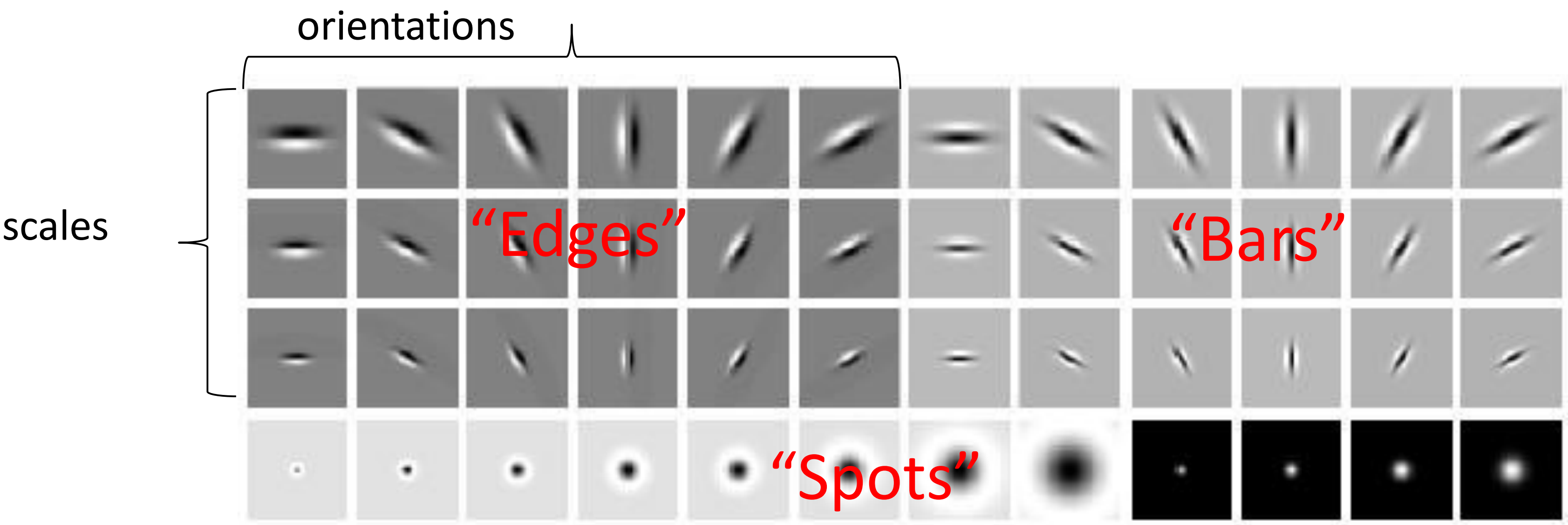
Motion

Vinay P. Namboodiri

- Slide credits to Kristen Grauman, Derek Hoiem, Steve Seitz, Lana Lazebnik, Rick Szeliski

Review: Texture

Filter banks



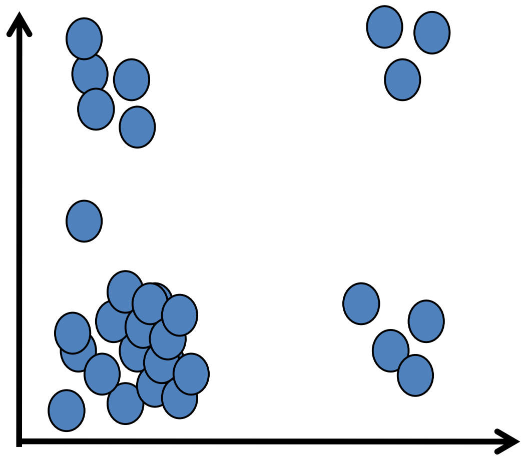
- What filters to put in the bank?
  - Typically we want a combination of scales and orientations, different types of patterns.

Matlab code available for these examples:
http://www.robots.ox.ac.uk/~vgg/research/texclass/filters.html

d-dimensional features

$$D(a,b) = \sqrt{\sum_{i=1}^{d} (a_i - b_i)^2}$$

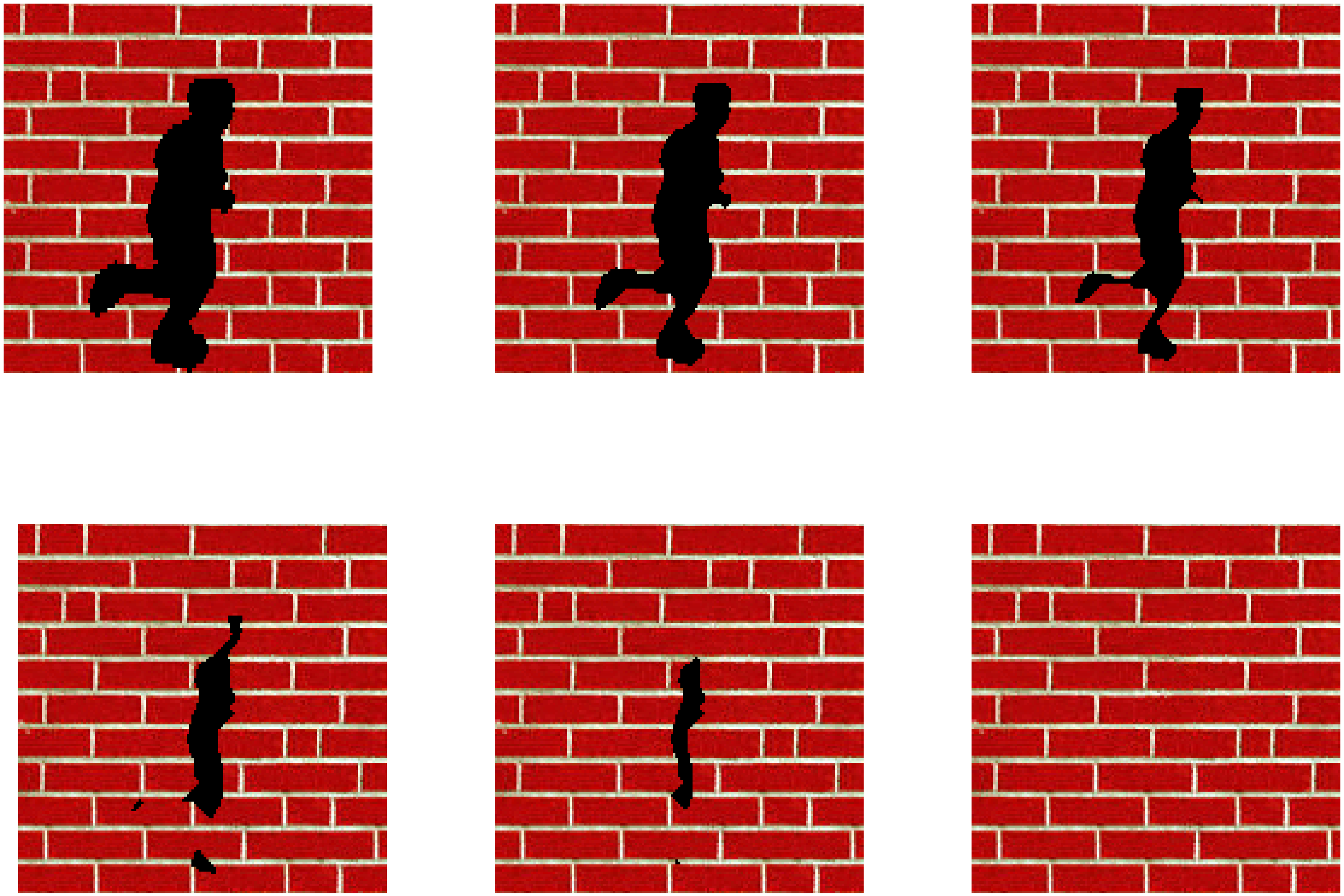
Euclidean distance (L_2)



2d

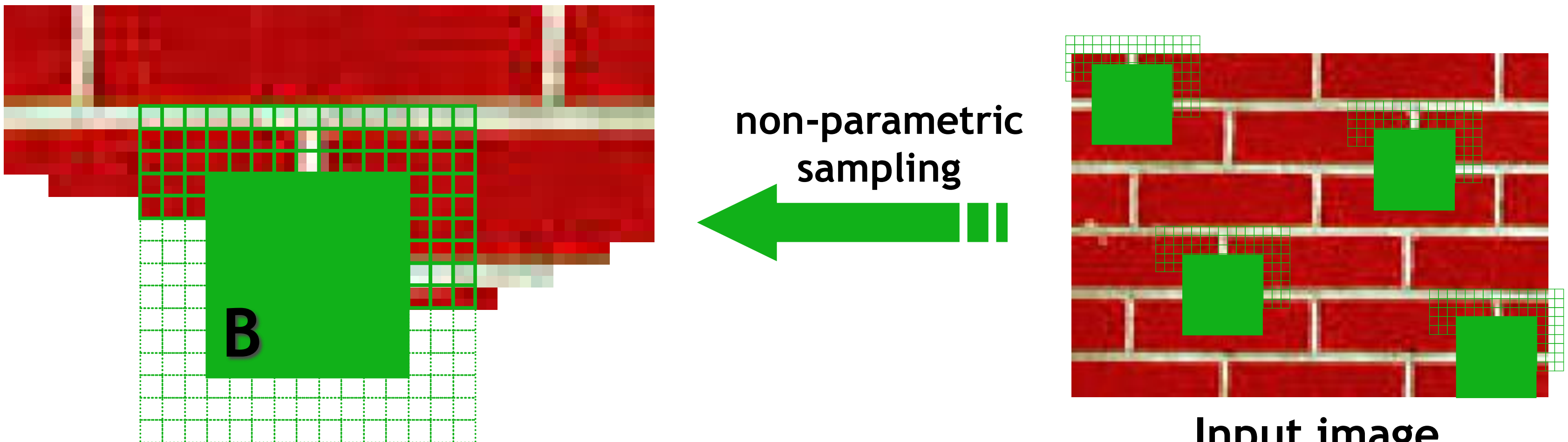
Kristen Grauman

Hole Filling



Slide from Alyosha Efros, ICCV 1999

Image Quilting [Efros & Freeman 2001]



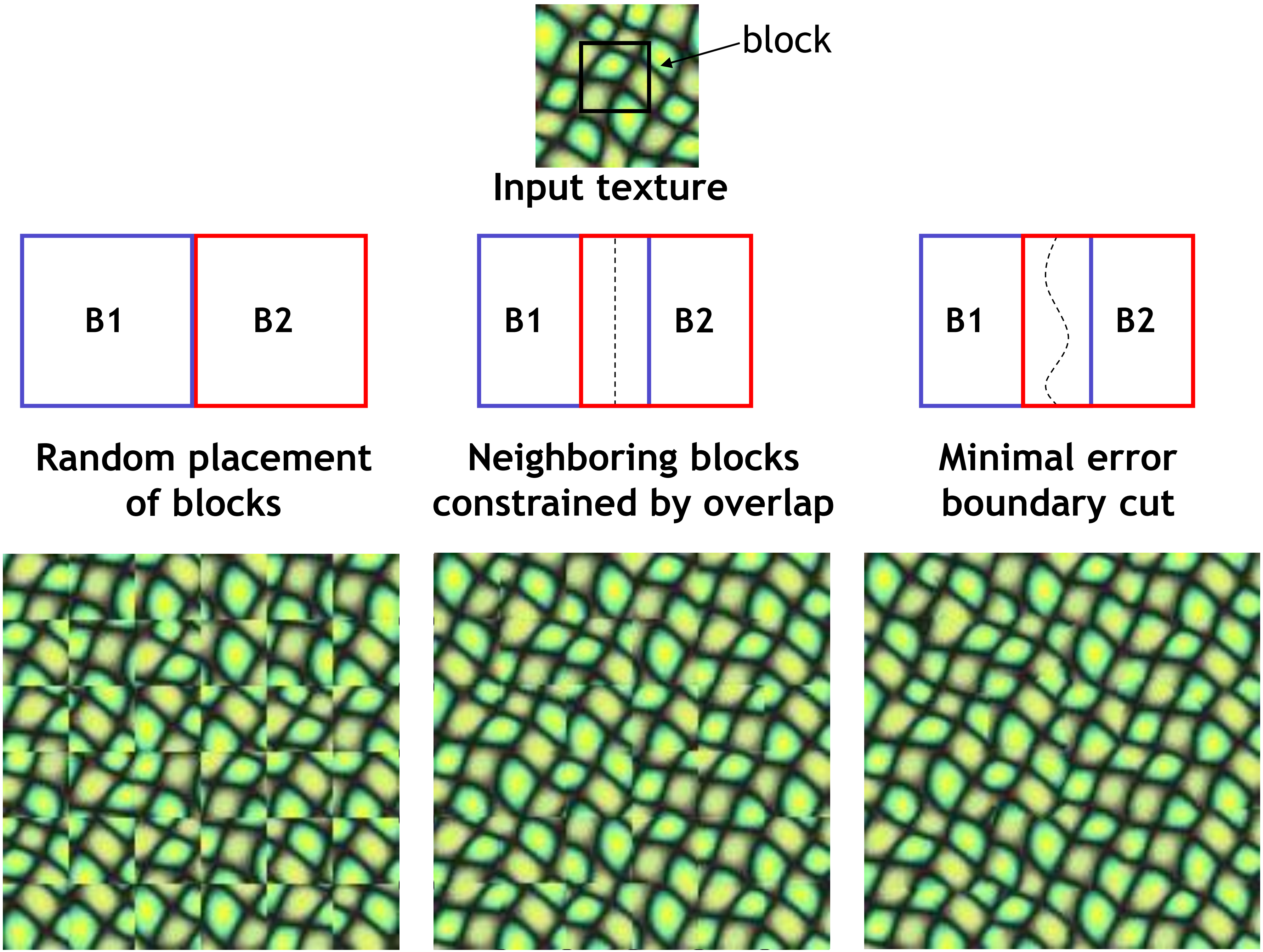
Input image

Synthesizing a block

- <u>Observation:</u> neighbor pixels are highly correlated

<u>Idea:</u> unit of synthesis = block

- Exactly the same but now we want P(**B**|N(**B**))
- Much faster: synthesize all pixels in a block at once


block
Input texture
B1
B2
Random placement of blocks
B1
B2
Neighboring blocks constrained by overlap
B1
B2
Minimal error boundary cut

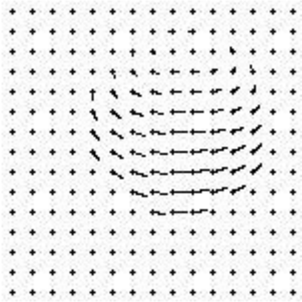
Texture

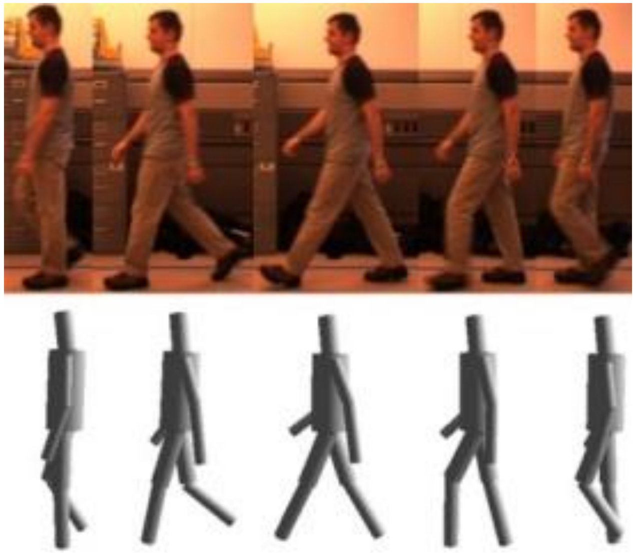
- Texture is a useful property that is often indicative of materials, appearance cues
- **Texture representations** attempt to summarize repeating patterns of local structure
- **Filter banks** useful to measure redundant variety of structures in local neighborhood
  – Feature spaces can be multi-dimensional
- Neighborhood statistics can be exploited to “sample” or **synthesize** new texture regions
  – Example-based technique

Kristen Grauman

Motion

Tracking objects, video analysis, low level motion

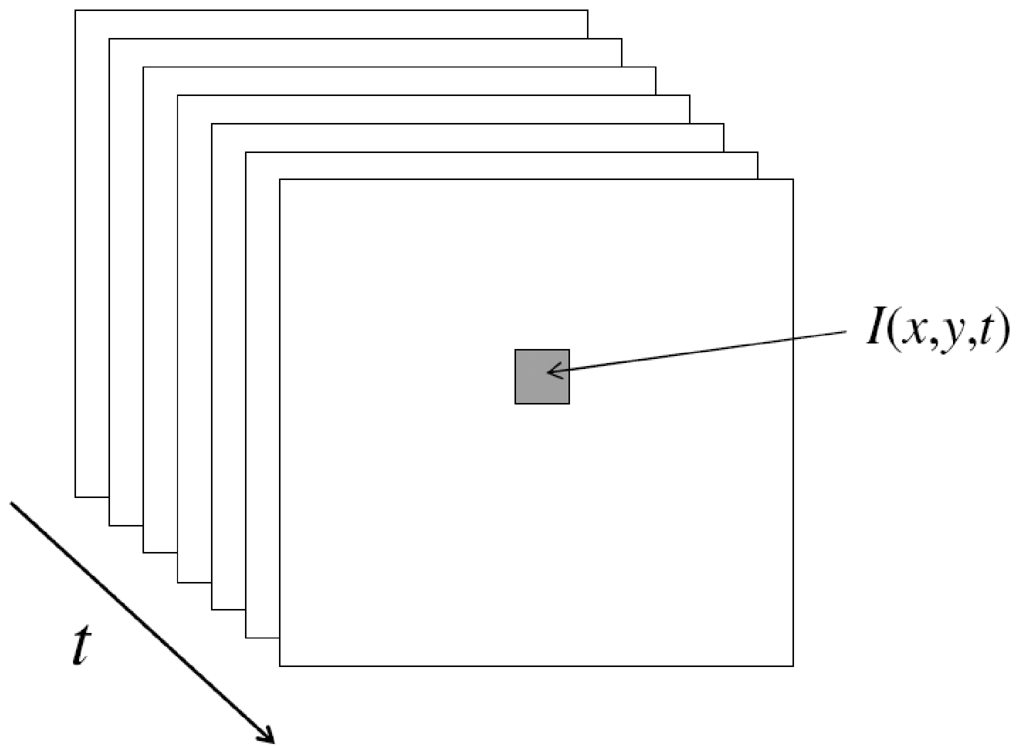




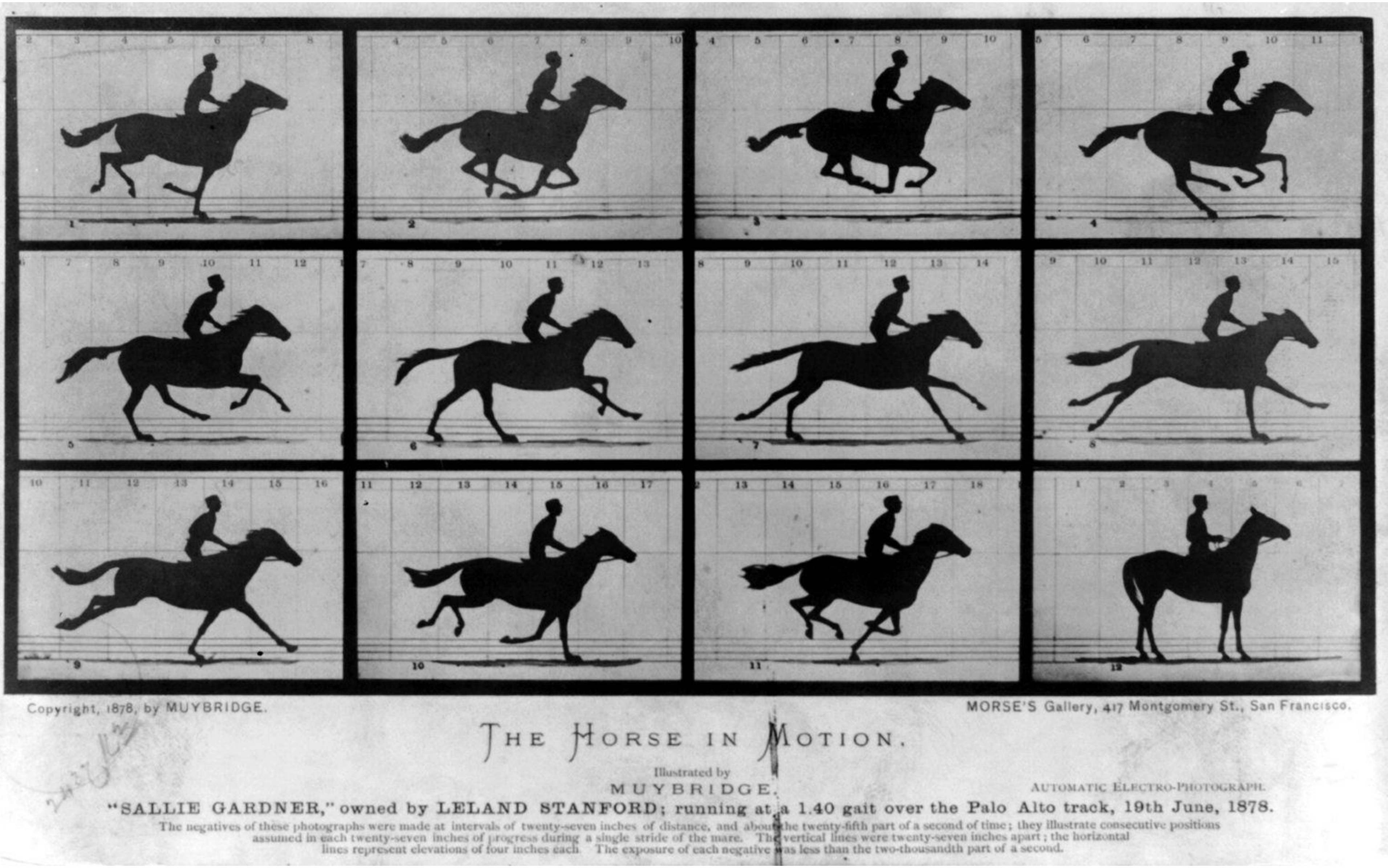
Tomas Izo

Video

- A video is a sequence of frames captured over time
- Now our image data is a function of space (x, y) and time (t)



First Moving Picture



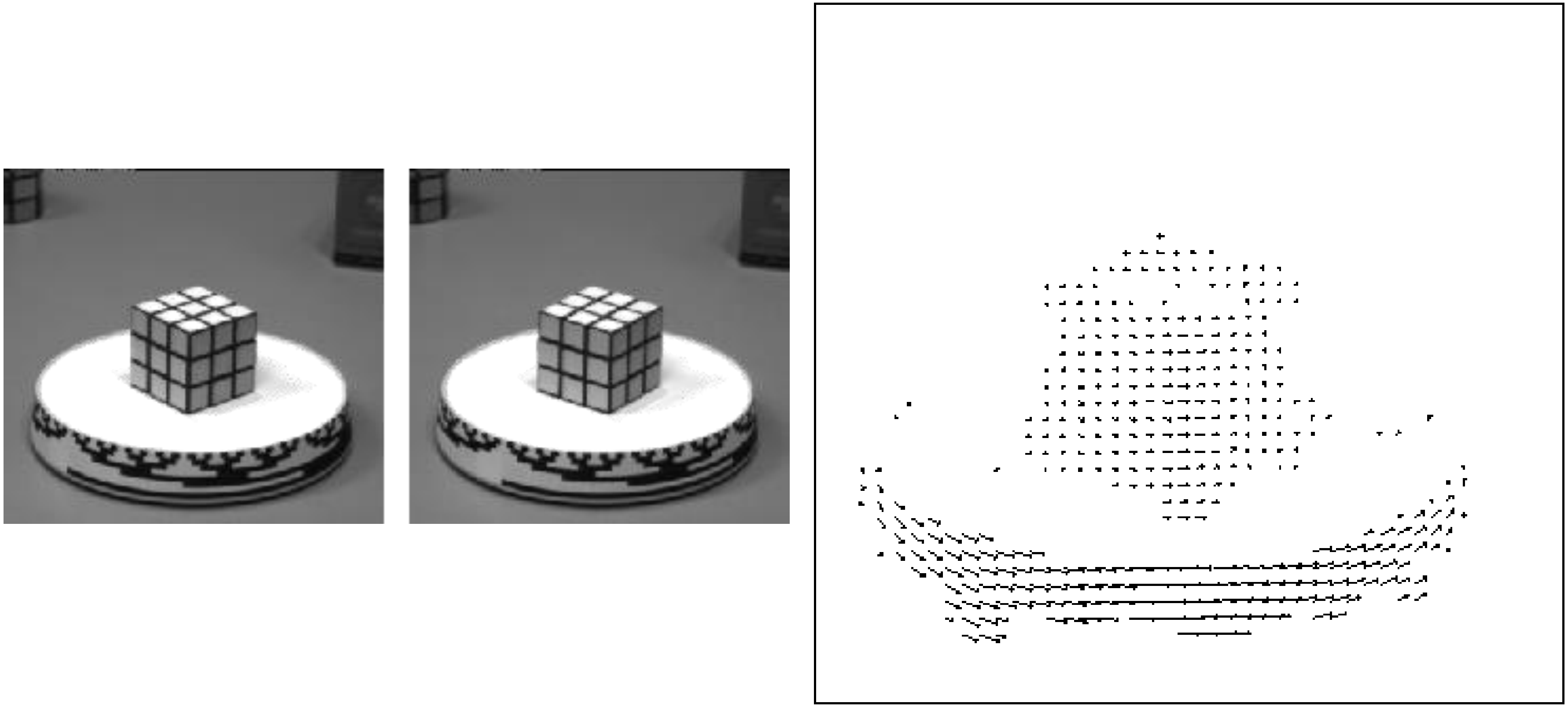
First Motion Picture

Uses of motion

- Estimating 3D structure
- Segmenting objects based on motion cues
- Learning dynamical models
- Recognizing events and activities
- Improving video quality (motion stabilization)

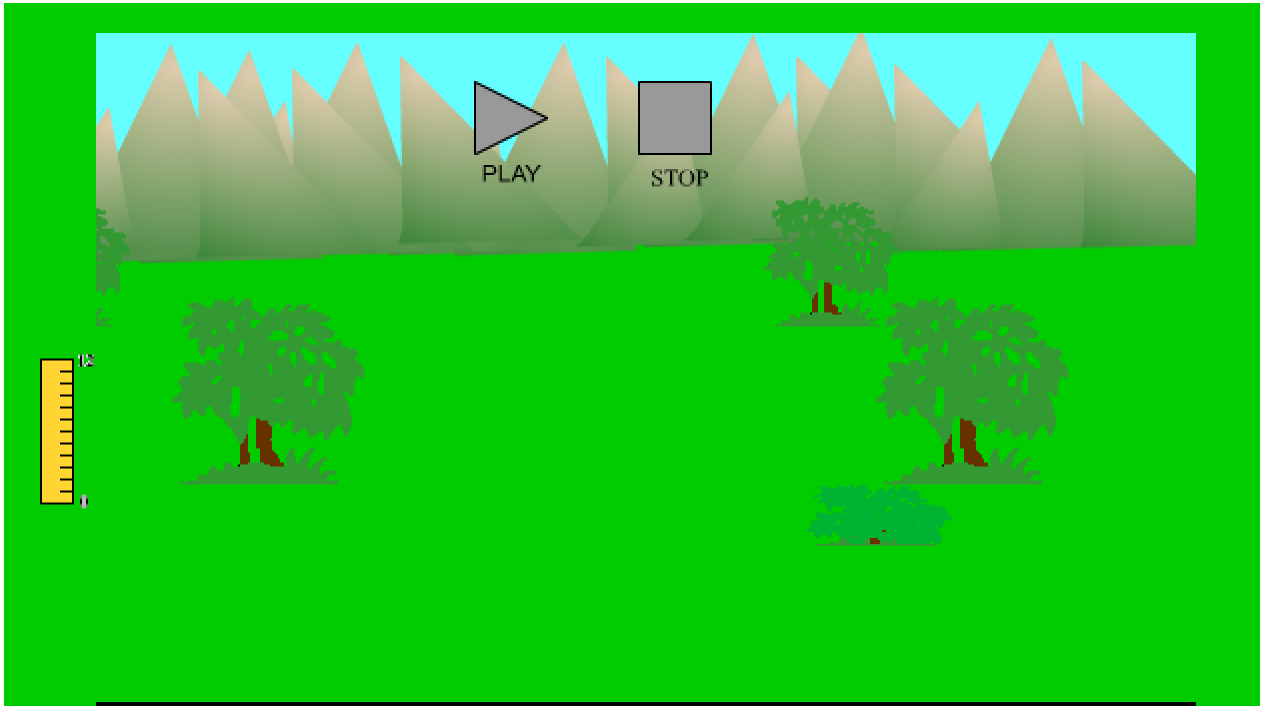
Motion field

- The motion field is the projection of the 3D scene motion into the image



Motion parallax

http://psych.hanover.edu/KRANTZ/MotionParallax/MotionParallax.html



Motion field + camera motion

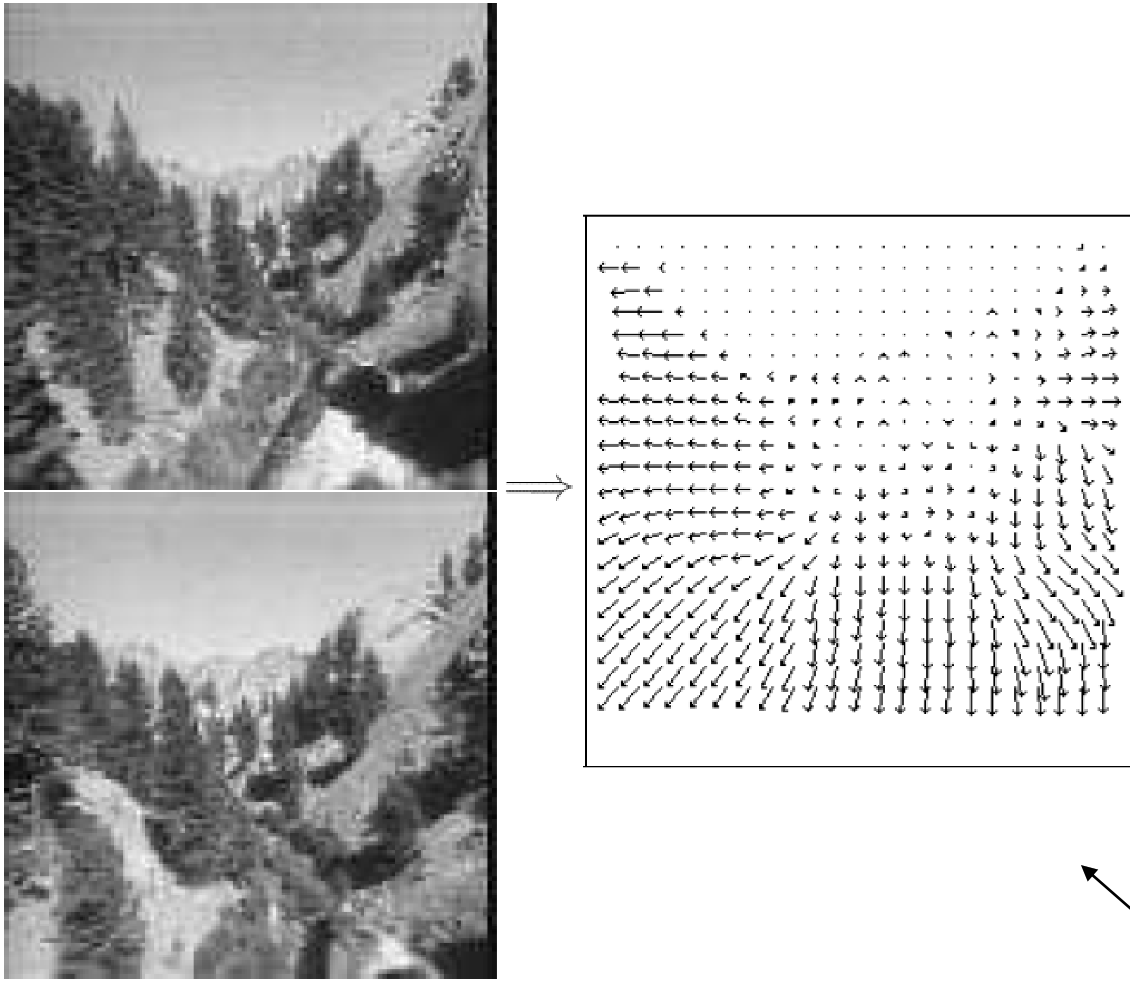


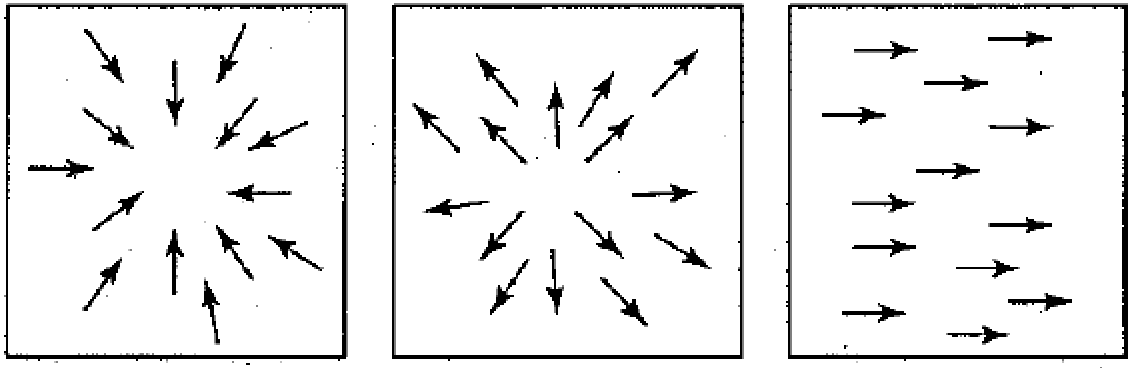
Figure 1.2: Two images taken from a helicopter flying through a canyon and the computed optical flow field.

Length of flow vectors inversely proportional to depth Z of 3d point

points closer to the camera move more quickly across the image plane

Figure from Michael Black, Ph.D. Thesis

Motion field + camera motion



Zoom out **Zoom in** **Pan right to left**

Motion estimation techniques

- Direct methods
  - Directly recover image motion at each pixel from spatio-temporal image brightness variations
  - Dense motion fields, but sensitive to appearance variations
  - Suitable for video and when image motion is small
- Feature-based methods
  - Extract visual features (corners, textured areas) and track them over multiple frames
  - Sparse motion fields, but more robust tracking
  - Suitable when image motion is large (10s of pixels)

Optical flow

- Definition: optical flow is the *apparent* motion of brightness patterns in the image
- Ideally, optical flow would be the same as the motion field
- Have to be careful: apparent motion can be caused by lighting changes without any actual motion

Apparent motion != motion field

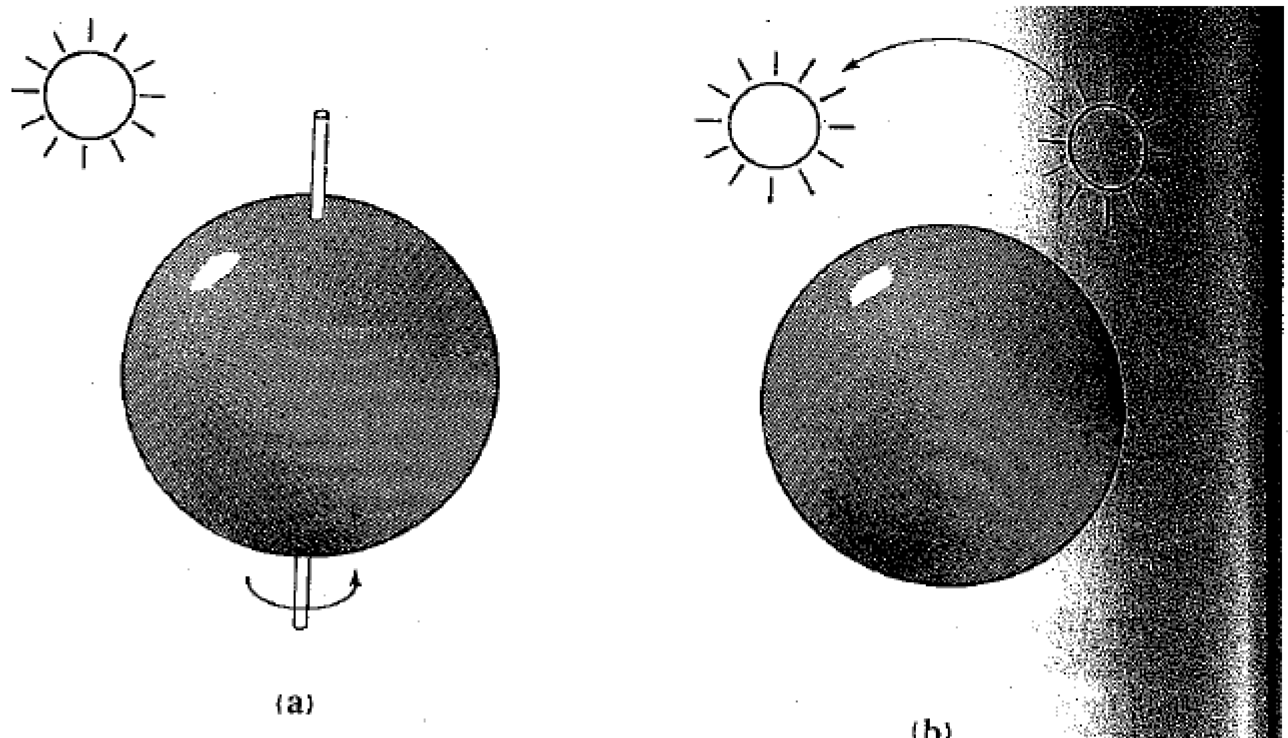
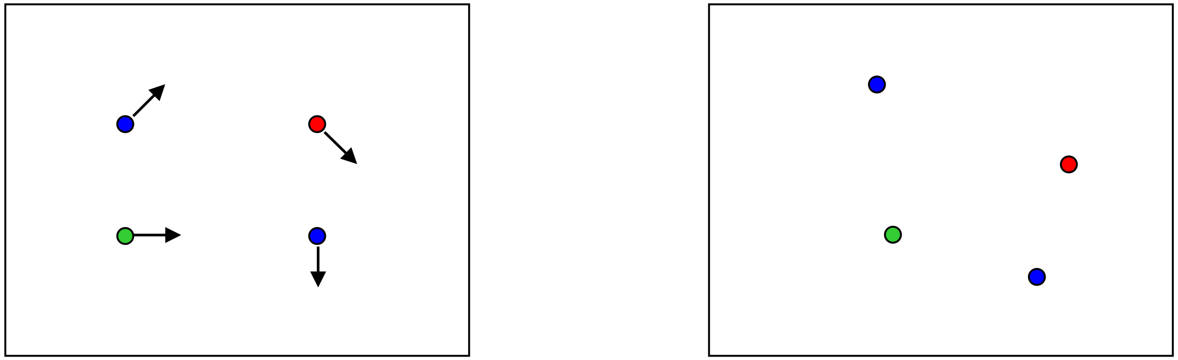


Figure 12-2. The optical flow is not always equal to the motion field. In (a) a smooth sphere is rotating under constant illumination—the image does not change, yet the motion field is nonzero. In (b) a fixed sphere is illuminated by a moving source—the shading in the image changes, yet the motion field is zero.

Figure from Horn book

Problem definition: optical flow



$H(x, y)$ $I(x, y)$

How to estimate pixel motion from image H to image I?

- Solve pixel correspondence problem
  - given a pixel in H, look for nearby pixels of the same color in I

Key assumptions

- **color constancy**: a point in H looks the same in I
  - For grayscale images, this is **brightness constancy**
- **small motion**: points do not move very far

This is called the **optical flow** problem

Steve Seitz

Brightness constancy

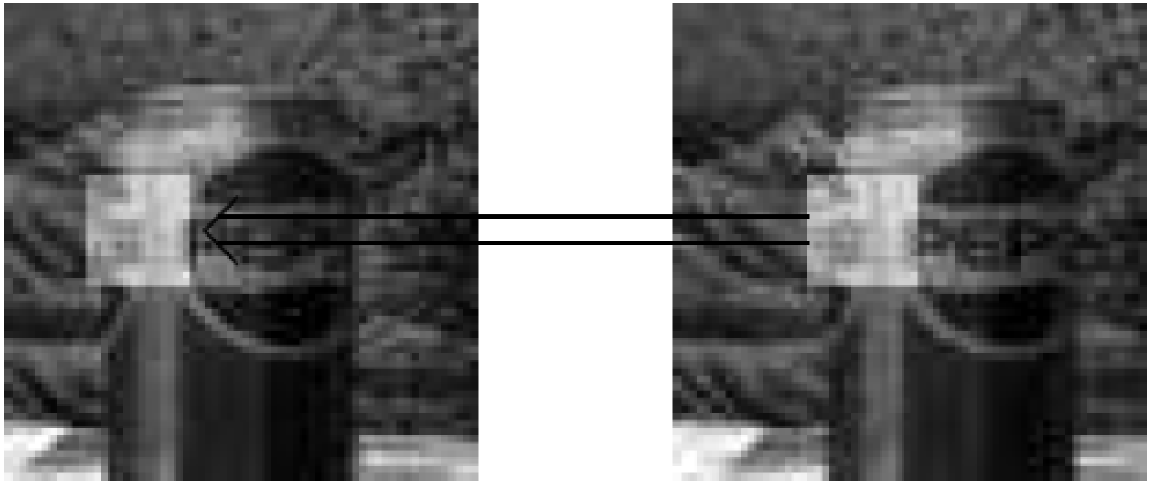
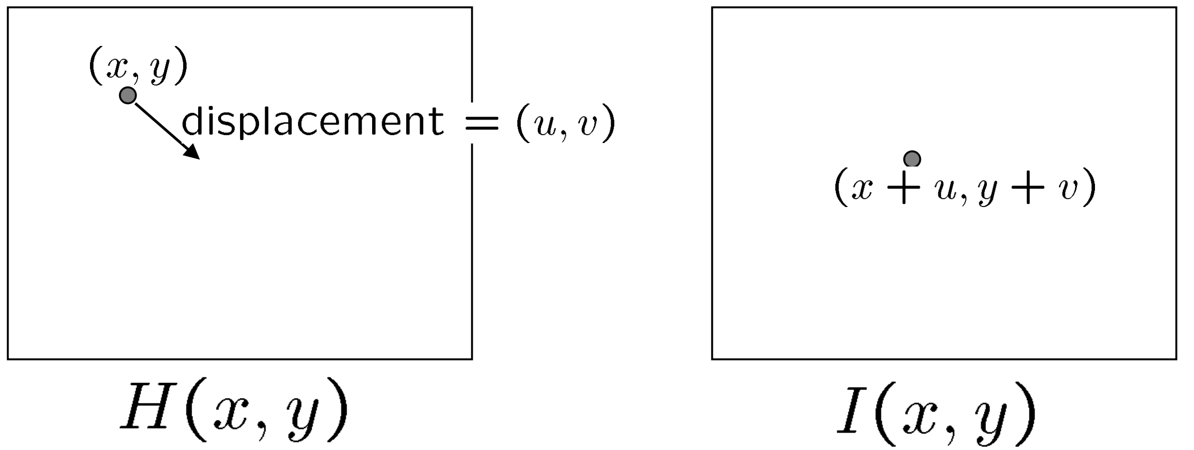


Figure 1.5: Data conservation assumption. The highlighted region in the right image looks roughly the same as the region in the left image, despite the fact that it has moved.

Figure by Michael Black

Optical flow constraints (grayscale images)



Let's look at these constraints more closely

- brightness constancy: Q: what's the equation?

$$H(x, y) = I(x+u, y+v)$$

- small motion:

$$I(x+u, y+v) = I(x, y) + \frac{\partial I}{\partial x}u + \frac{\partial I}{\partial y}v + \text{higher order terms}$$

$$\approx I(x, y) + \frac{\partial I}{\partial x}u + \frac{\partial I}{\partial y}v$$

Steve Seitz

Optical flow equation

Combining these two equations

shorthand: $I_x = \frac{\partial I}{\partial x}$

$$
\begin{aligned}
0 &= I(x+u, y+v) - H(x,y) \\
&\approx I(x,y) + I_x u + I_y v - H(x,y) \\
&\approx (I(x,y) - H(x,y)) + I_x u + I_y v \\
&\approx I_t + I_x u + I_y v \\
&\approx I_t + \nabla I \cdot [u \;\; v]
\end{aligned}
$$

Steve Seitz

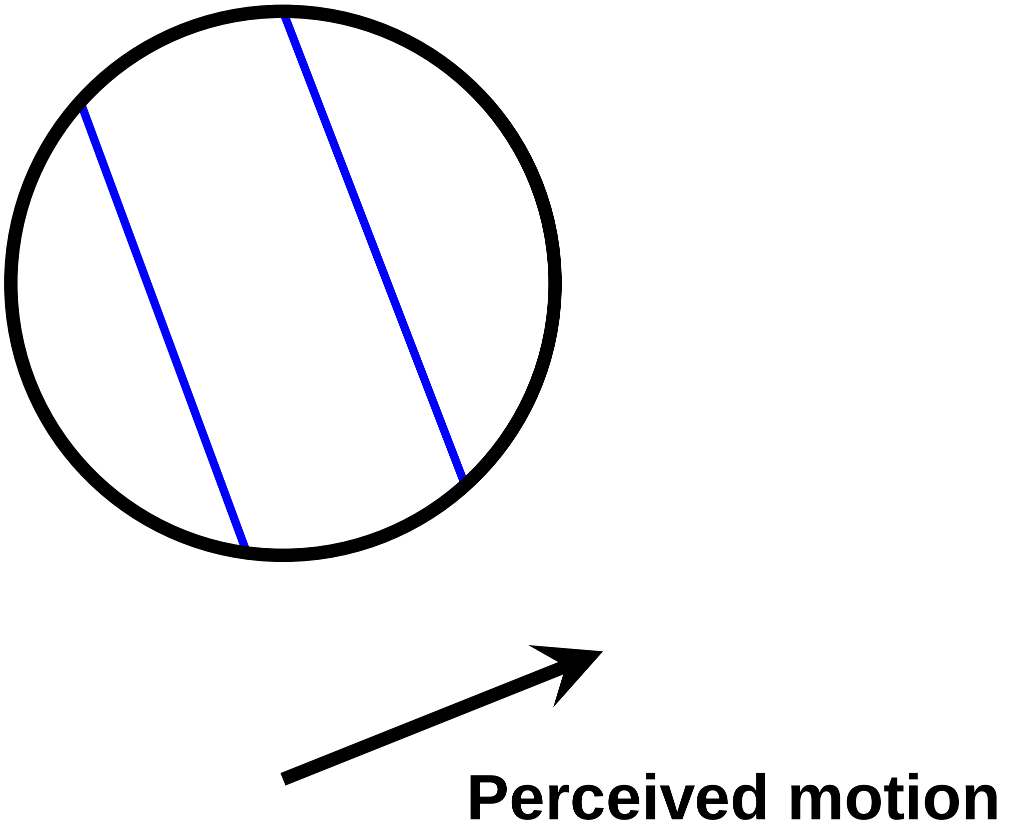
Optical flow equation

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

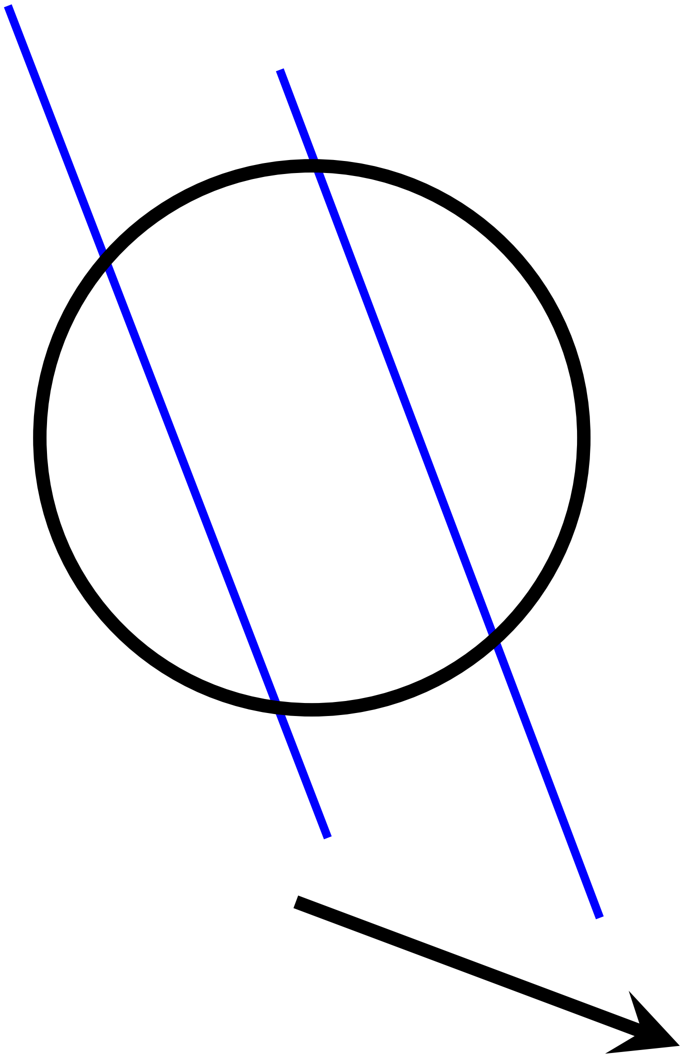
Q: how many unknowns and equations per pixel?

Intuitively, what does this ambiguity mean?

The aperture problem

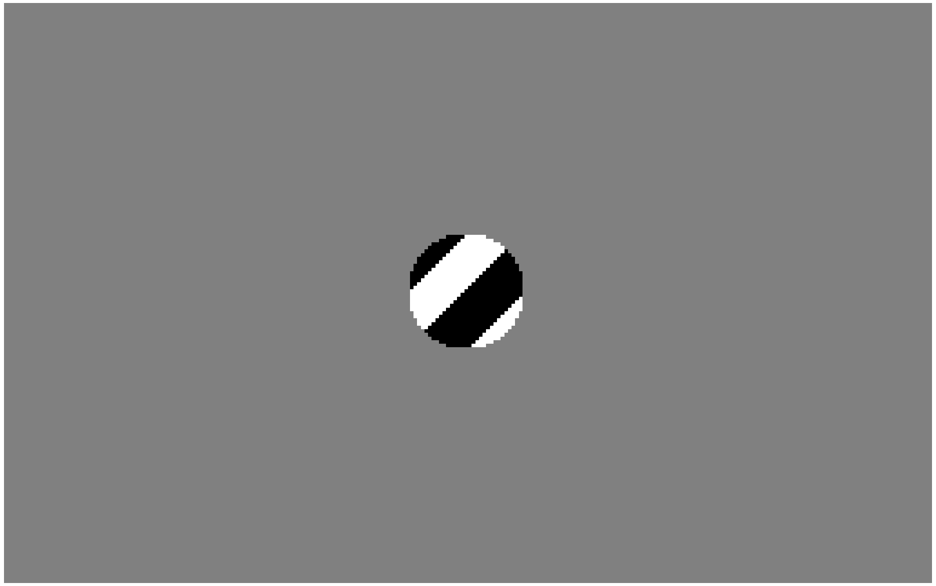


The aperture problem



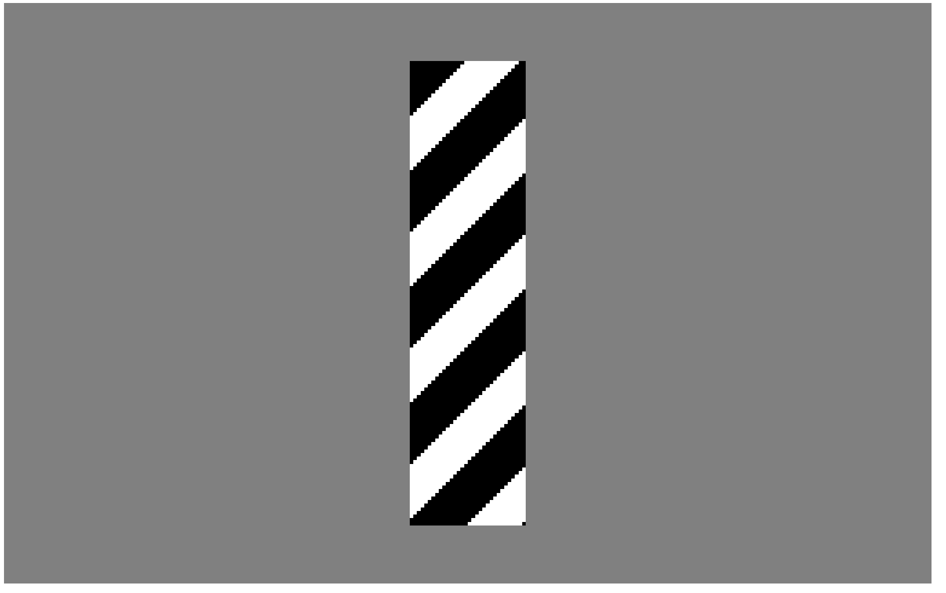
Actual motion

The barber pole illusion



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

The barber pole illusion



http://www.sandlotscience.com/Ambiguous/Barberpole_Illusion.htm

Solving the aperture problem (grayscale image)

- How to get more equations for a pixel?
- **Spatial coherence constraint:** pretend the pixel's neighbors have the same (u,v)

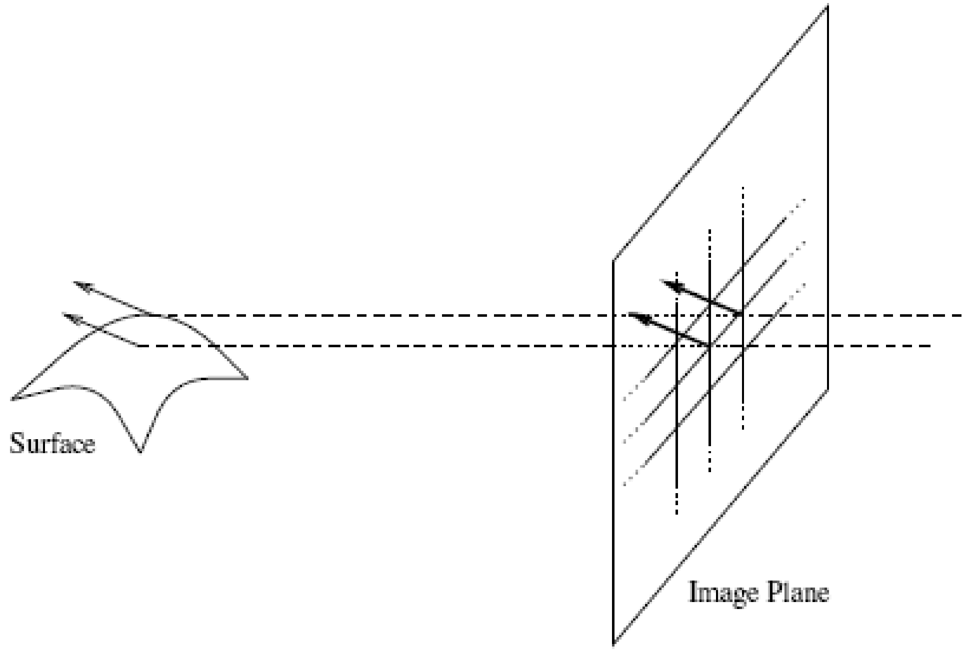


Figure 1.7: Spatial coherence assumption. Neighboring points in the image are assumed to belong to the same surface in the scene.

Figure by Michael Black

Solving the aperture problem (grayscale image)

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

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

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

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

Steve Seitz

Solving the aperture problem

Prob: we have more equations than unknowns

$$\underset{25\times2}{A}\ \underset{2\times1}{d} = \underset{25\times1}{b} \longrightarrow \text{minimize } \|Ad - b\|^2$$

Solution: solve least squares problem

- minimum least squares solution given by solution (in d) of:

$$\underset{2\times2}{(A^T A)}\ \underset{2\times1}{d} = \underset{2\times1}{A^T b}$$

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

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

Conditions for solvability

$$\begin{bmatrix} \sum I_x I_x & \sum I_x I_y \\ \sum I_x I_y & \sum I_y I_y \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = - \begin{bmatrix} \sum I_x I_t \\ \sum I_y I_t \end{bmatrix}$$

$$A^T A \qquad\qquad\qquad A^T b$$

When is this solvable?

- **A^TA** should be invertible
- **A^TA** should not be too small
  - eigenvalues λ_1 and λ_2 of **A^TA** should not be too small
- **A^TA** should be well-conditioned
  - λ_1 / λ_2 should not be too large (λ_1 = larger eigenvalue)

Edge

– gradients very large or very small

– large λ_1, small λ_2

Low-texture region

– gradients have small magnitude

– small λ_1, small λ_2

High-texture region

– gradients are different, large magnitudes

– large λ_1, large λ_2

Dealing with larger movements: Iterative refinement

Original (x,y) position

$I_t = I(x', y', t+1) - I(x, y, t)$

1. Initialize (x',y') = (x,y)
2. Compute (u,v) by

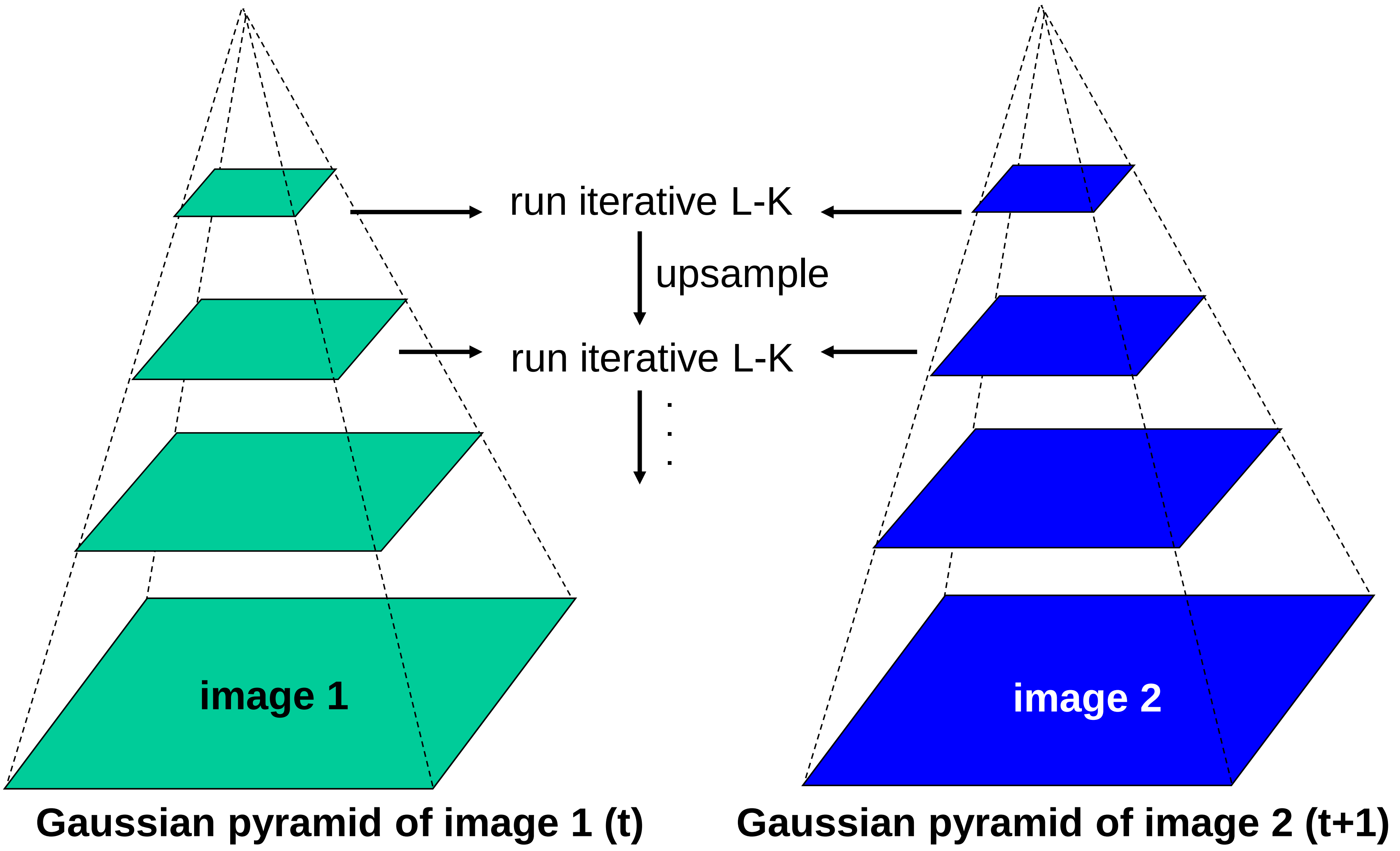
$$\begin{bmatrix} \sum I_x I_x & \sum I_x I_y \\ \sum I_x I_y & \sum I_y I_y \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = - \begin{bmatrix} \sum I_x I_t \\ \sum I_y I_t \end{bmatrix}$$

2nd moment matrix for feature patch in first image

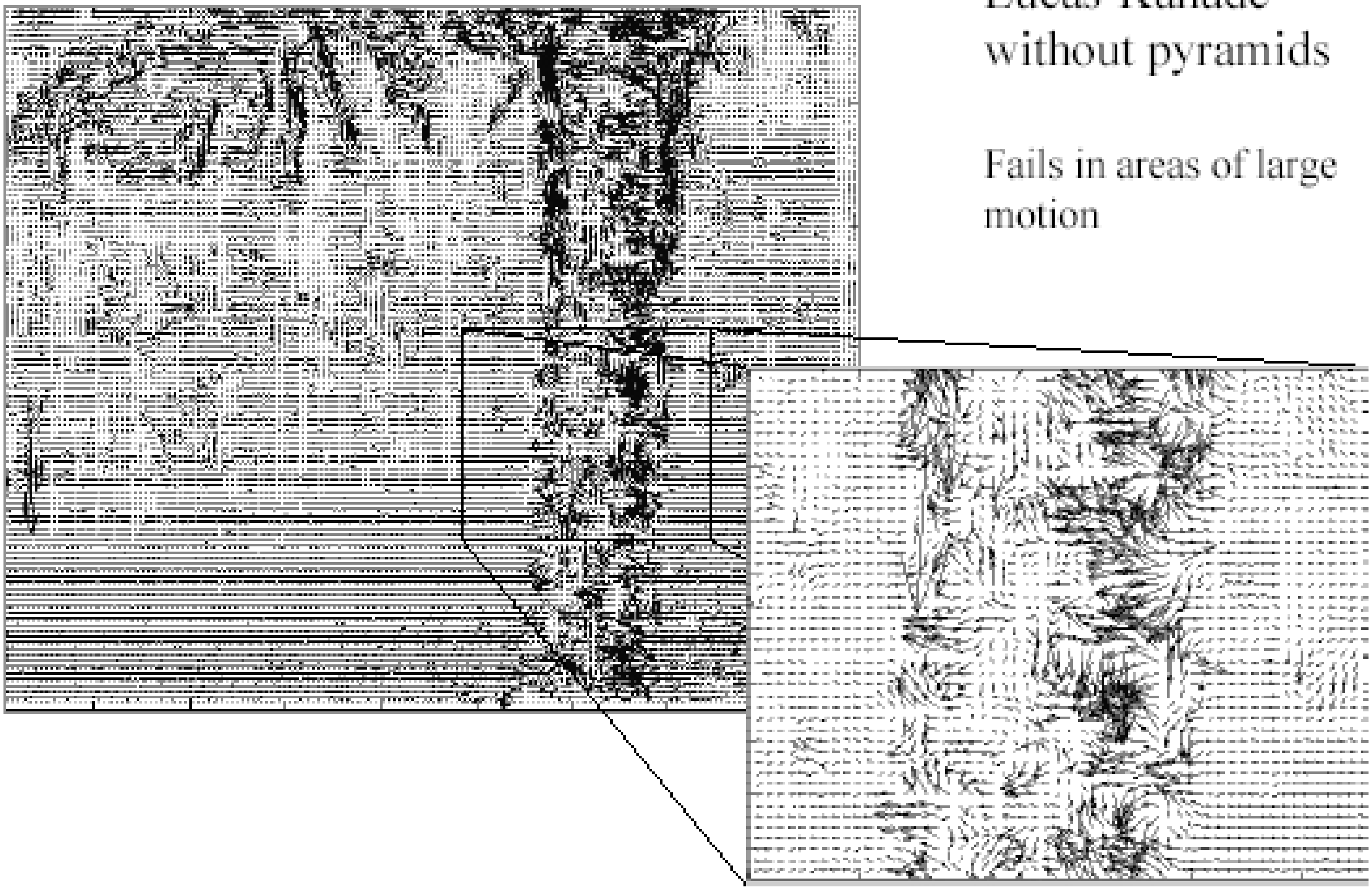
displacement

3. Shift window by (u, v): `x'=x'+u; y'=y'+v;`
4. Recalculate I_t
5. Repeat steps 2-4 until small change
   – Use interpolation for subpixel values

Dealing with larger movements: coarse-to-fine registration



Optical Flow Results

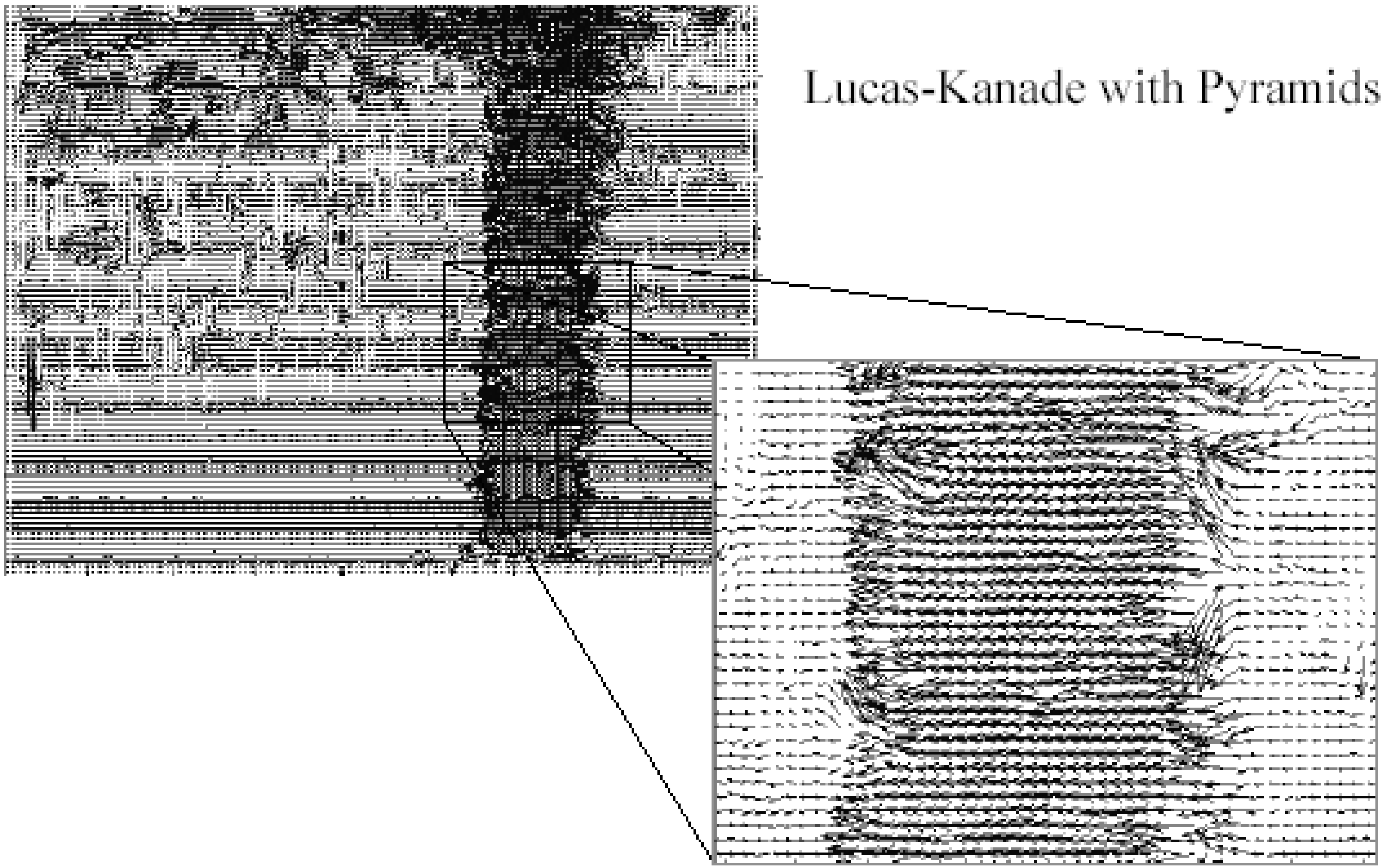


Lucas-Kanade without pyramids

Fails in areas of large motion

* From Khurram Hassan-Shafique CAP5415 Computer Vision 2003

Optical Flow Results



Lucas-Kanade with Pyramids

* From Khurram Hassan-Shafique CAP5415 Computer Vision 2003

Shi-Tomasi feature tracker

- Find good features using eigenvalues of second-moment matrix (e.g., Harris detector or threshold on the smallest eigenvalue)
    - Key idea: “good” features to track are the ones whose motion can be estimated reliably
- Track from frame to frame with Lucas-Kanade
    - This amounts to assuming a translation model for frame-to-frame feature movement
- Check consistency of tracks by *affine* registration to the first observed instance of the feature
    - Affine model is more accurate for larger displacements
    - Comparing to the first frame helps to minimize drift

J. Shi and C. Tomasi. [Good Features to Track](). CVPR 1994.

Tracking example

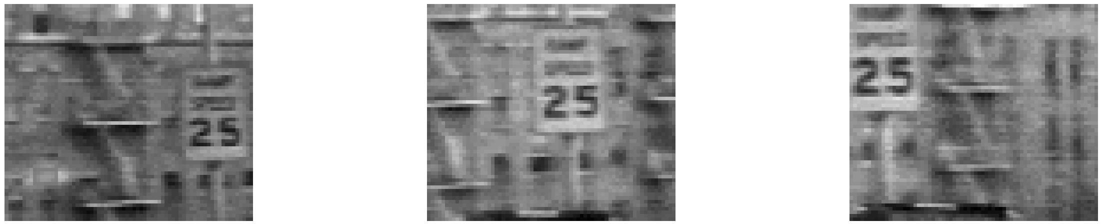


Figure 1: Three frame details from Woody Allen's *Manhattan*. The details are from the 1st, 11th, and 21st frames of a subsequence from the movie.

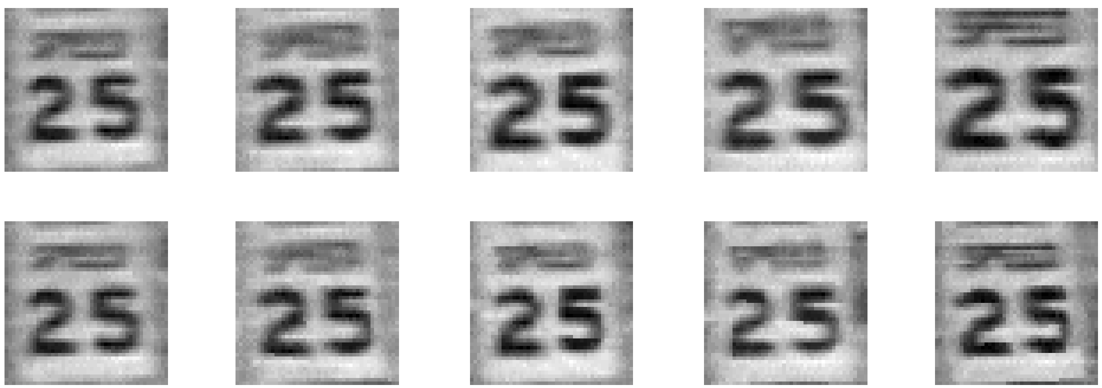


Figure 2: The traffic sign windows from frames 1,6,11,16,21 as tracked (top), and warped by the computed deformation matrices (bottom).

J. Shi and C. Tomasi. Good Features to Track. CVPR 1994.

Summary of KLT tracking

Find a good point to track (harris corner)

Use intensity second moment matrix and difference across frames to find displacement

Iterate and use coarse-to-fine search to deal with larger movements

When creating long tracks, check appearance of registered patch against appearance of initial patch to find points that have drifted

Implementation issues

Window size

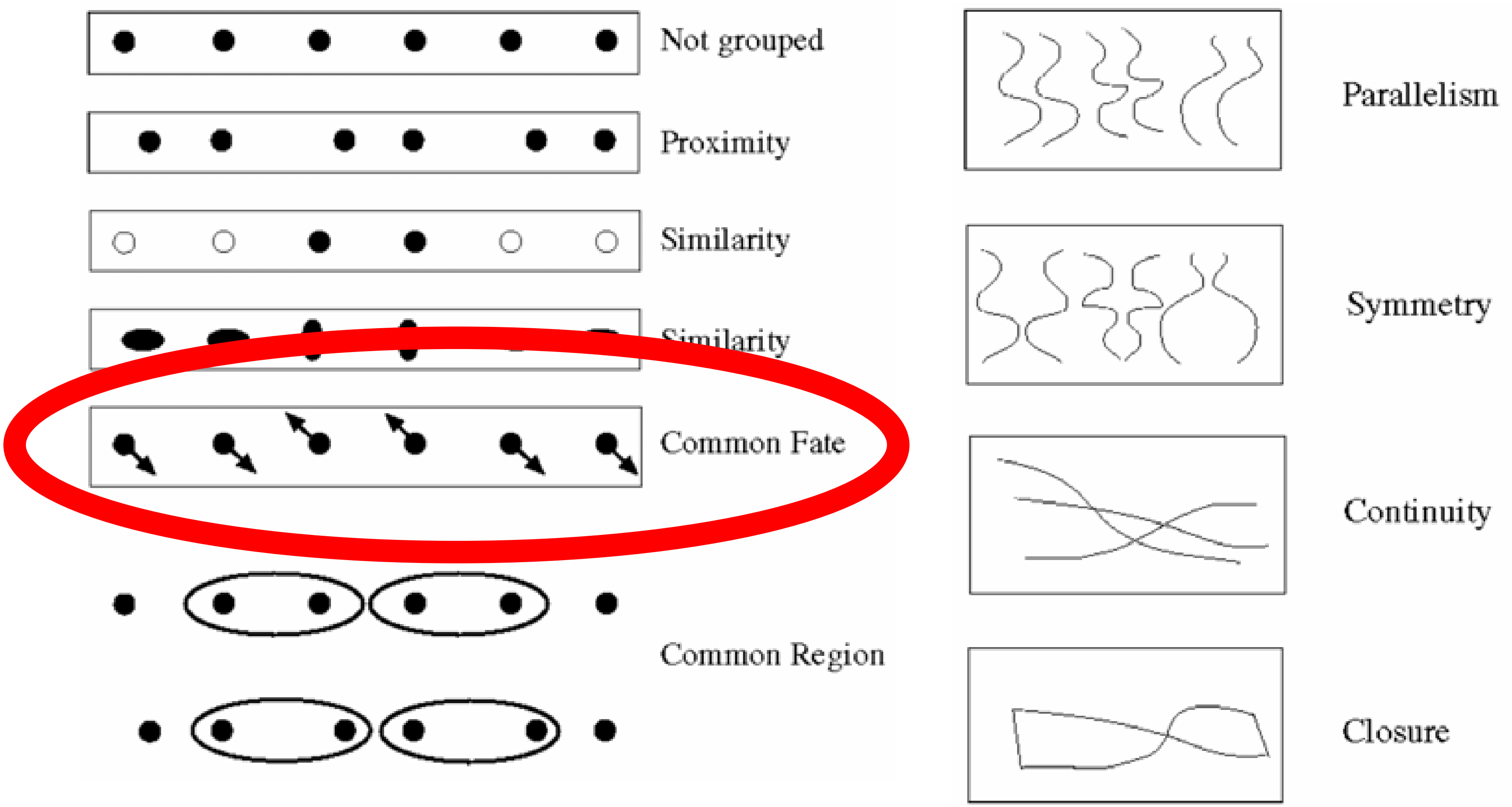
- Small window more sensitive to noise and may miss larger motions (without pyramid)
- Large window more likely to cross an occlusion boundary (and it’s slower)
- 15x15 to 31x31 seems typical

Weighting the window

- Common to apply weights so that center matters more (e.g., with Gaussian)

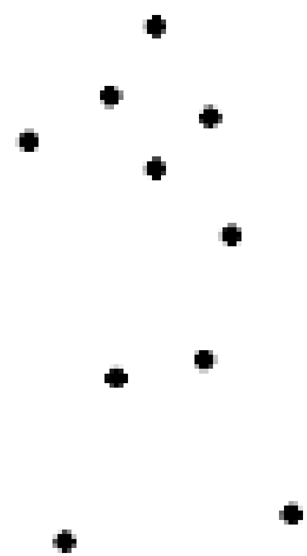
Motion and perceptual organization

- Sometimes, motion is the only cue



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

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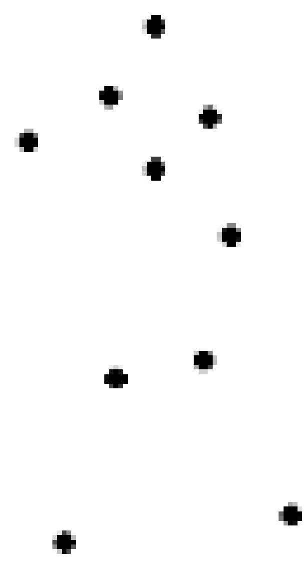


G. Johansson, “Visual Perception of Biological Motion and a Model For Its Analysis", *Perception and Psychophysics 14, 201-211, 1973.*

Errors in Lucas-Kanade

- The motion is large
  - Possible Fix: Keypoint matching
- A point does not move like its neighbors
  - Possible Fix: Region-based matching
- Brightness constancy does not hold
  - Possible Fix: Gradient constancy

State-of-the-art optical flow

Start with something similar to Lucas-Kanade

+ gradient constancy

+ energy minimization with smoothing term

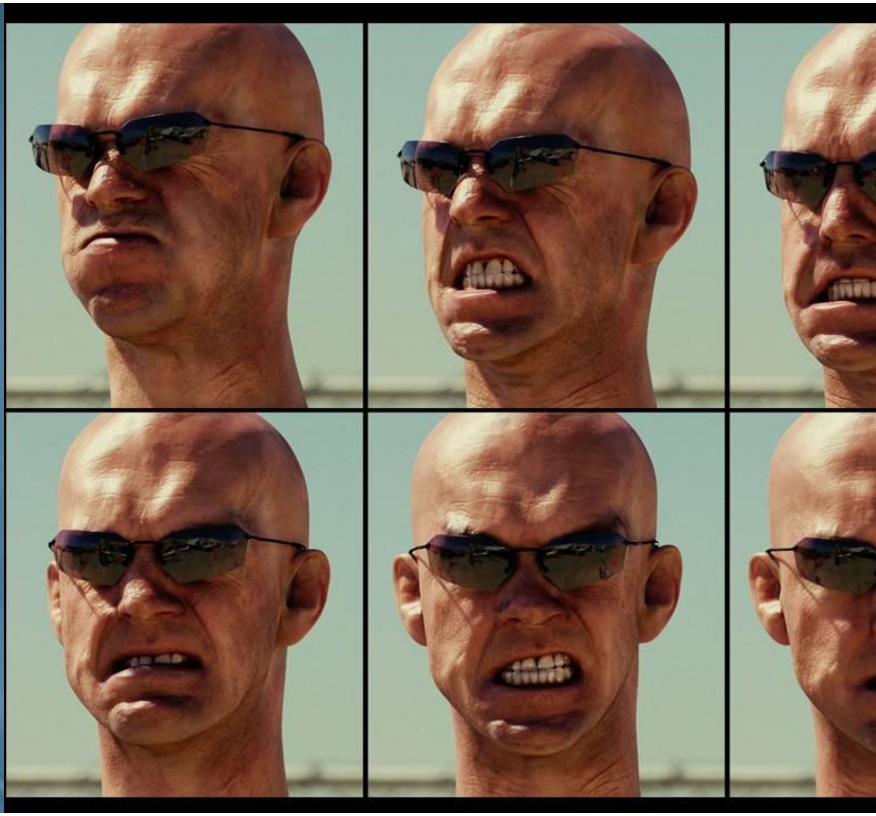
+ region matching

+ keypoint matching (long-range)

Region-based +Pixel-based +Keypoint-based

Large displacement optical flow, Brox et al., CVPR 2009

Example use of optical flow: facial animation



http://www.fxguide.com/article333.html

Example use of optical flow: Motion Paint

Use optical flow to track brush strokes, in order to animate them to follow underlying scene motion.

http://www.fxguide.com/article333.html

Fun with flow

- http://www.youtube.com/watch?v=TbJrc6QCeU0&feature=related
- http://www.youtube.com/watch?v=pckFacsIWg4

Motion vs. Stereo: Similarities

- Both involve solving
  - Correspondence: disparities, motion vectors
  - Reconstruction

Motion vs. Stereo: Differences

- **Motion**:
  - Uses velocity: consecutive frames must be close to get good approximate time derivative
  - 3d movement between camera and scene not necessarily single 3d rigid transformation
- **Whereas with stereo**:
  - Could have any disparity value
  - View pair separated by a single 3d transformation