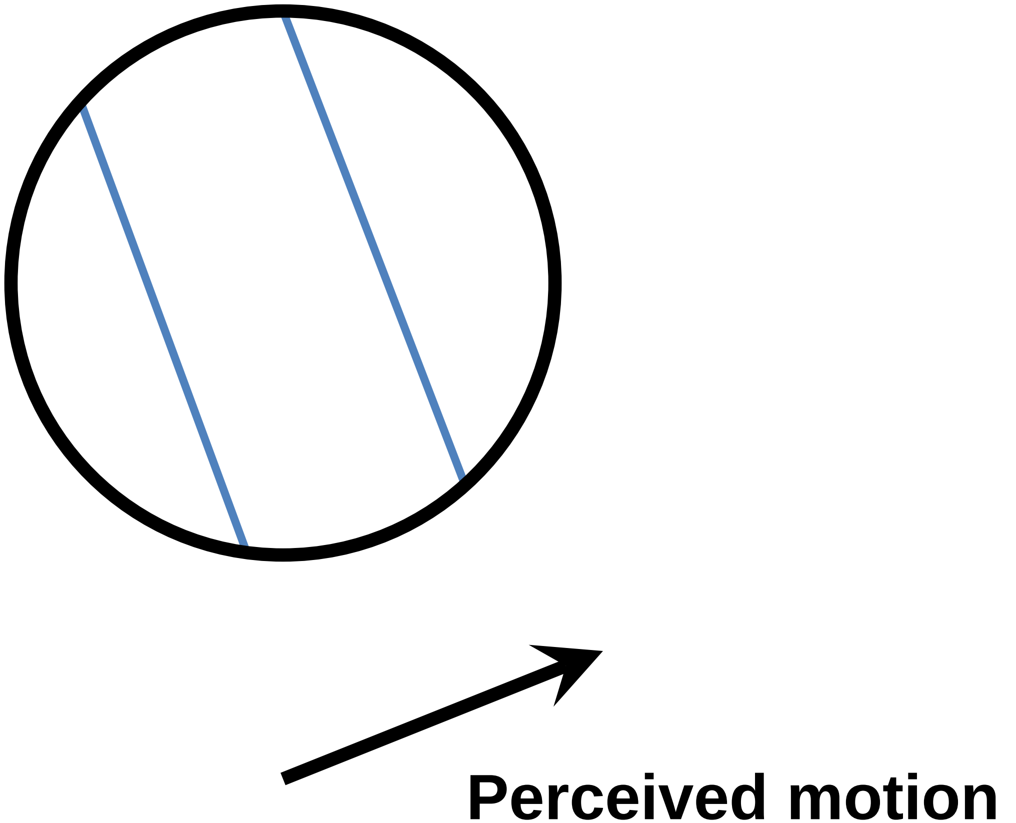
$$\nabla I \cdot [u' \;\; v']^T = 0$$



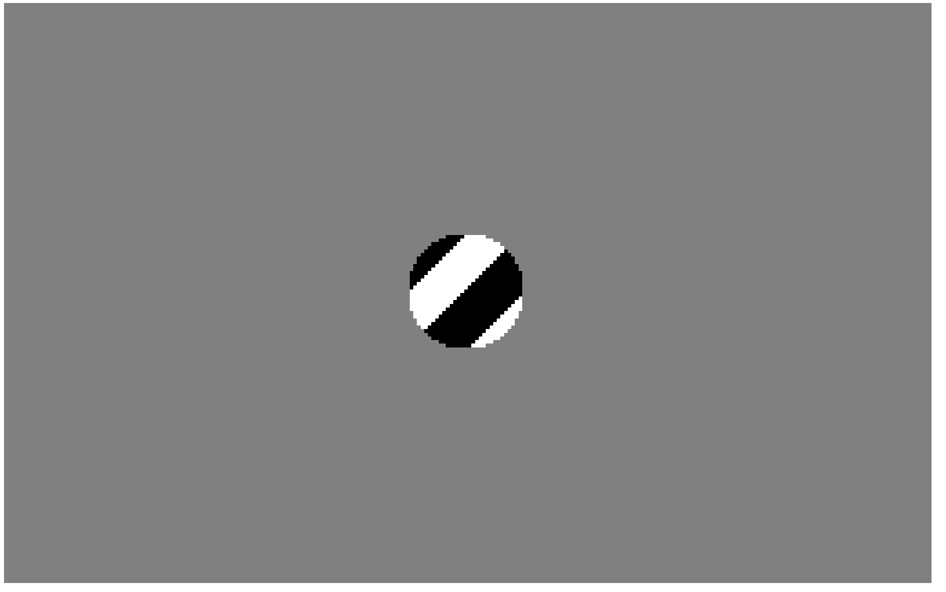
The aperture problem



The aperture problem

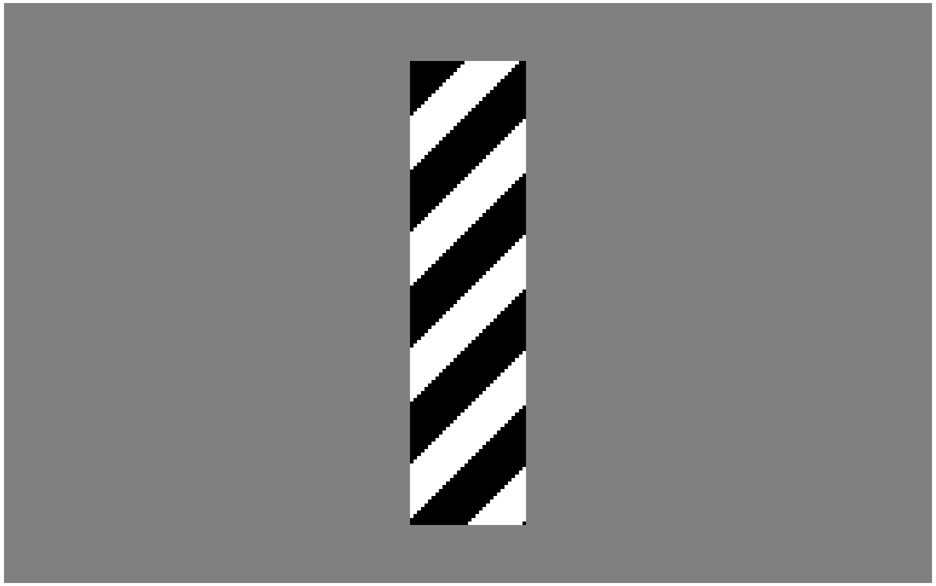


The barber pole illusion



http://en.wikipedia.org/wiki/Barberpole_illusion

The barber pole illusion



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Solving the ambiguity…

B. Lucas and T. Kanade. An iterative image registration technique with an application to stereo vision. In *Proceedings of th International Joint Conference on Artificial Intelligence*, pp. 674–679, 1981.

- How to get more equations for a pixel?
- **Spatial coherence constraint**
- Assume the pixel's neighbors have the same (u,v)
  - If we use a 5x5 window, that gives us 25 equations per pixel

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

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

Solving the ambiguity…

- Least squares problem:

$$\begin{bmatrix} I_x(\mathbf{p_1}) & I_y(\mathbf{p_1}) \\ I_x(\mathbf{p_2}) & I_y(\mathbf{p_2}) \\ \vdots & \vdots \\ I_x(\mathbf{p_{25}}) & I_y(\mathbf{p_{25}}) \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = - \begin{bmatrix} I_t(\mathbf{p_1}) \\ I_t(\mathbf{p_2}) \\ \vdots \\ I_t(\mathbf{p_{25}}) \end{bmatrix}$$

$$\underset{25\times 2}{A} \; \underset{2\times 1}{d} = \underset{25\times 1}{b}$$

Matching patches across images

- Overconstrained linear system

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

$$\underset{25\times2}{A} \; \underset{2\times1}{d} = \underset{25\times1}{b}$$

Least squares solution for *d* given by

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

$$\underbrace{\begin{bmatrix} \sum I_x I_x & \sum I_x I_y \\ \sum I_x I_y & \sum I_y I_y \end{bmatrix}}_{A^T A} \begin{bmatrix} u \\ v \end{bmatrix} = - \underbrace{\begin{bmatrix} \sum I_x I_t \\ \sum I_y I_t \end{bmatrix}}_{A^T b}$$

The summations are over all pixels in the K x K window

Conditions for solvability

Optimal (u, v) satisfies Lucas-Kanade equation

$$\underbrace{\begin{bmatrix} \sum I_x I_x & \sum I_x I_y \\ \sum I_x I_y & \sum I_y I_y \end{bmatrix}}_{A^T A} \begin{bmatrix} u \\ v \end{bmatrix} = - \underbrace{\begin{bmatrix} \sum I_x I_t \\ \sum I_y I_t \end{bmatrix}}_{A^T b}$$

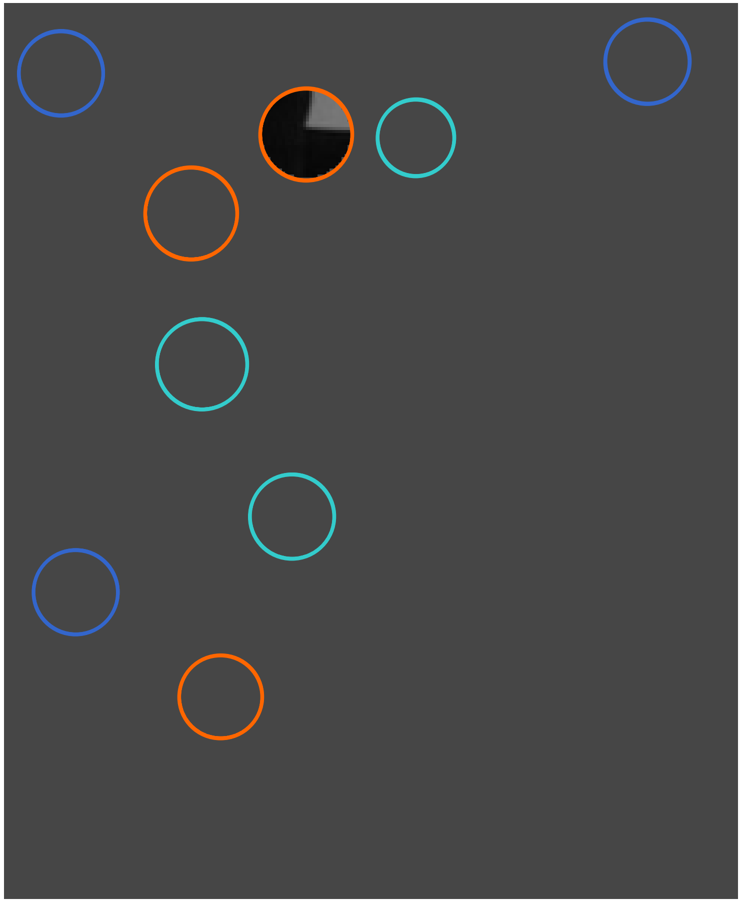
When is this solvable? I.e., what are good points to track?

- $\mathbf{A^T A}$ should be invertible
- $\mathbf{A^T A}$ should not be too small due to noise
  - eigenvalues λ_1 and λ_2 of $\mathbf{A^T A}$ should not be too small
- $\mathbf{A^T A}$ should be well-conditioned
  - λ_1 / λ_2 should not be too large (λ_1 = larger eigenvalue)

Does this remind you of anything?

Criteria for Harris corner detector

Aperture problem

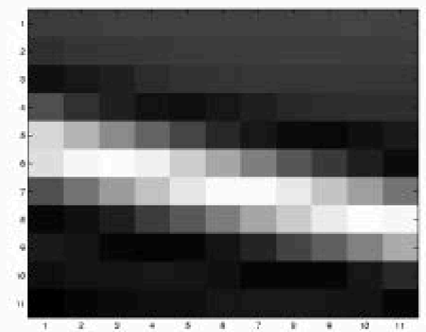


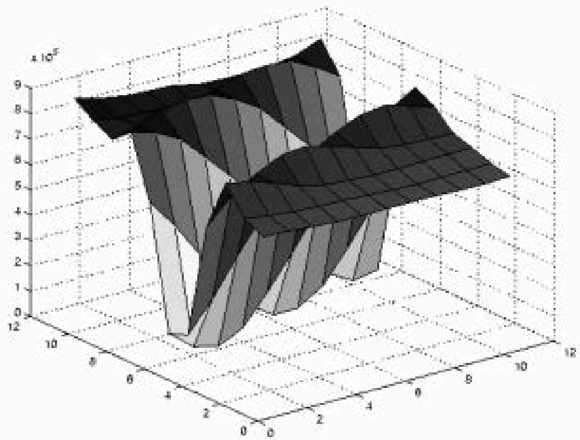
Corners

Lines

Flat regions

Edge



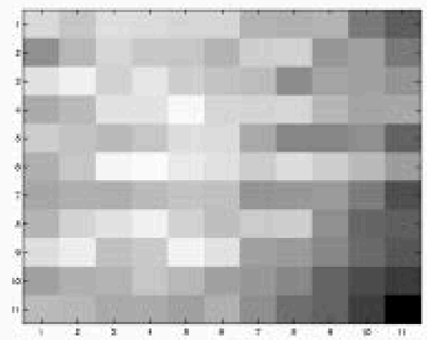


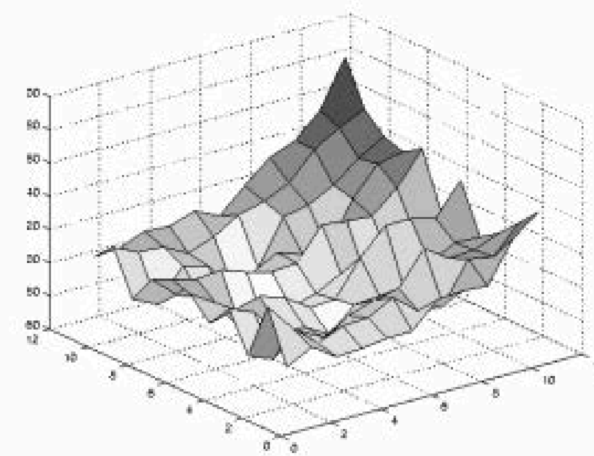
$$\sum \nabla I (\nabla I)^T$$

– large gradients, all the same

– large λ_1, small λ_2

Low Texture Region



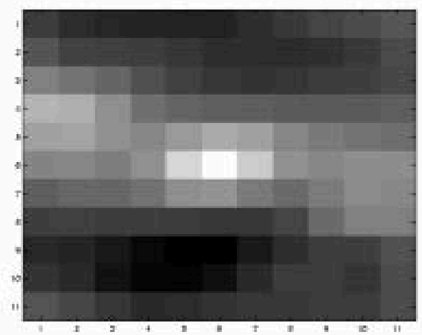


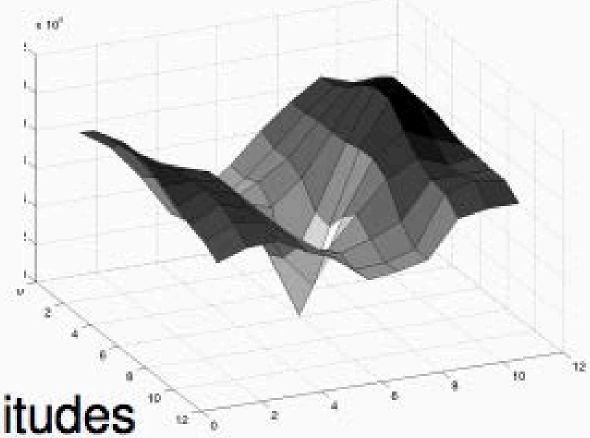
$$\sum \nabla I (\nabla I)^T$$

– gradients have small magnitude

– small λ_1, small λ_2

High Texture Region





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

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

Errors in Lukas-Kanade

- What are the potential causes of errors in this procedure?
  - Suppose A^TA is easily invertible
  - Suppose there is not much noise in the image

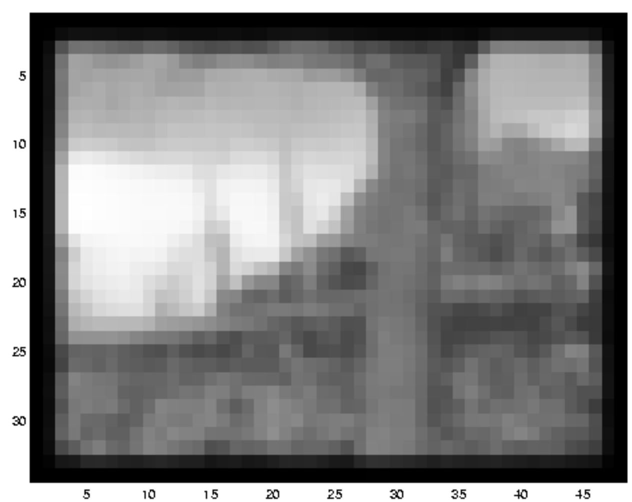
When our assumptions are violated

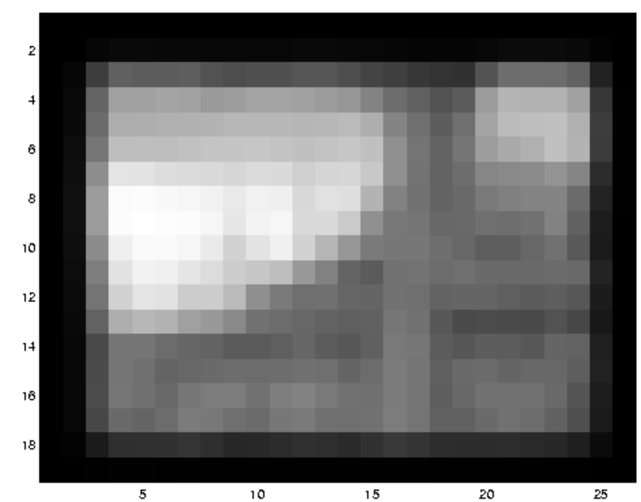
- Brightness constancy is **not** satisfied
- The motion is **not** small
- A point does **not** move like its neighbors
  - window size is too large
  - what is the ideal window size?

Revisiting the small motion assumption

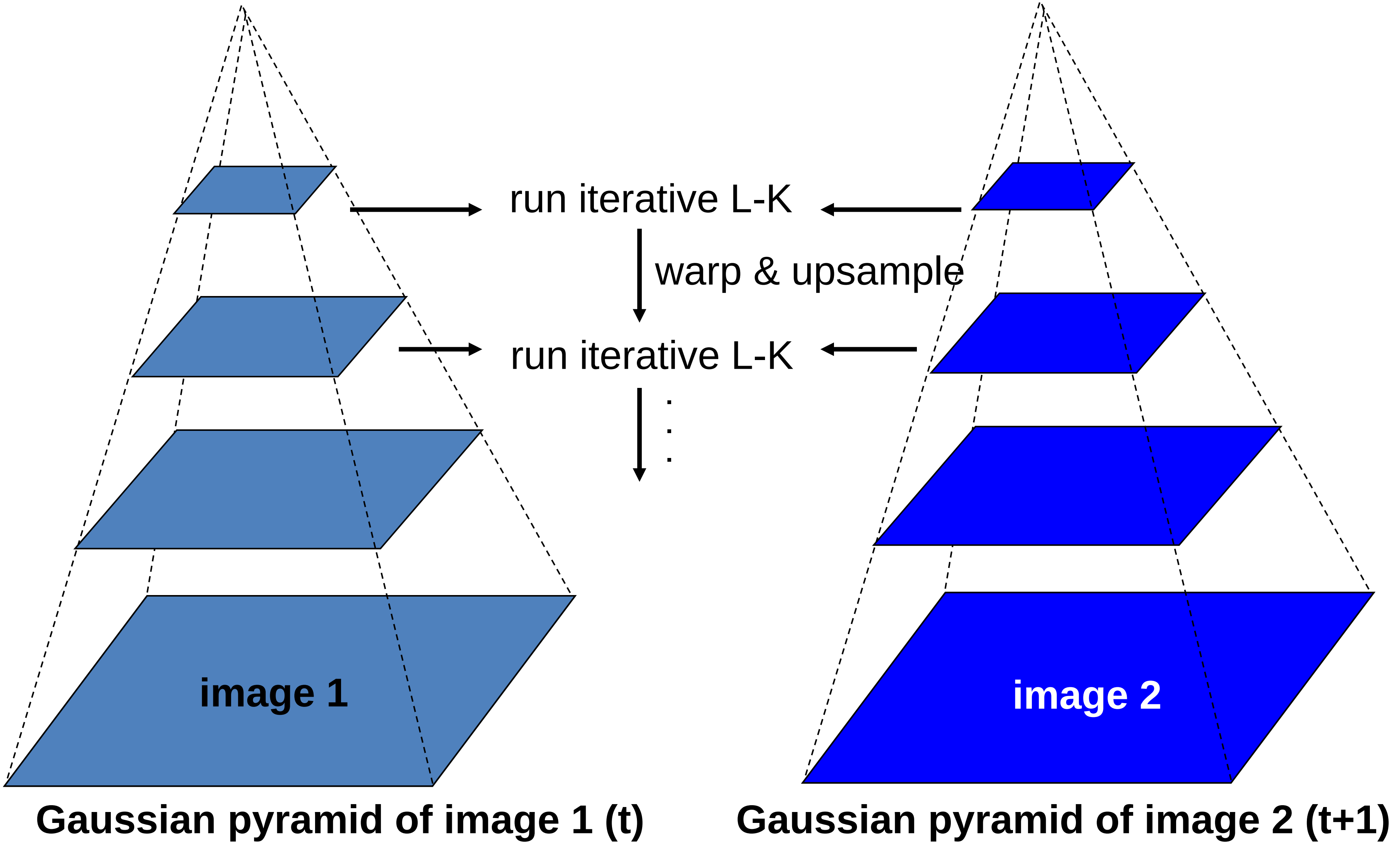
- Is this motion small enough?
  - Probably not—it's much larger than one pixel (2^{nd} order terms dominate)
  - How might we solve this problem?

Reduce the resolution!





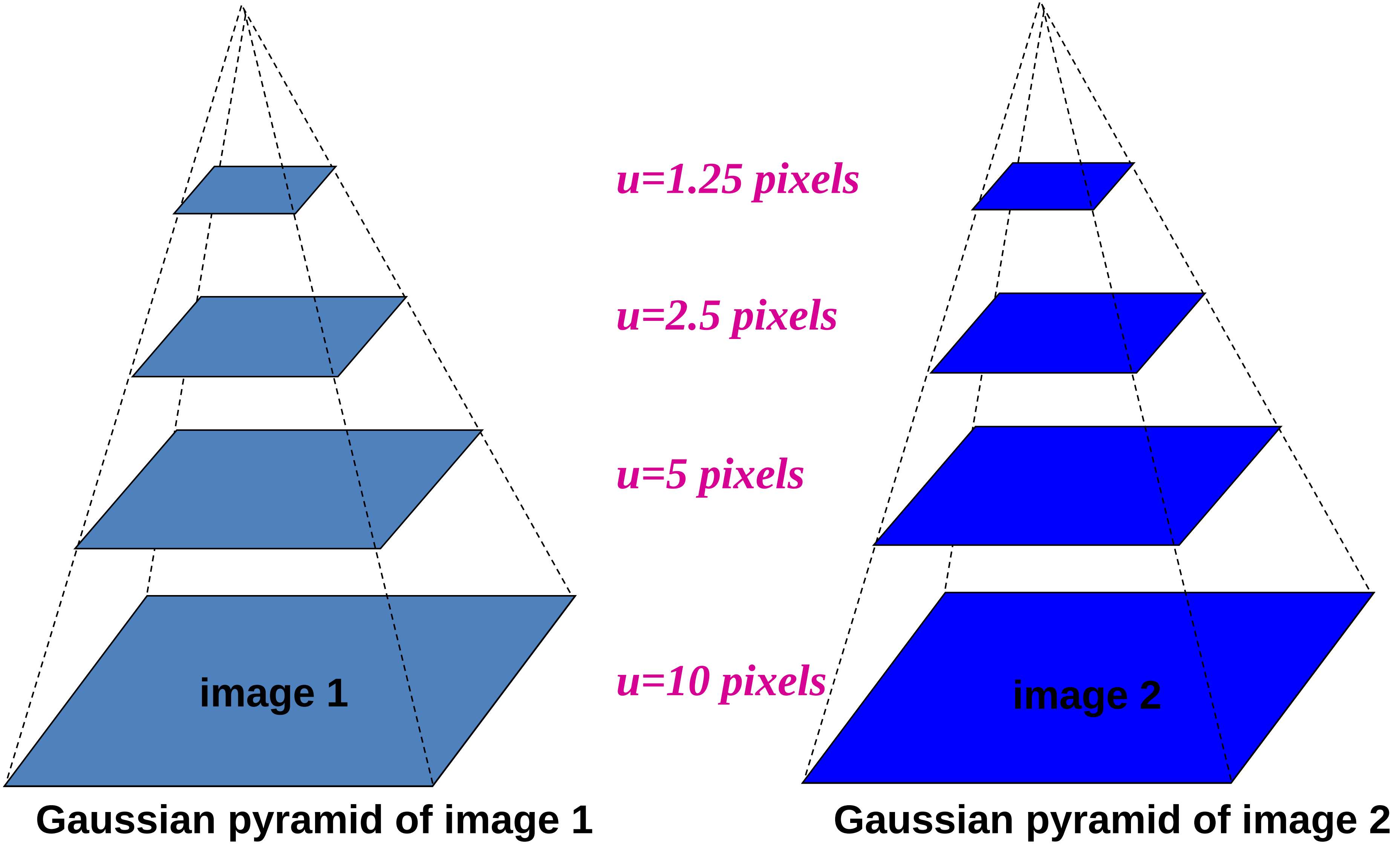
Coarse-to-fine optical flow estimation



A Few Details

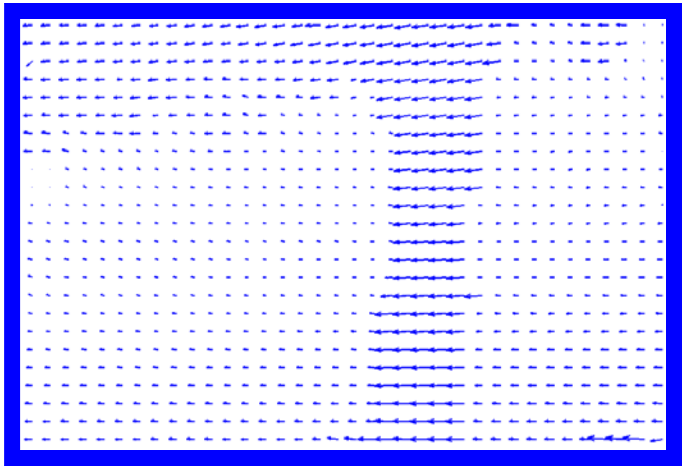
- Top Level
  - Apply L-K to get a flow field representing the flow from the first frame to the second frame.
  - Apply this flow field to warp the first frame toward the second frame.
  - Rerun L-K on the new warped image to get a flow field from it to the second frame.
  - Repeat till convergence.
- Next Level
  - Upsample the flow field to the next level as the first guess of the flow at that level.
  - Apply this flow field to warp the first frame toward the second frame.
  - Rerun L-K and warping till convergence as above.
- Etc.

Coarse-to-fine optical flow estimation

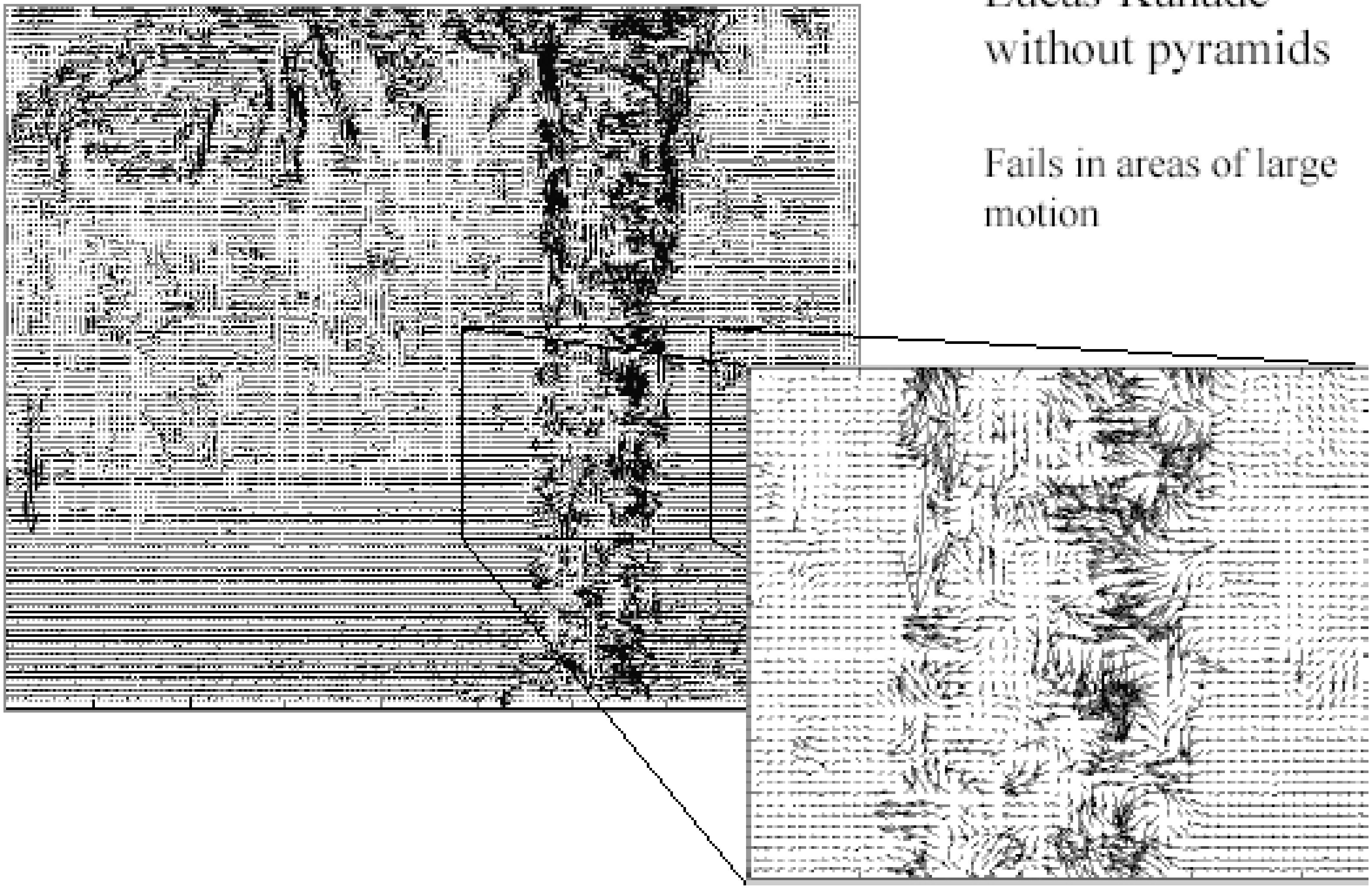


The Flower Garden Video

What should the
optical flow be?



Optical Flow Results

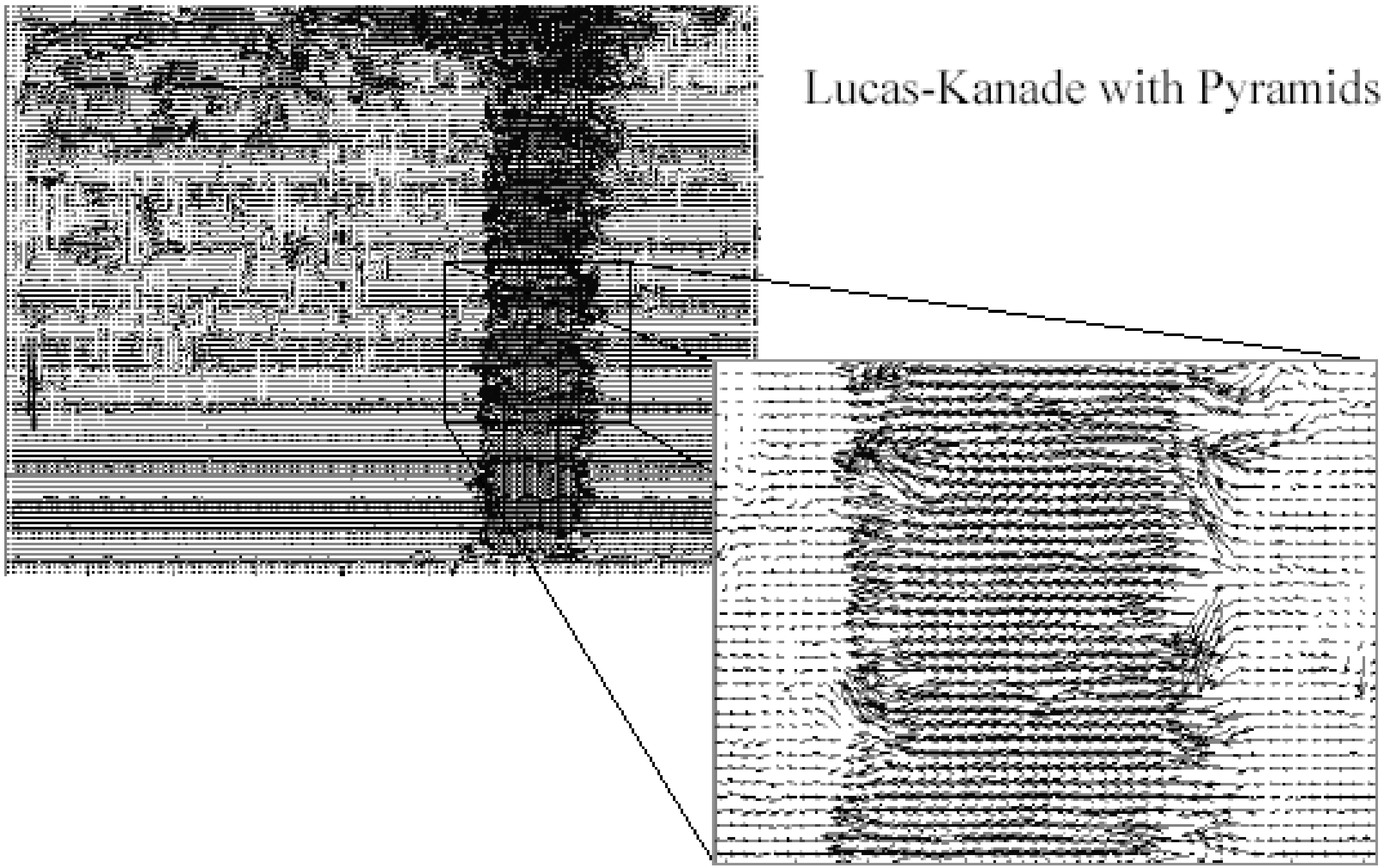


Lucas-Kanade without pyramids

Fails in areas of large motion

* From Khurram Hassan-Shafique CAP5415 Computer Vision 2003

Optical Flow Results



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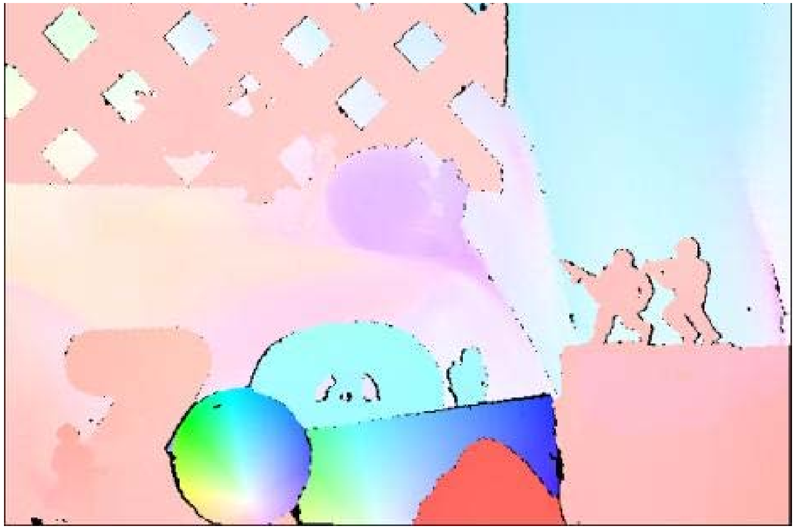
Flow quality evaluation

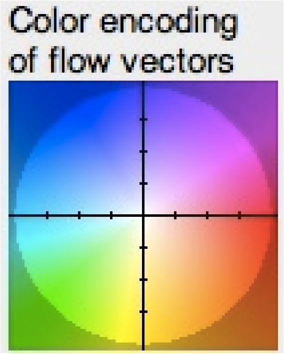
Flow quality evaluation

Flow quality evaluation

- Middlebury flow page
  - http://vision.middlebury.edu/flow/



Ground Truth



Flow quality evaluation

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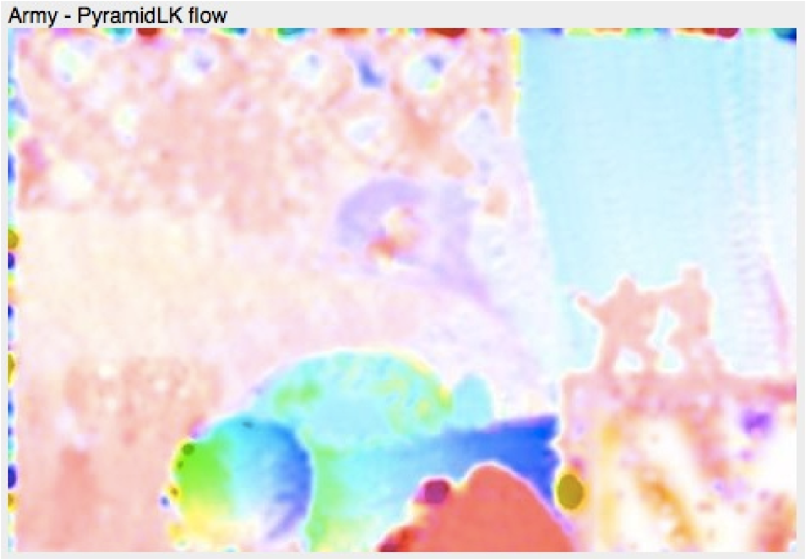
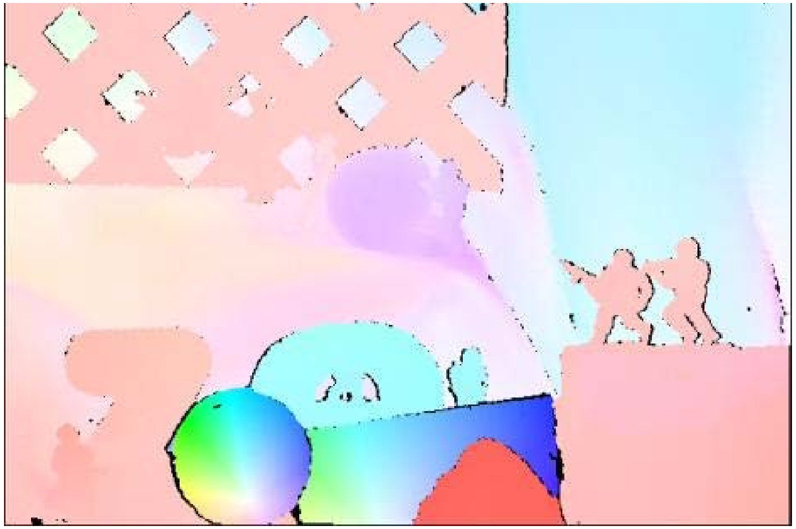


Lucas-Kanade flow



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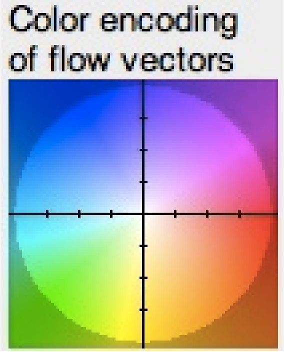

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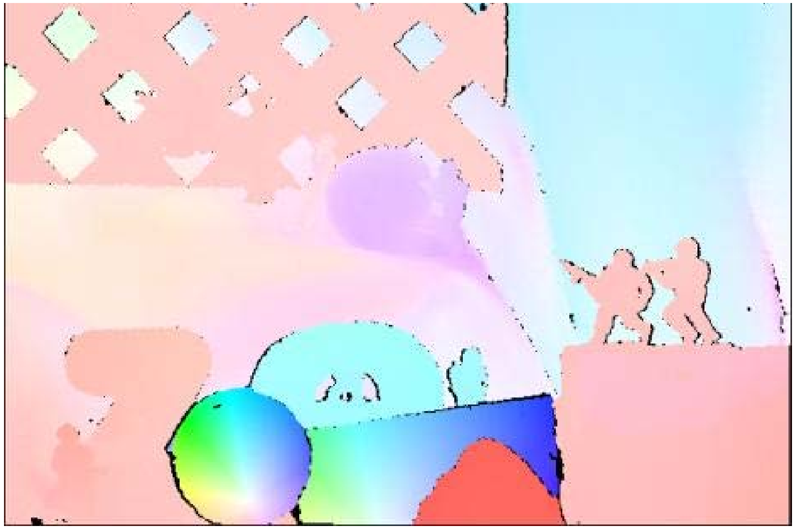
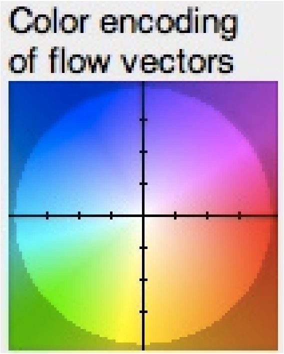
Best-in-class alg



Ground Truth



Video stabilization

Video denoising

Video super resolution

Robust Visual Motion Analysis:
Piecewise-Smooth Optical Flow

Ming Ye
Electrical Engineering
University of Washington

Estimating Piecewise-Smooth Optical Flow with Global Matching and Graduated Optimization

Problem Statement:

Assuming only brightness conservation and piecewise-smooth motion, find the optical flow to best describe the intensity change in three frames.

Approach: Matching-Based Global Optimization

- **Step 1. Robust local gradient-based method for high-quality initial flow estimate.**

  Uses least median of squares instead of regular least squares.

- **Step 2. Global gradient-based method to improve the flow-field coherence.**

  Minimizes a global energy function $E = \Sigma\,(E_B(V_i) + E_S(V_i))$ where E_B is the brightness difference and E_S is the smoothness at flow vector V_i

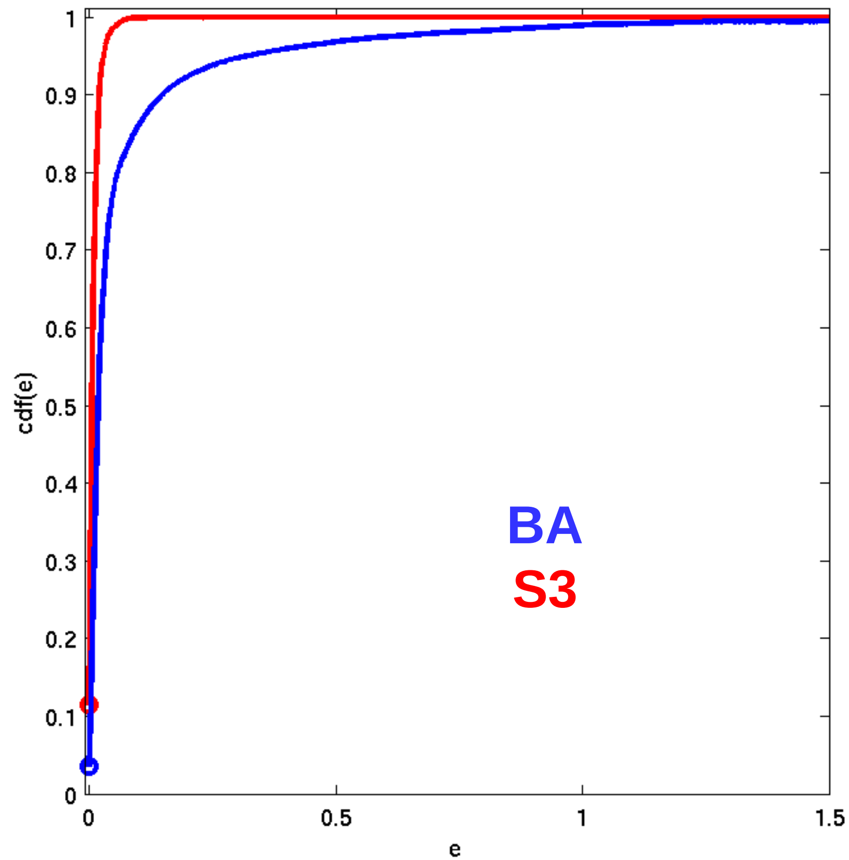
- **Step 3. Global matching that minimizes energy by a greedy approach.**

  Visits each pixel and updates it to be consistent with neighbors, iteratively.

TT: Translating Tree

150x150 (Barron 94)

	$e_{\angle}(^{\circ})$	$e_{\lvert\bullet\rvert}(\text{pix})$	$\bar{e}(\text{pix})$
BA	2.60	0.128	0.0724
S3	0.248	0.0167	0.00984

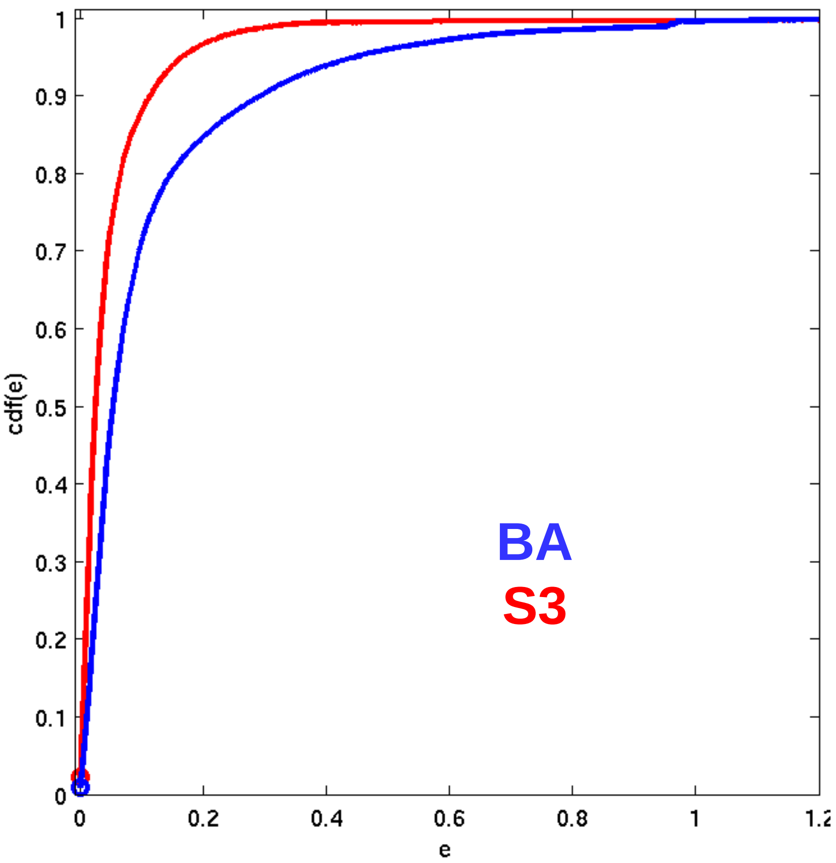


e: error in pixels, cdf: culmulative distribution function for all pixels

DT: Diverging Tree

150x150 (Barron 94)

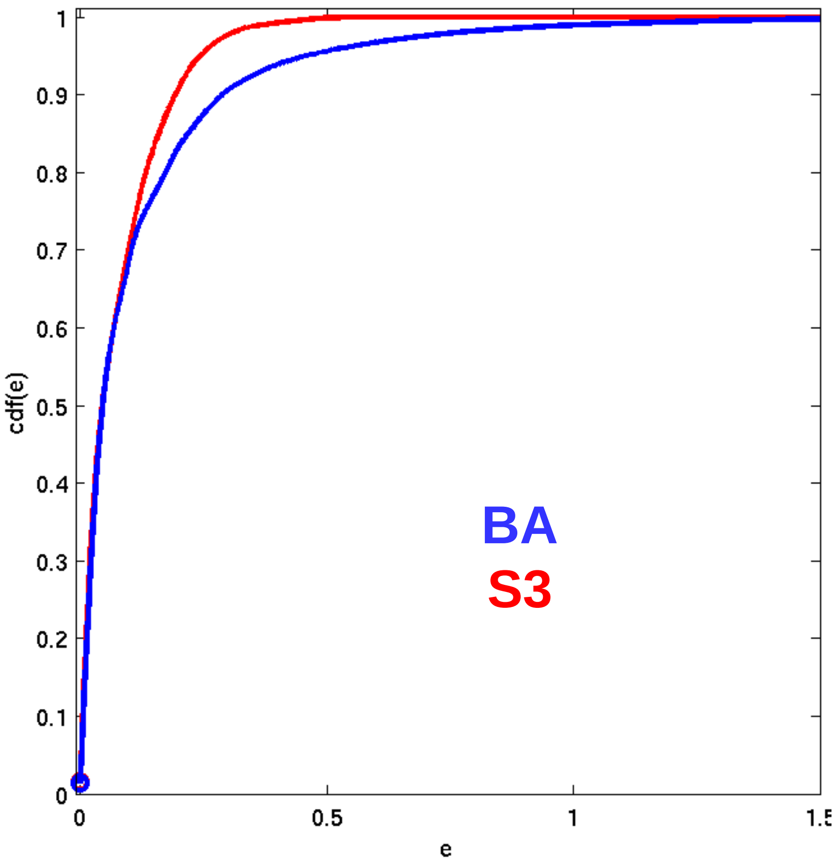
	$e_{\angle}(^\circ)$	$e_{\|\bullet\|}(\text{pix})$	$\overline{e}(\text{pix})$
BA	6.36	0.182	0.114
S3	2.60	0.0813	0.0507



YOS: Yosemite Fly-Through

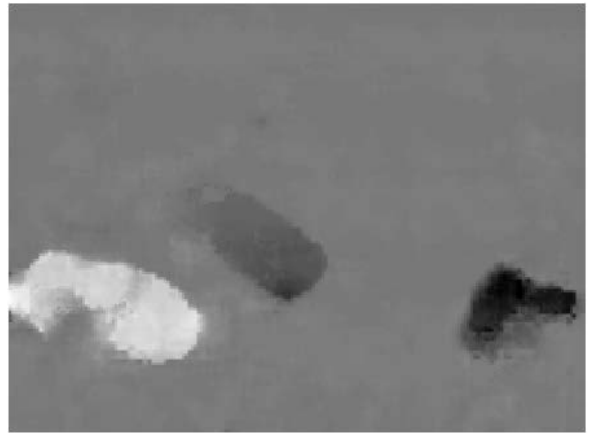
316x252 (Barron, cloud excluded)

	$e_{\angle}(^{\circ})$	$e_{\lvert\bullet\rvert}(\text{pix})$	$\bar{e}(\text{pix})$
BA	2.71	0.185	0.118
S3	1.92	0.120	0.0776



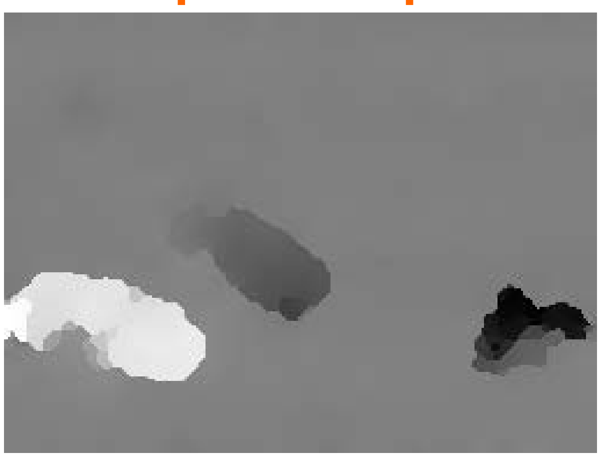
TAXI: Hamburg Taxi

256x190, (Barron 94)
max speed 3.0 pix/frame

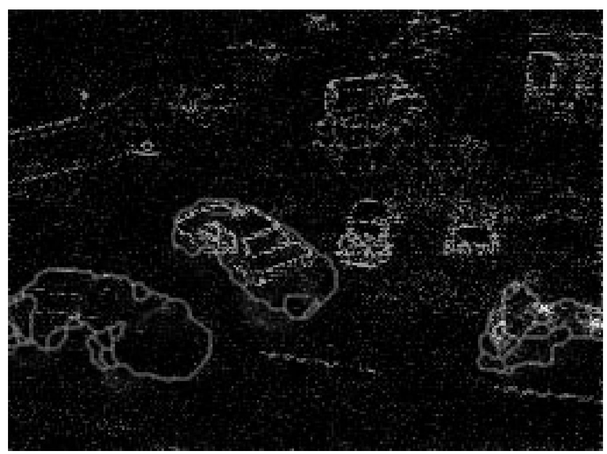


LMS

BA



Ours

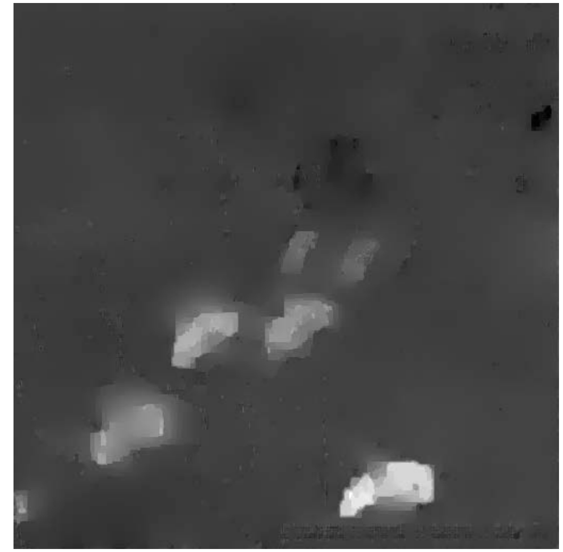


Error map

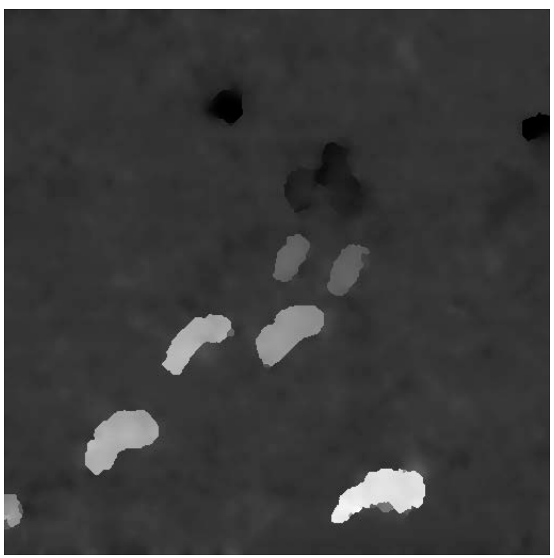
Smoothness error

Traffic

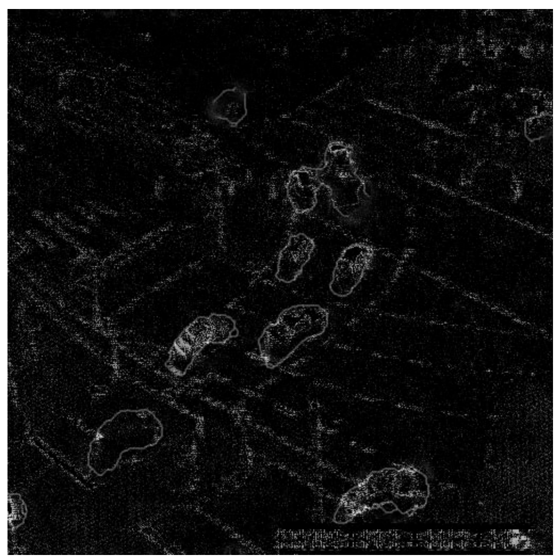
512x512
(Nagel)
max speed:
6.0 pix/frame



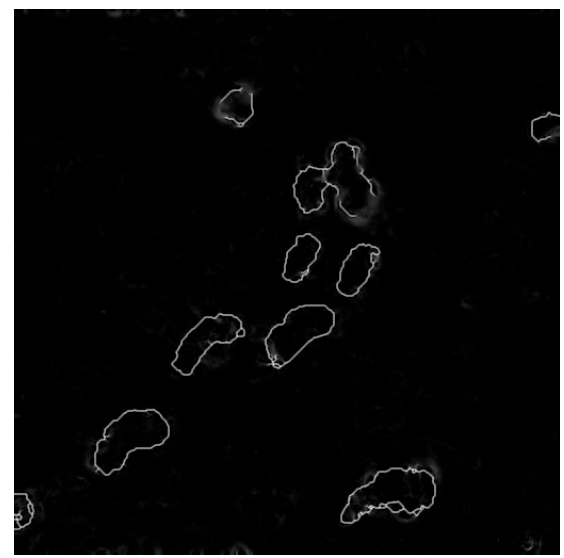
BA



Ours



Error map

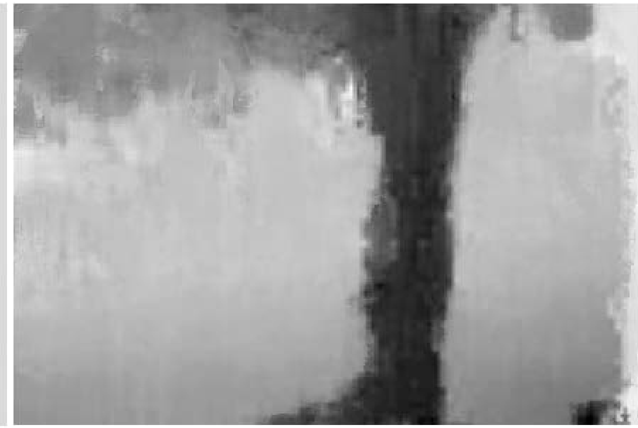


Smoothness error

FG: Flower Garden

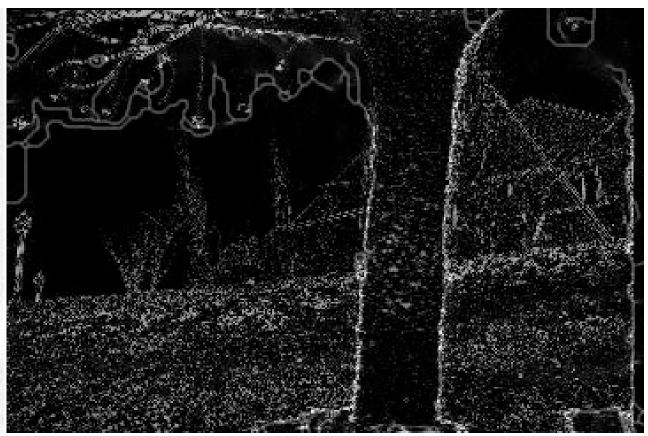
360x240 (Black)
Max speed: 7pix/frame

BA

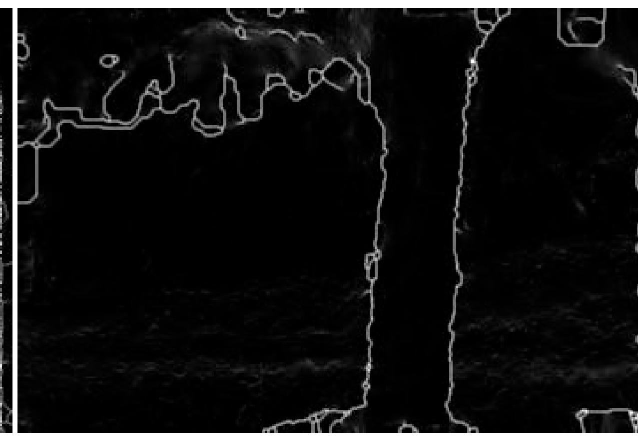


LMS

Ours



Error map



Smoothness error

Summary

- Major contributions from Lucas, Tomasi, Kanade
  - Tracking feature points
  - Optical flow
  - Stereo
  - Structure from motion

- Key ideas
  - By assuming brightness constancy, truncated Taylor expansion leads to simple and fast patch matching across frames
  - Coarse-to-fine registration
  - Global approach by former EE student Ming Ye