CS231M · Mobile Computer Vision

Announcements

- Next Wed team presentations start
- Please select the paper you want to present
- P2 submission deadline has been postponed to Friday 16th
-

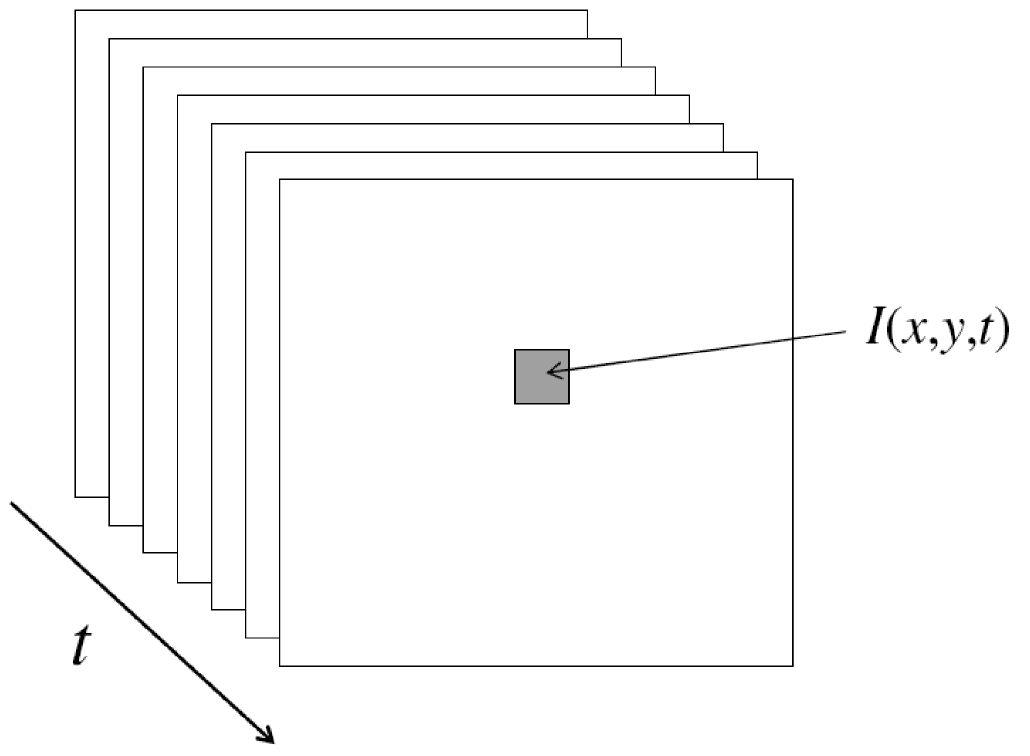
CS231M · Mobile Computer Vision

Optical flow and tracking

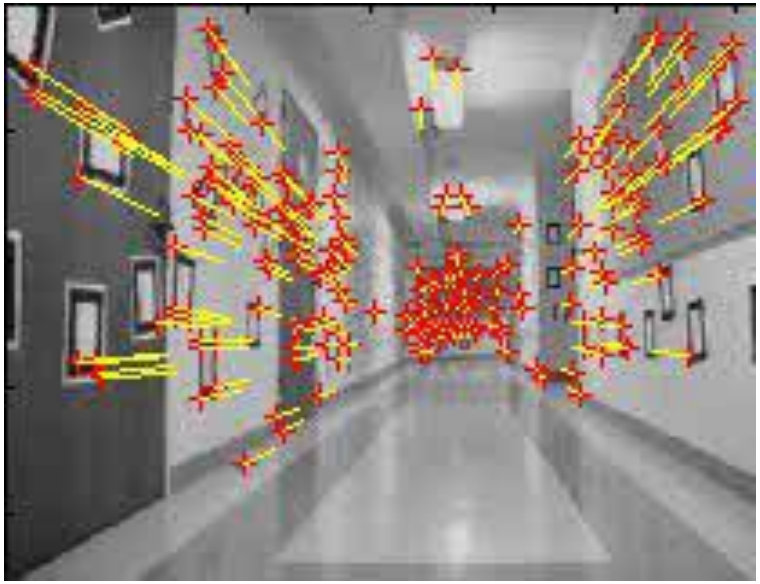
- Introduction
- Optical flow & KLT tracker
- Motion segmentation

From images to videos

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



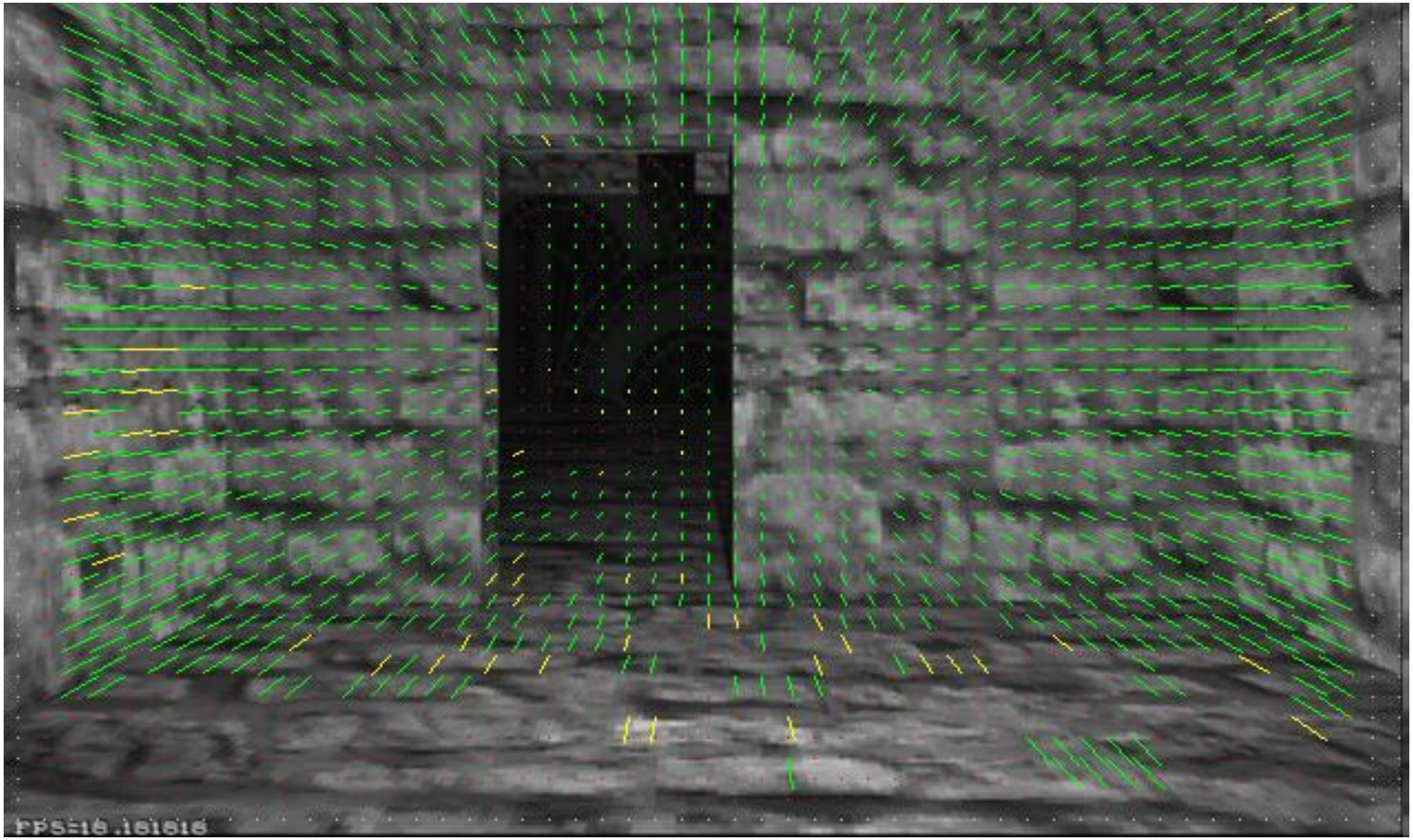
Tracking features

Courtesy of Jean-Yves Bouguet – Vision Lab, California Institute of Technology

Optical flow

Vector field function of the spatio-temporal image brightness variations



Picture courtesy of Selim Temizer - Learning and Intelligent Systems (LIS) Group, MIT

Optical flow

Vector field function of the spatio-temporal image brightness variations

http://www.youtube.com/watch?v=JlLkkom6tWw

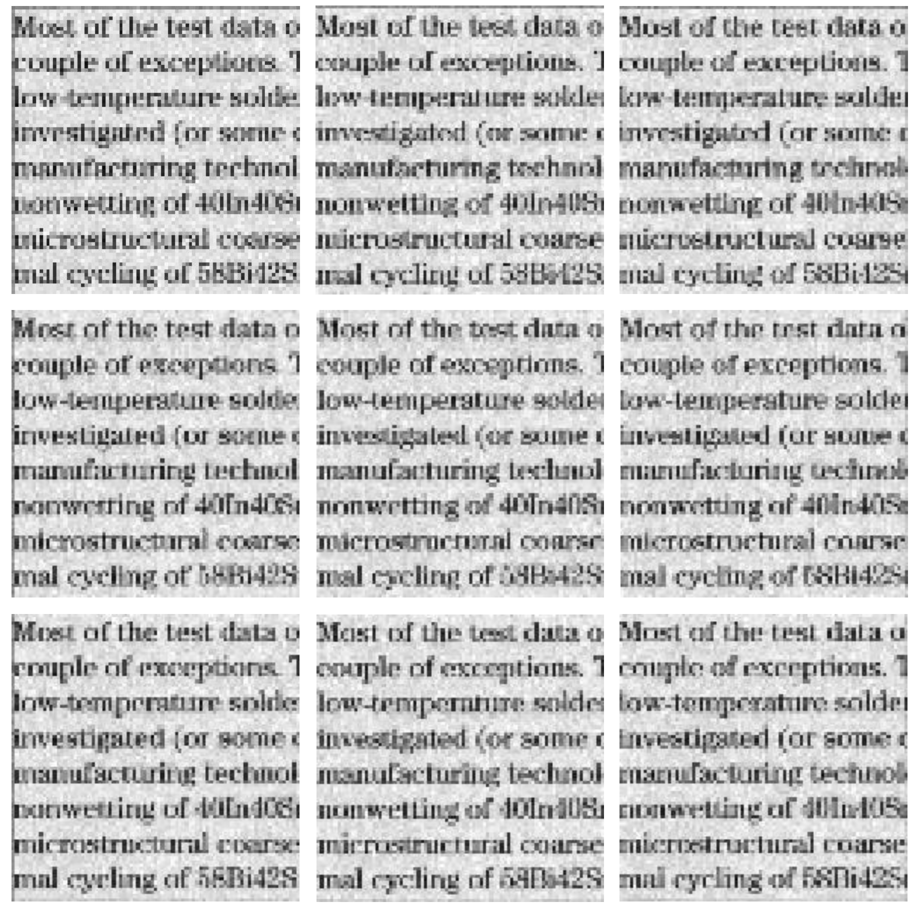
Uses of motion

- Improving video quality
  - Motion stabilization
  - Super resolution
- Segmenting objects based on motion cues
- Tracking objects
- Recognizing events and activities

Super-resolution

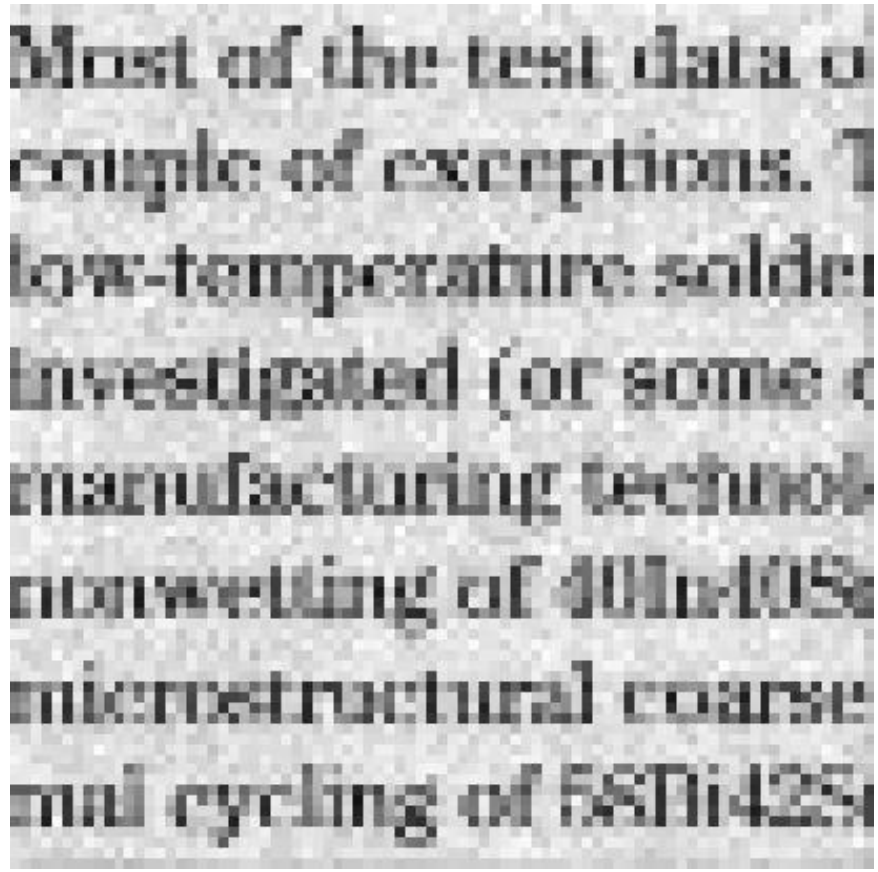
- Irani, M.; Peleg, S. (June 1990). "Super Resolution From Image Sequences". International Conference on Pattern Recognition
- Fast and Robust Multiframe Super Resolution, Sina Farsiu, M. Dirk Robinson, Michael Elad, and Peyman Milanfar, EEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 13, NO. 10, OCTOBER 2004

Example: A set of low quality images



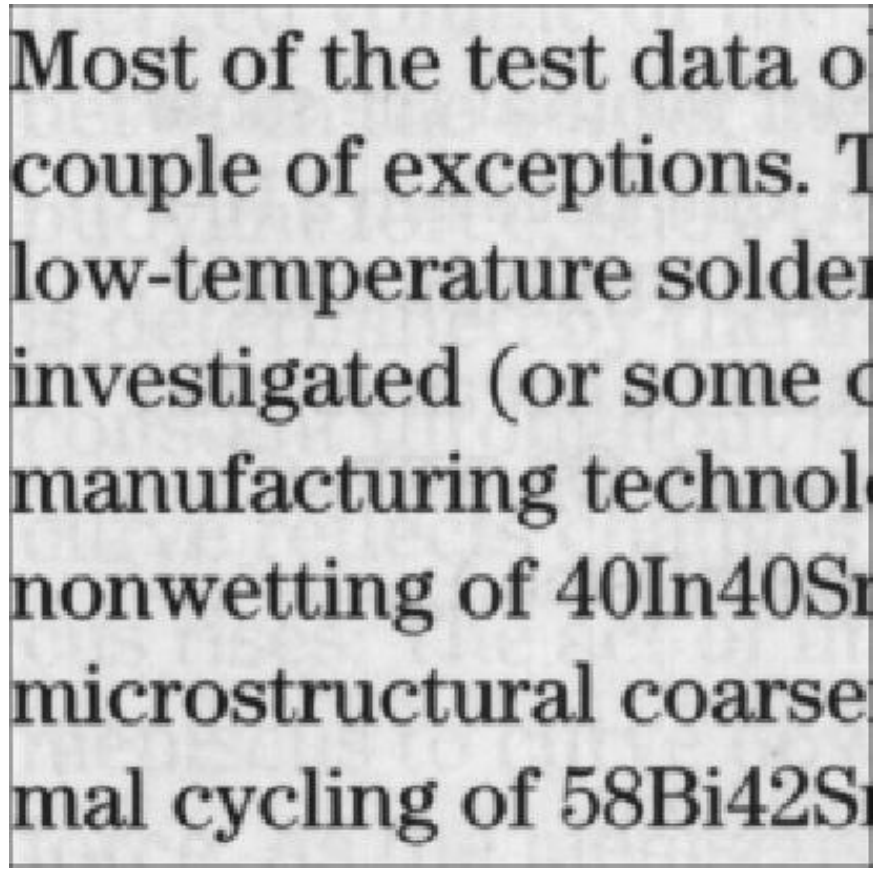
Super-resolution

Each of these images looks like this:


Most of the test data o
couple of exceptions. T
low-temperature solder
investigated (or some c
manufacturing technol
converting of 40In40S
microstructural coarse
and cycling of 58Bi42S

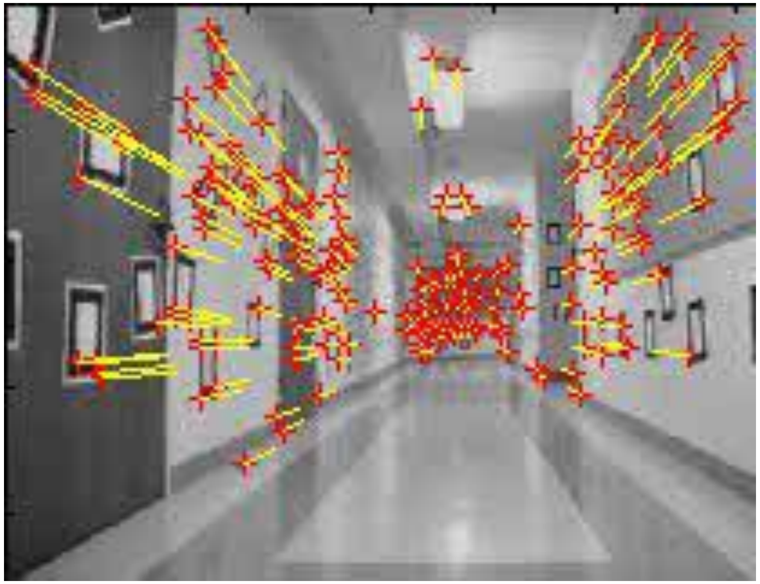
Super-resolution

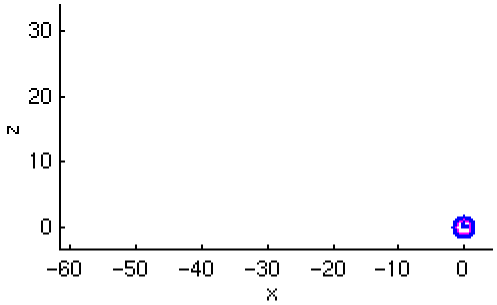
The recovery result:



Most of the test data o
couple of exceptions. T
low-temperature solder
investigated (or some c
manufacturing technol
nonwetting of 40In40Sn
microstructural coarse
mal cycling of 58Bi42Sn

Visual SLAM

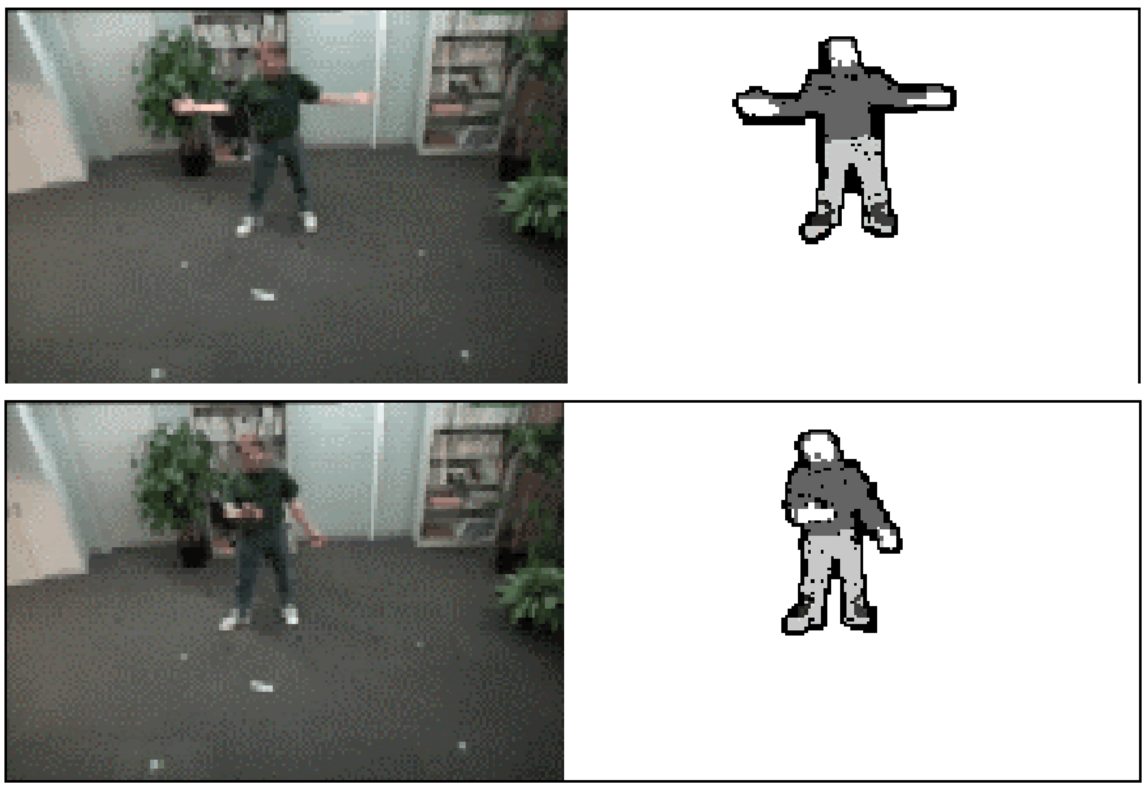




Courtesy of Jean-Yves Bouguet – Vision Lab, California Institute of Technology

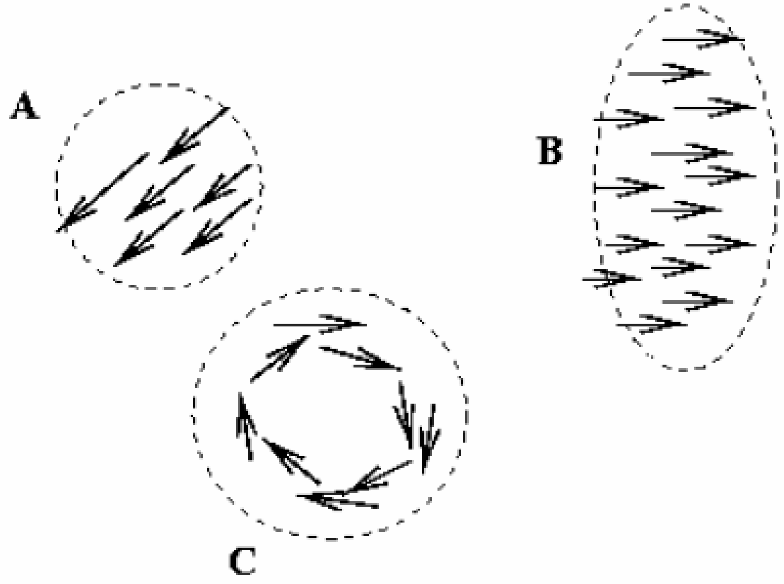
Segmenting objects based on motion cues

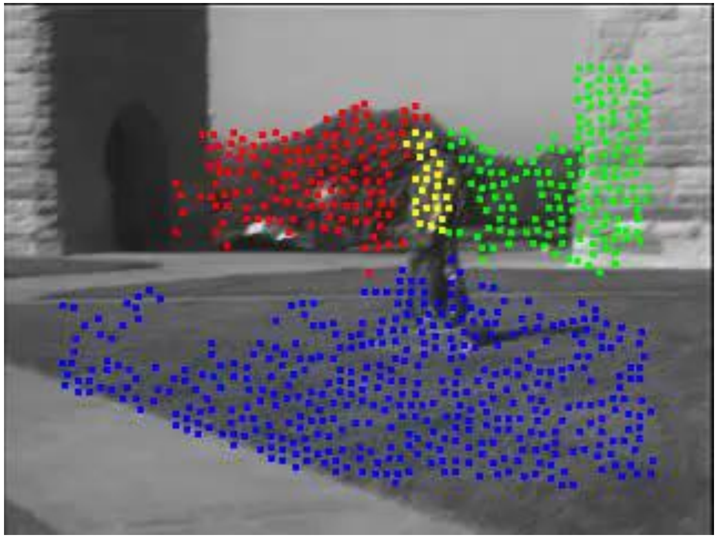
- Background subtraction
  - A static camera is observing a scene
  - Goal: separate the static *background* from the moving *foreground*



Segmenting objects based on motion cues

- Motion segmentation
  - Segment the video into multiple *coherently* moving objects

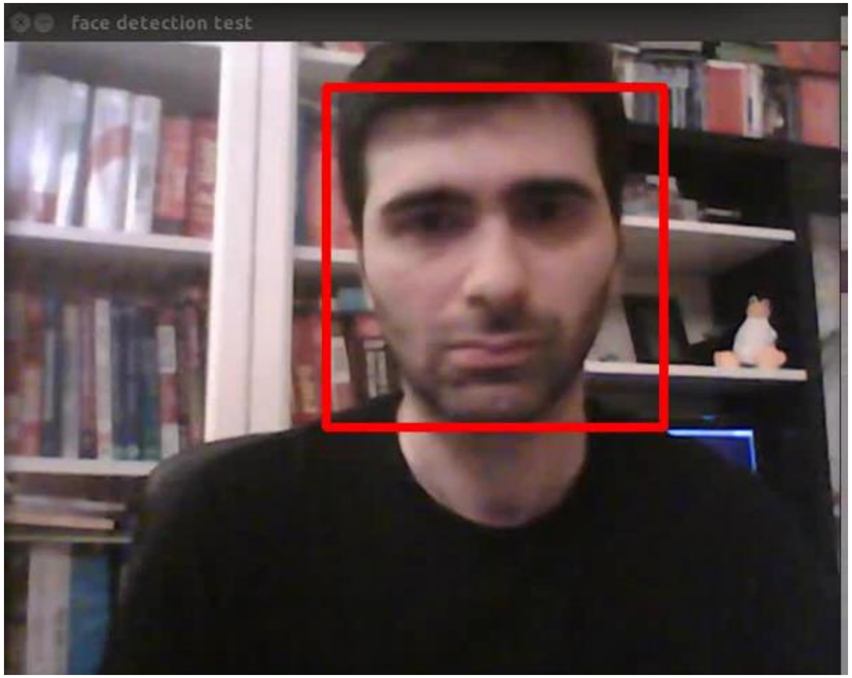




S. J. Pundlik and S. T. Birchfield, Motion Segmentation at Any Speed, Proceedings of the British Machine Vision Conference 06

Tracking objects

- Facing tracking on openCV



OpenCV's face tracker uses an algorithm called Camshift (based on the meanshift algorithm)

http://www.youtube.com/watch?v=HTk_UwAYzVk

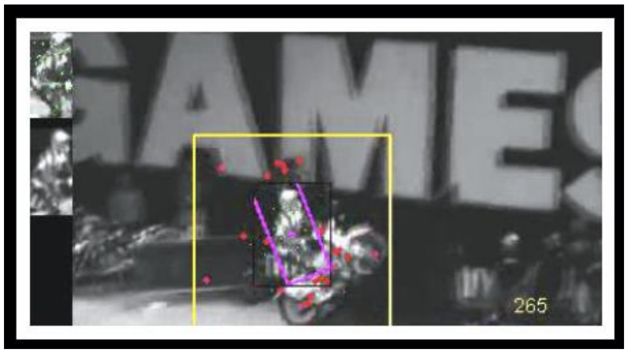
Tracking objects

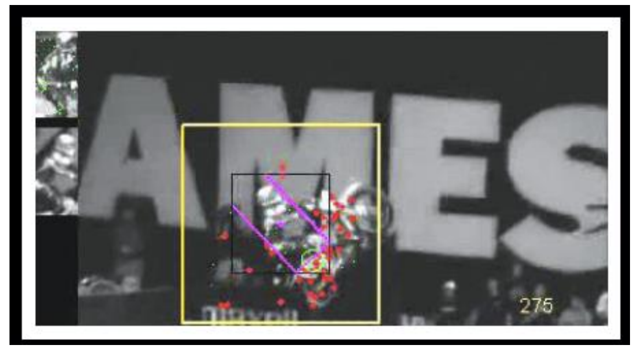
Tracking objectsReal-Time Facial Feature Tracking on a Mobile Device
P. A. Tresadern, M. C. Ionita, T. F. Cootes in IJCV (2012)

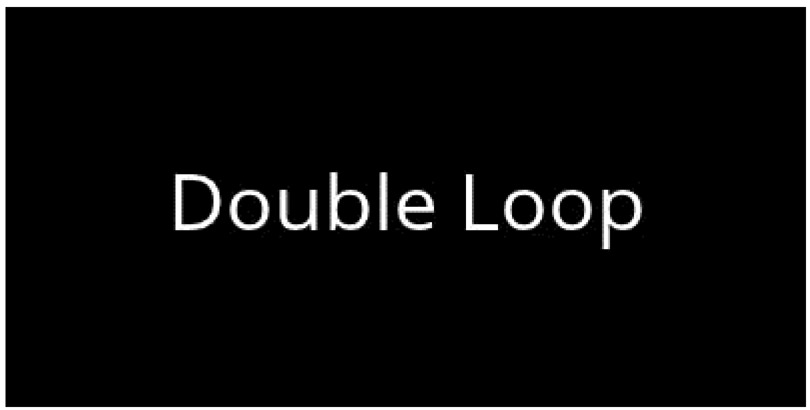
Fig. 1 Facial feature tracking running in real-time on the Nokia N900 smartphone. A video is available from http://www.youtube.com/watch?v=Y86rOh1Y_kk

FaceHugger: The ALIEN Tracker

Object Tracking by Oversampling Local Features. Del Bimbo, and F. Pernici, IEEE Transaction On Pattern Analisys And Machine Intelligence, 2014





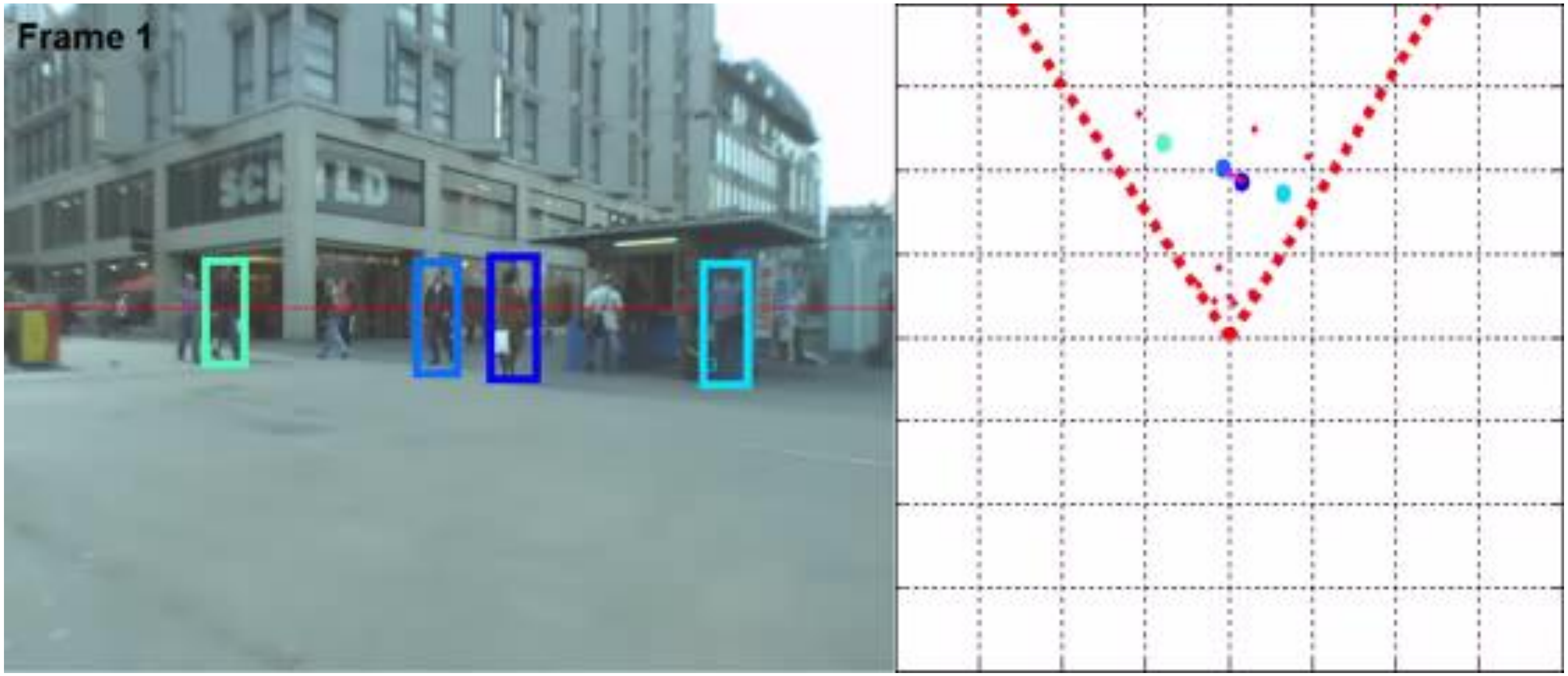


- Use Scale Invariant Feature Transform (SIFT) when applied to (flat) objects

http://www.micc.unifi.it/pernici/#alien

DOWNLOAD http://www.micc.unifi.it/pernici/

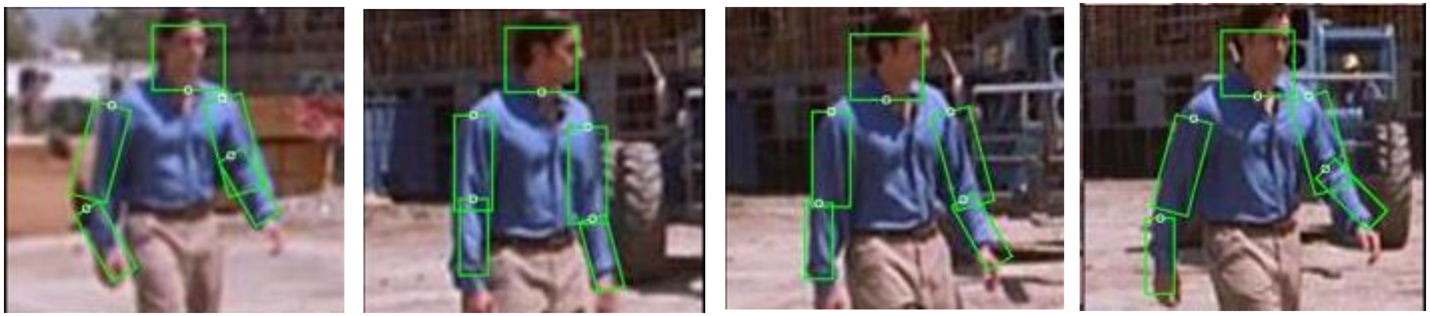
Joint tracking and 3D localization



W. Choi & K. Shahid & S. Savarese WMC 2009
W. Choi & S. Savarese , ECCV, 2010

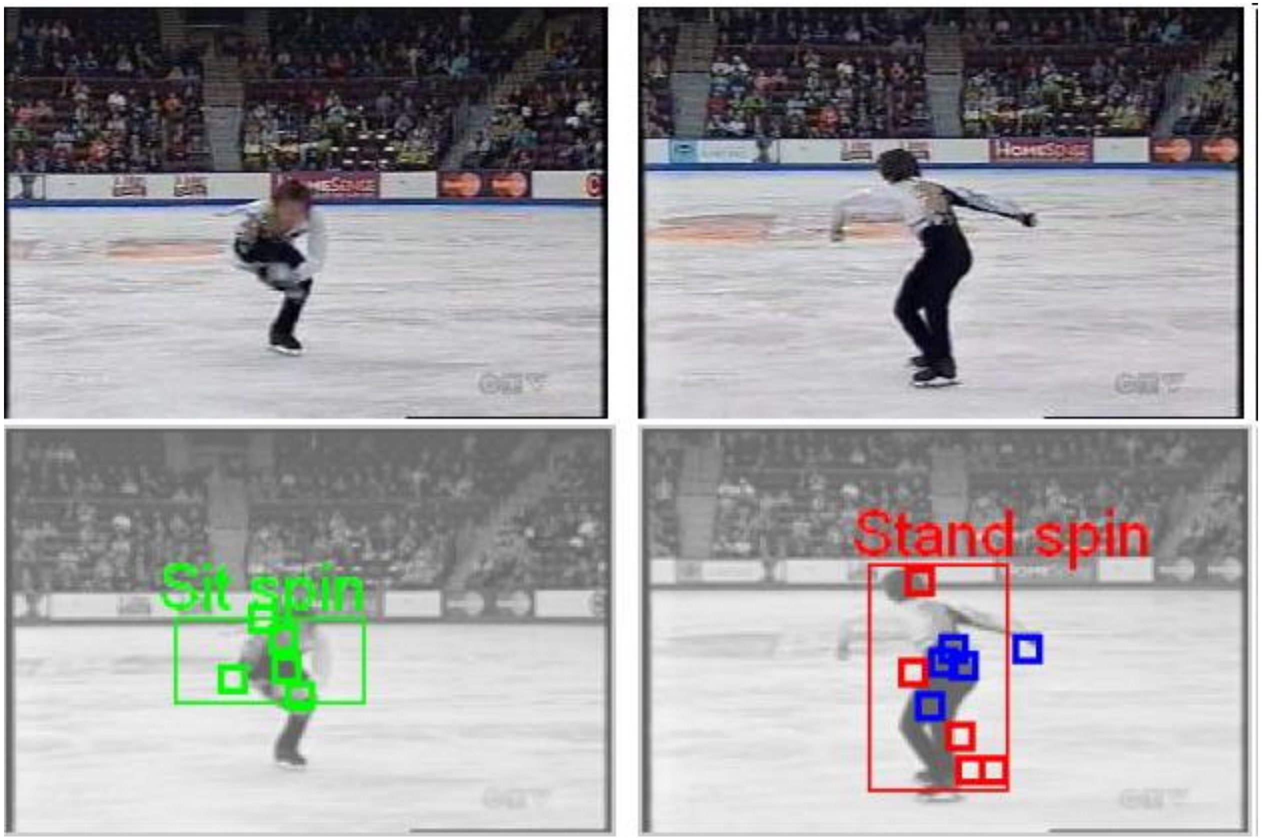
Tracking body parts

Cascaded Models for Articulated Pose Estimation, B Sapp, A Toshev, B Taskar, Computer Vision–ECCV 2010, 406-420



Courtesy of Benjamin Sapp

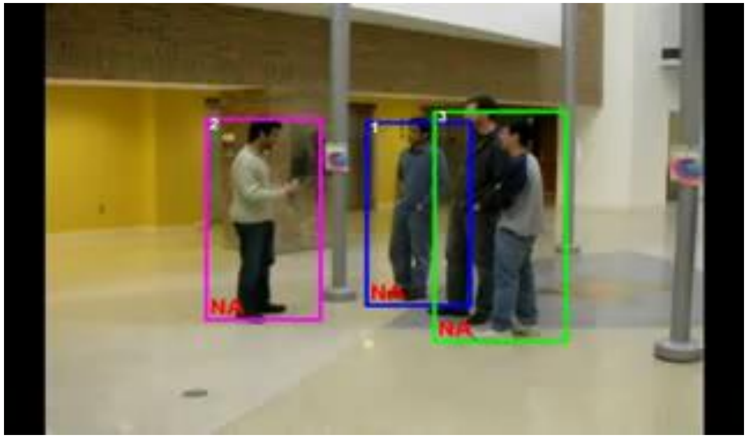
Recognizing events and activities

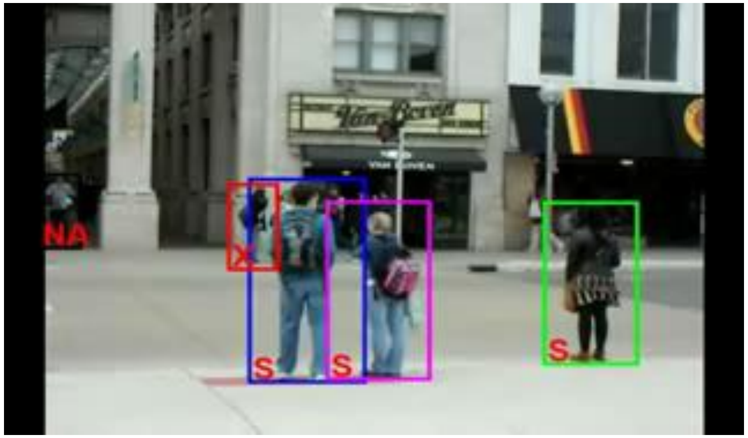


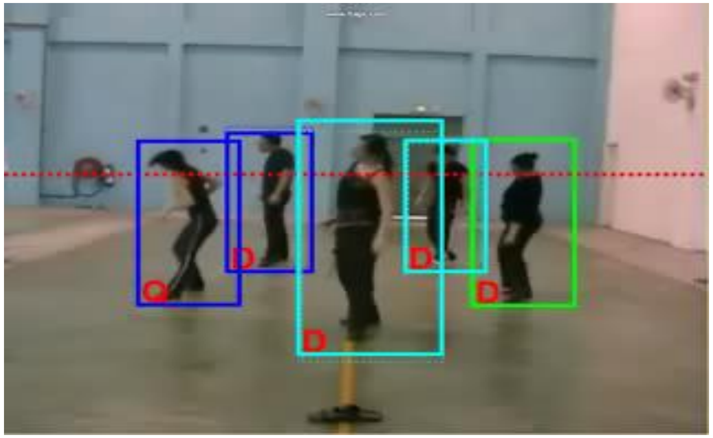
Juan Carlos Niebles, Hongcheng Wang and Li Fei-Fei, **Unsupervised Learning of Human Action Categories Using Spatial-Temporal Words**, *(BMVC)*, Edinburgh, 2006.

Recognizing group activities

Crossing – Talking – Queuing – Dancing – jogging







Choi & Savarese, CVPR 11
Choi & Savarese, ECCV 2012

X: Crossing, S: Waiting, Q: Queuing,
W: Walking, T: Talking, D: Dancing

Motion estimation techniques

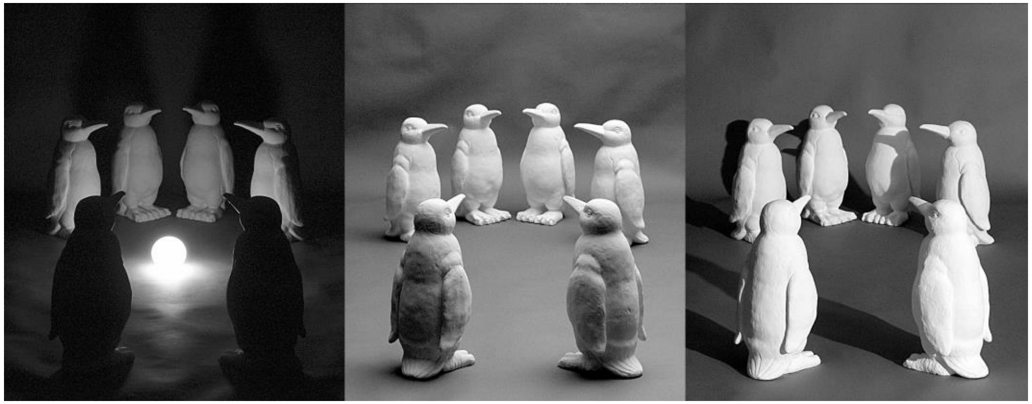
- Optical flow
  - Recover image motion at each pixel from spatio-temporal image brightness variations (optical flow)
- Feature-tracking
  - Extract visual features (corners, textured areas) and "track" them over multiple frames

Optical flow

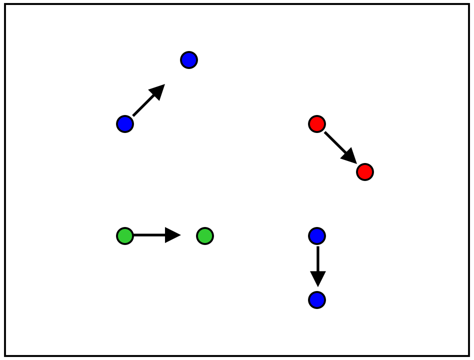
Definition: optical flow is the *apparent* motion of brightness patterns in the image

GOAL: Recover image motion at each pixel by optical flow

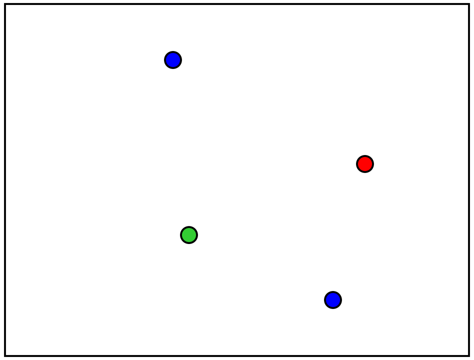
Note: apparent motion can be caused by lighting changes without any actual motion



Estimating optical flow



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

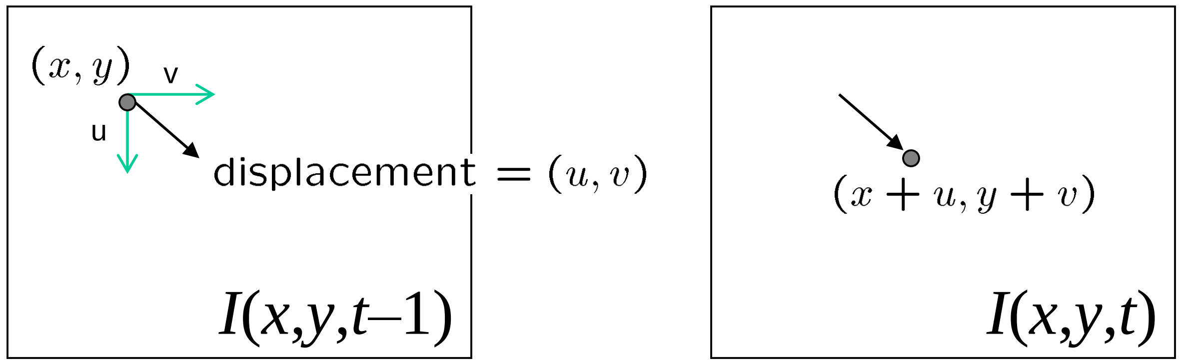


$I(x,y,t)$

Given two subsequent frames, estimate the apparent motion field u(x,y), v(x,y) between them

- Key assumptions
  - **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:

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

Linearizing the right side using Taylor expansion:

Image derivative along x

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

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

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

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)

Adding constraints….

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.

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

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

$p_i = (x_i, y_i)$

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

Lucas-Kanade flow

Overconstrained linear system:

$$\begin{bmatrix} I_x(\mathbf{p_1}) & I_y(\mathbf{p_1}) \\ I_x(\mathbf{p_2}) & I_y(\mathbf{p_2}) \\ \vdots & \vdots \\ I_x(\mathbf{p_{25}}) & I_y(\mathbf{p_{25}}) \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = - \begin{bmatrix} I_t(\mathbf{p_1}) \\ I_t(\mathbf{p_2}) \\ \vdots \\ I_t(\mathbf{p_{25}}) \end{bmatrix} \qquad \underset{25\times2}{A}\ \underset{2\times1}{d} = \underset{25\times1}{b}$$

Lucas-Kanade flow

Overconstrained linear system

$$\begin{bmatrix} I_x(\mathbf{p_1}) & I_y(\mathbf{p_1}) \\ I_x(\mathbf{p_2}) & I_y(\mathbf{p_2}) \\ \vdots & \vdots \\ I_x(\mathbf{p_{25}}) & I_y(\mathbf{p_{25}}) \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = - \begin{bmatrix} I_t(\mathbf{p_1}) \\ I_t(\mathbf{p_2}) \\ \vdots \\ I_t(\mathbf{p_{25}}) \end{bmatrix} \qquad \underset{25\text{x}2}{A} \; \underset{2\text{x}1}{d} = \underset{25\text{x}1}{b}$$

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?

- **A^{T}A** should be invertible
- Eigenvalues λ_1 and λ_2 of **A^{T}A** should not be too small
- **A^{T}A** should be well-conditioned
  - λ_1 / λ_2 should not be too large (λ_1 = larger eigenvalue)

Does this remind anything to you?

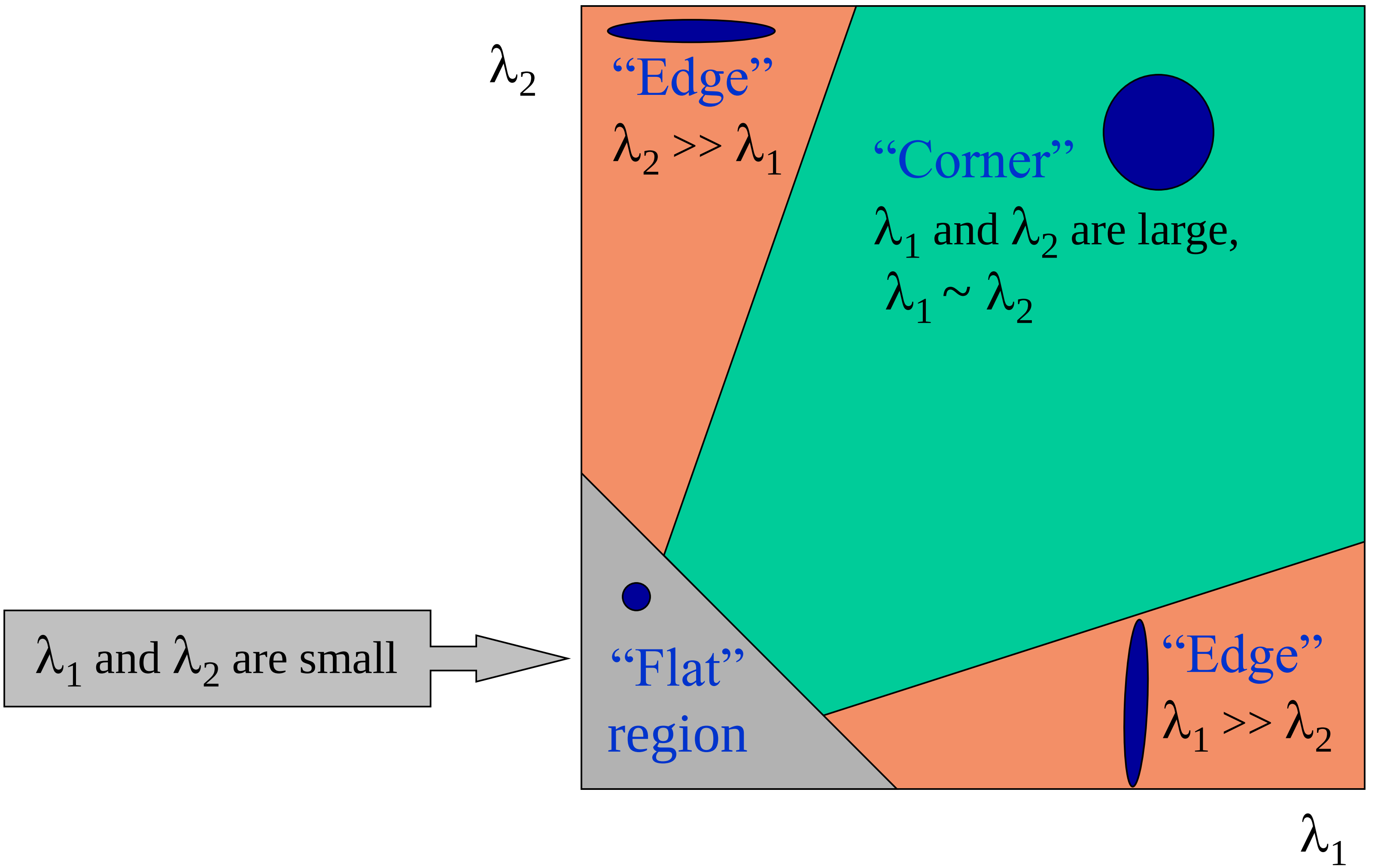
M = $A^T A$ is the *second moment matrix* !
(Harris corner detector…)

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

- Eigenvectors and eigenvalues of $A^T A$ relate to edge direction and magnitude
  - The eigenvector associated with the larger eigenvalue points in the direction of fastest intensity change
  - The other eigenvector is orthogonal to it

Interpreting the eigenvalues

Classification of image points using eigenvalues of the second moment matrix:



Edge

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

– gradients very large or very small

– 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

What are good features to track?

Can we measure “quality” of features from just a single image

Good features to track:

- Harris corners (guarantee small error sensitivity)

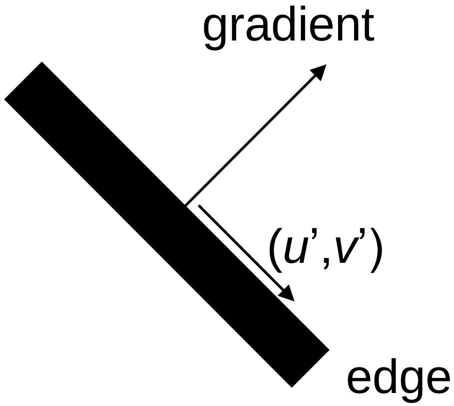
Bad features to track:

- Image points when either λ_1 or λ_2 (or both) is small (i.e., edges or uniform textured regions)

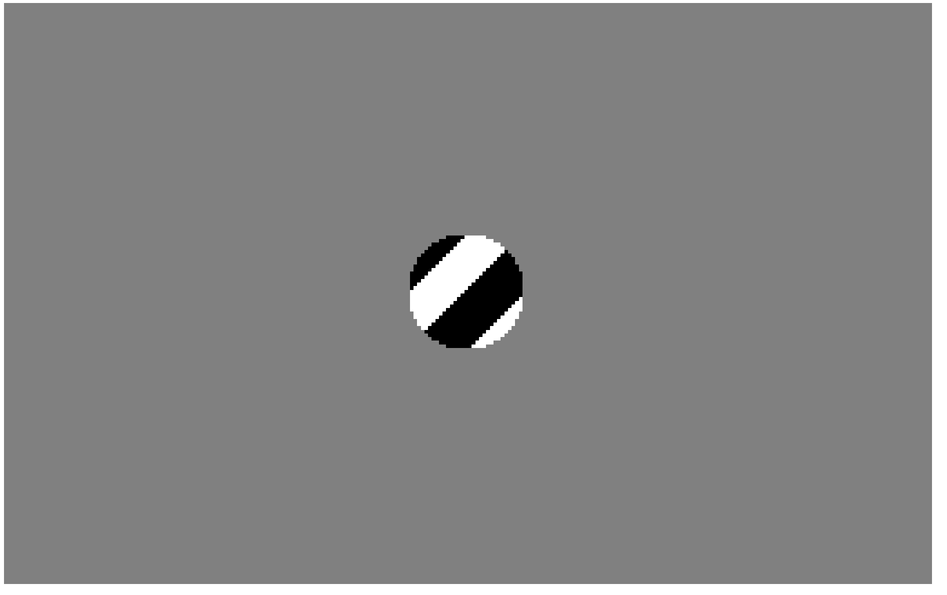
Ambiguities in tracking a point on a line

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

This equation $\nabla I \cdot [u' \;\; v']^T = 0$ is always satisfied when (*u'*, *v'*) is perpendicular to the image gradient

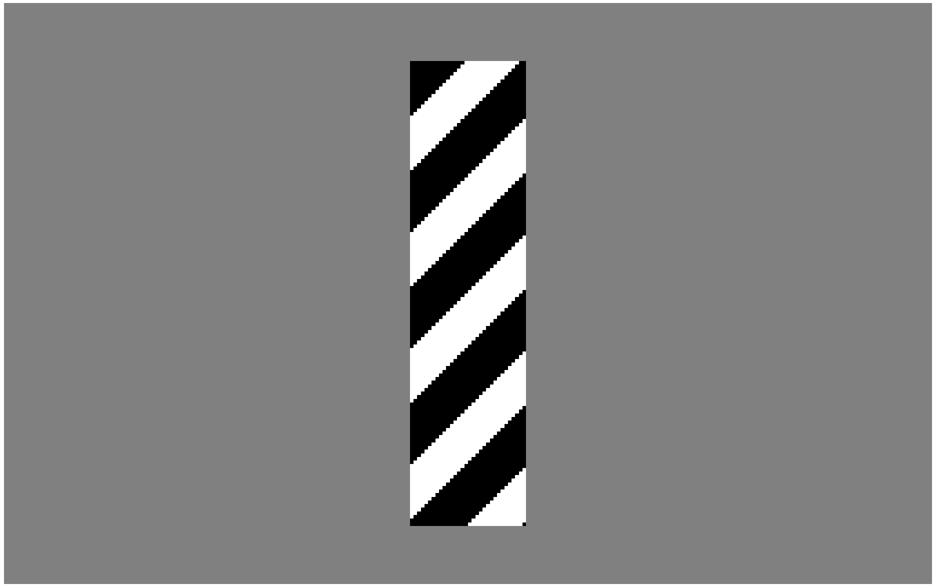


The barber pole illusion



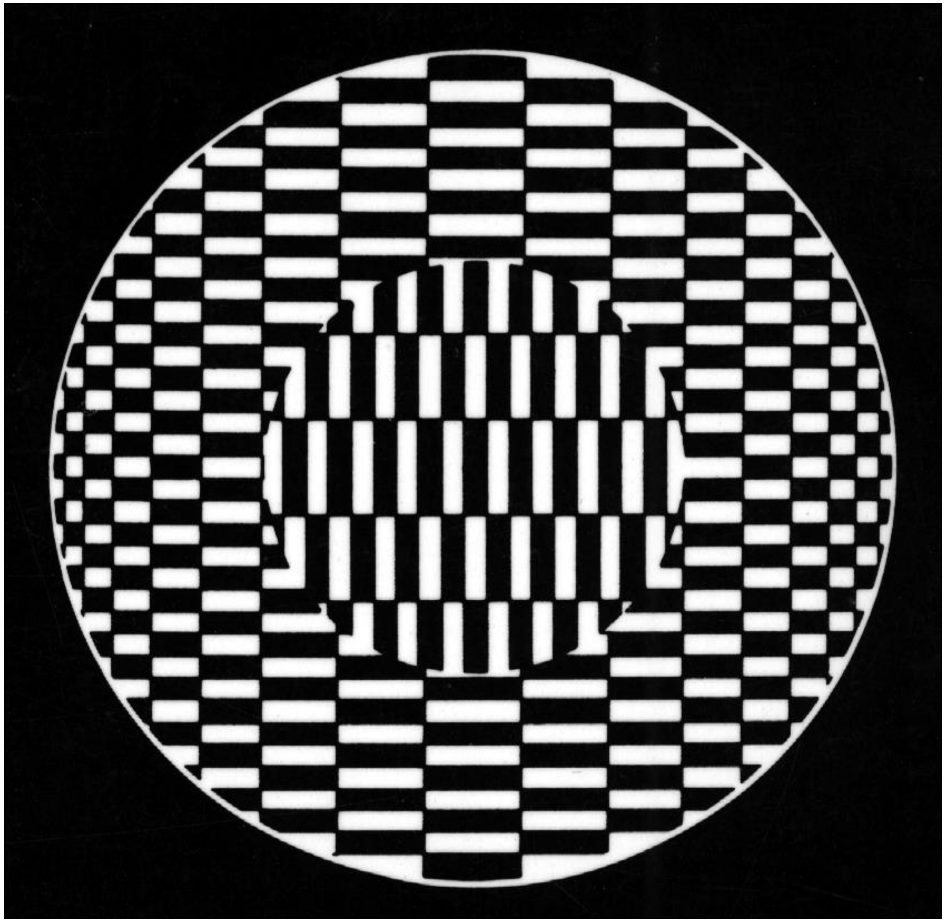
http://en.wikipedia.org/wiki/Barberpole_illusion

The barber pole illusion



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

Aperture problem cont'd



* From Marc Pollefeys COMP 256 2003

Motion estimation techniques

Optical flow

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

Feature-tracking

- Extract visual features (corners, textured areas) and "track" them over multiple frames

  - Shi-Tomasi feature tracker
  - Tracking with dynamics

- Implemented in Open CV

Shi-Tomasi feature tracker

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

Find good features using eigenvalues of second-moment matrix

- Key idea: “good” features to track are the ones that can be tracked reliably

From frame to frame, track with Lucas-Kanade and a pure *translation* model

- More robust for small displacements, can be estimated from smaller neighborhoods

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

Tracking example

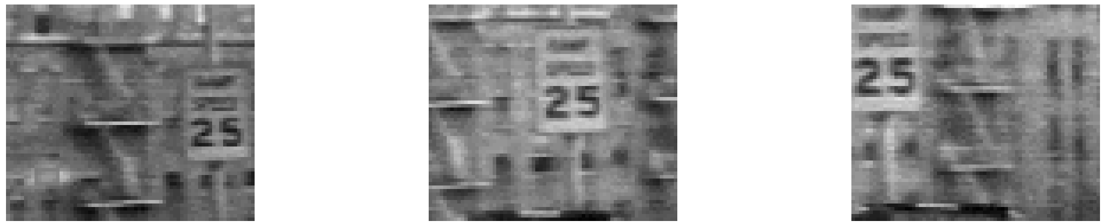


Figure 1: Three frame details from Woody Allen's *Manhattan*. The details are from the 1st, 11th, and 21st frames of a subsequence from the movie.

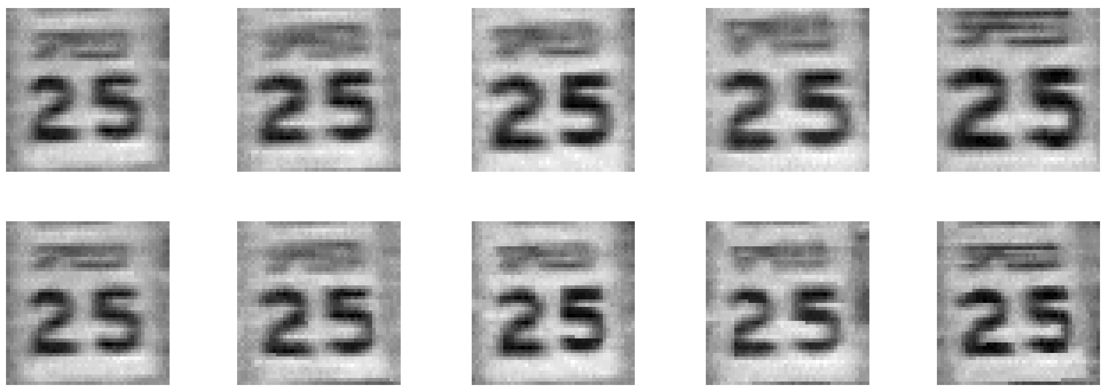


Figure 2: The traffic sign windows from frames 1,6,11,16,21 as tracked (top), and warped by the computed deformation matrices (bottom).

Recap

- Key assumptions (Errors in Lucas-Kanade)
  - $\boxed{\textbf{Small motion: } \text{points do not move very far}}$
  - **Brightness constancy:** projection of the same point looks the same in every frame
  - **Spatial coherence:** points move like their neighbors

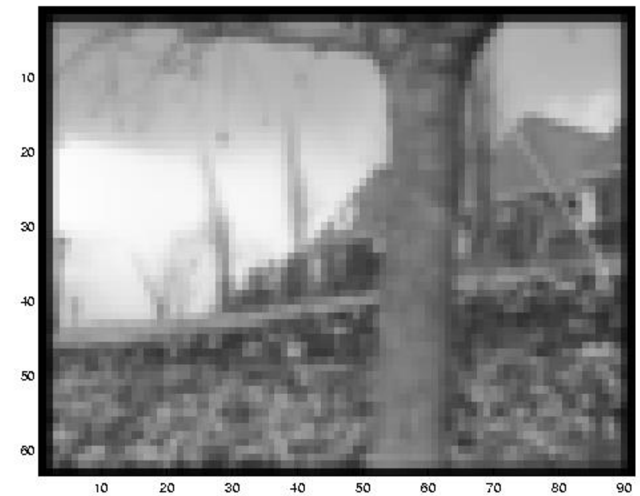
Revisiting the small motion assumption

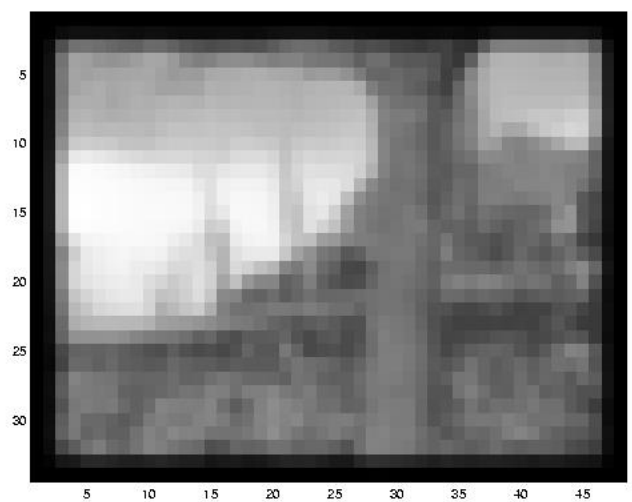
Is this motion small enough?

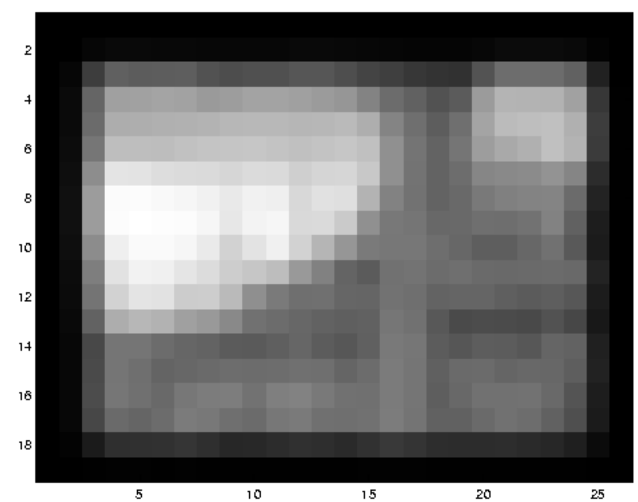
- Probably not—it's much larger than one pixel (2^{nd} order terms dominate)
- How might we solve this problem?

* From Khurram Hassan-Shafique CAP5415 Computer Vision 2003

Reduce the resolution!

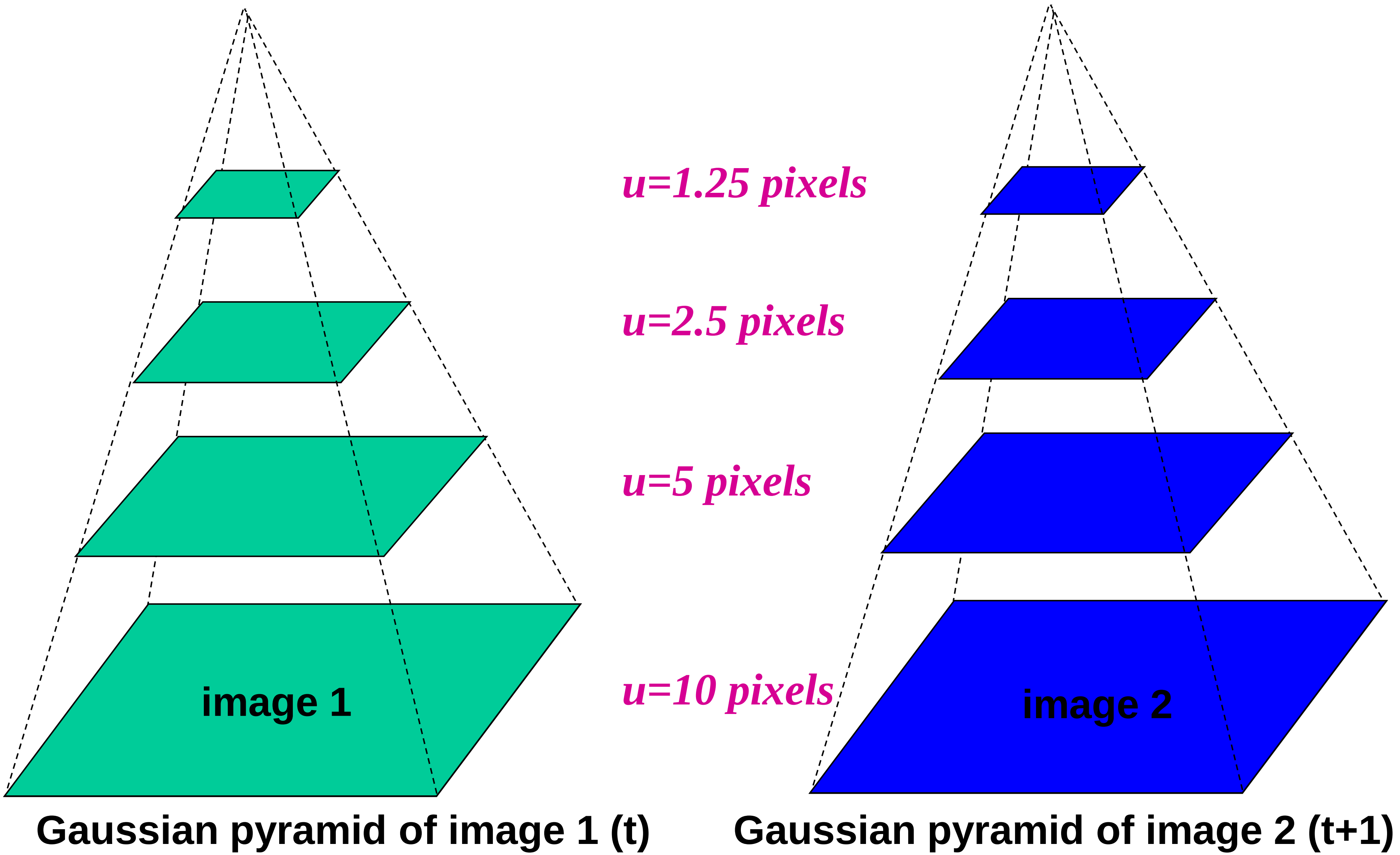




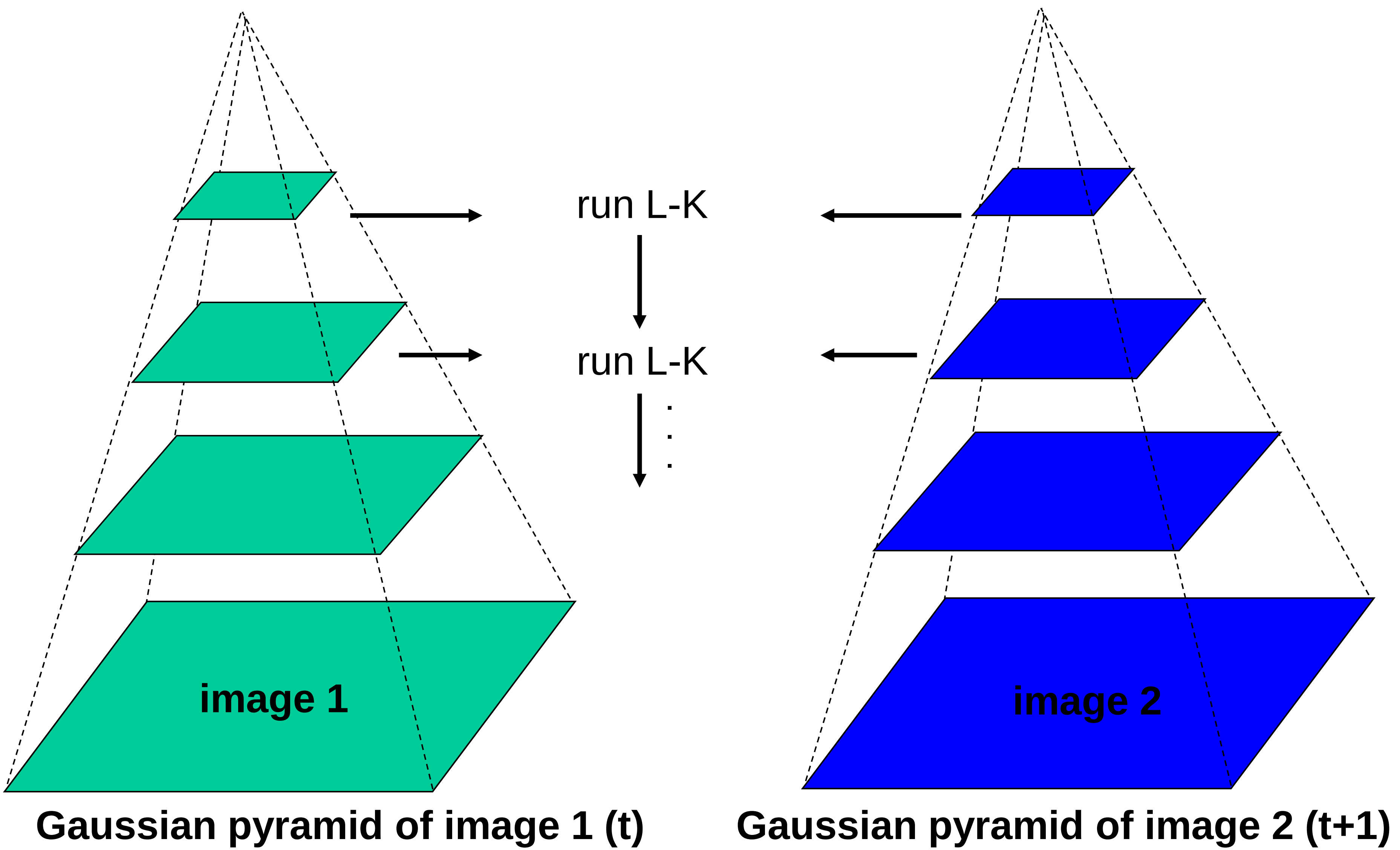


* From Khurram Hassan-Shafique CAP5415 Computer Vision 2003

Coarse-to-fine optical flow estimation



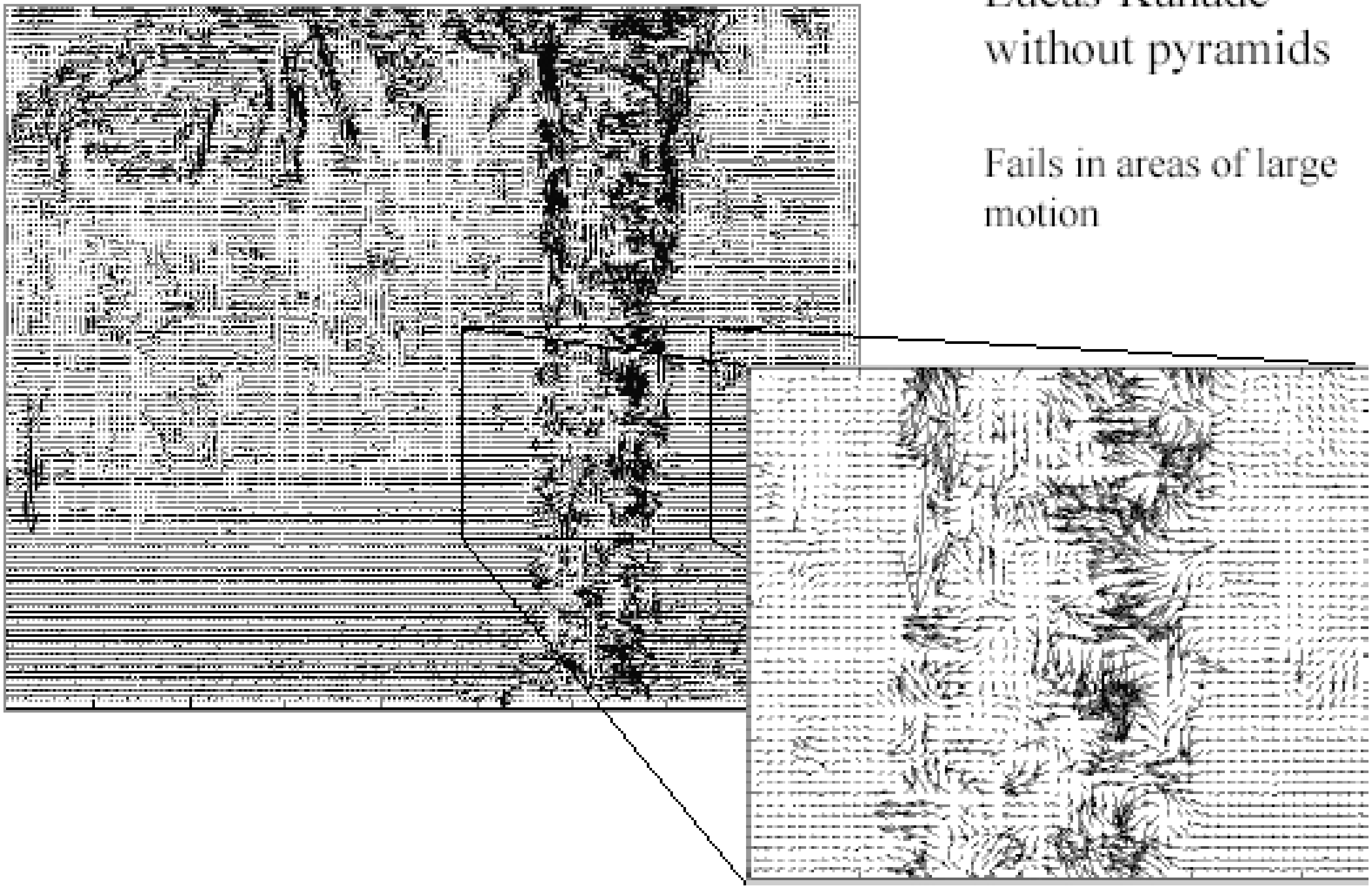
Coarse-to-fine optical flow estimation



Multi-resolution Lucas Kanade Algorithm

- Compute ‘simple’ LK at highest level
- At level i
  - Take flow u_{i-1}, v_{i-1} from level i-1
  - bilinear interpolate it to create u_i^*, v_i^* matrices of twice resolution for level i
  - multiply u_i^*, v_i^* by 2
  - compute f_t from a block displaced by $u_i^*(x,y)$, $v_i^*(x,y)$
  - Apply LK to get $u_i'(x, y)$, $v_i'(x, y)$ (the correction in flow)
  - Add corrections u_i' v_i', *i.e.* $u_i = u_i^* + u_i'$, $v_i = v_i^* + v_i'$.

Optical Flow Results

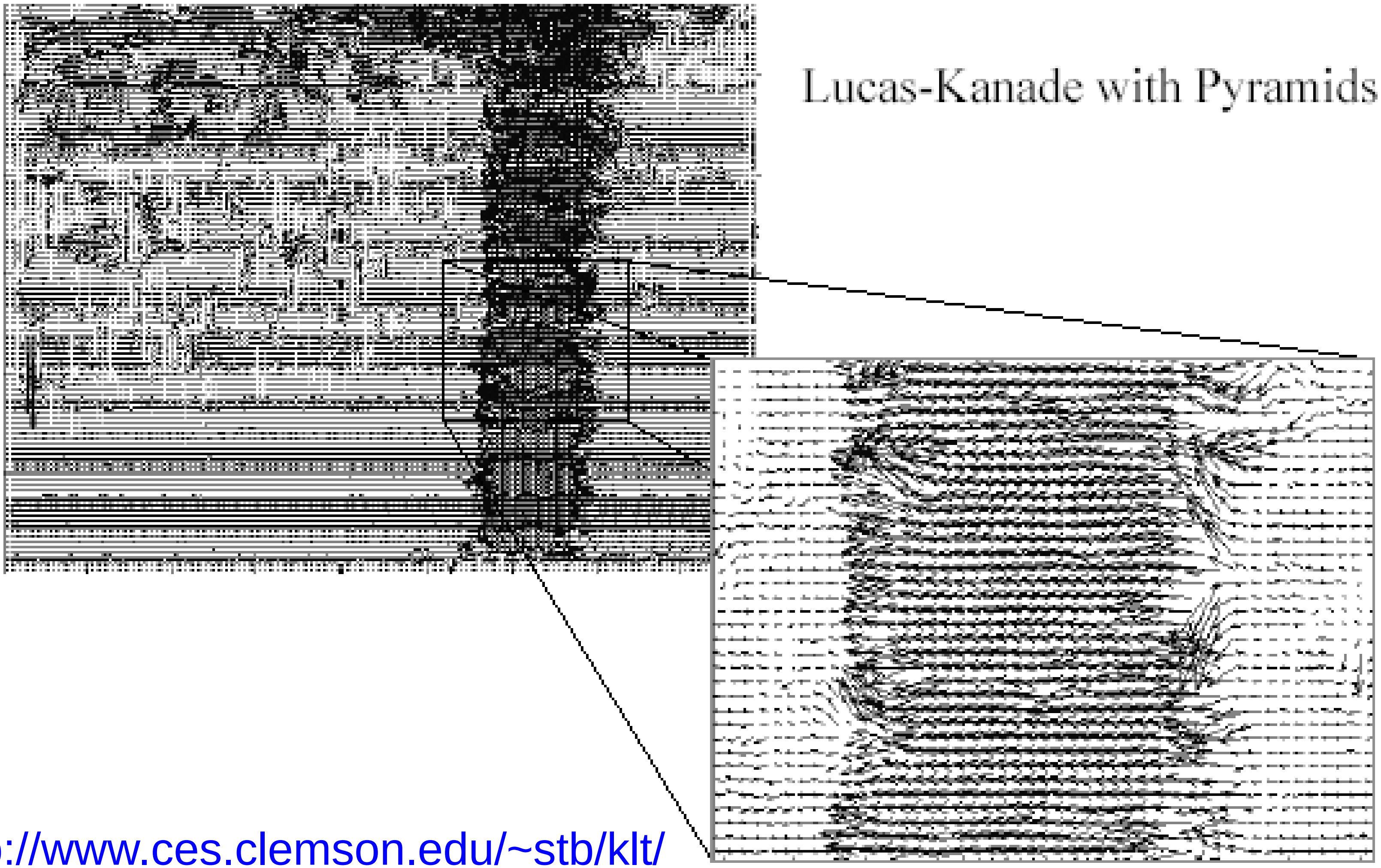


Lucas-Kanade without pyramids

Fails in areas of large motion

* From Khurram Hassan-Shafique CAP5415 Computer Vision 2003

Optical Flow Results



- http://www.ces.clemson.edu/~stb/klt/
- OpenCV

* From Khurram Hassan-Shafique CAP5415 Computer Vision 2003

Recap

- Key assumptions (Errors in Lucas-Kanade)

  - **Small motion:** points do not move very far
  - **Brightness constancy:** projection of the same point looks the same in every frame
  - **Spatial coherence:** points move like their neighbors

Motion segmentation

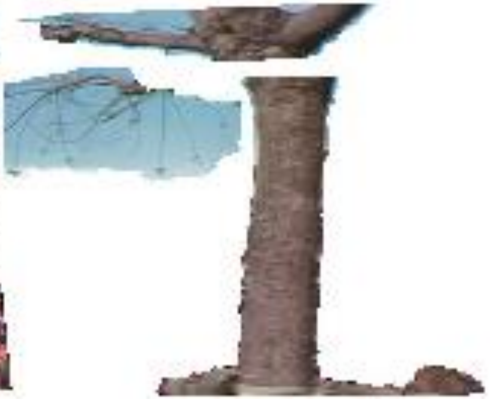
How do we represent the motion in this scene?

Motion segmentation

J. Wang and E. Adelson. Layered Representation for Motion Analysis. *CVPR 1993*.

- Break image sequence into “layers” each of which has a coherent (affine) motion

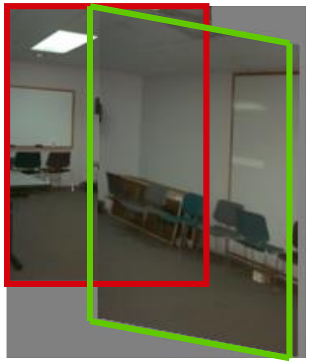


Affine motion

$$u(x, y) = a_1 + a_2 x + a_3 y$$

$$v(x, y) = a_4 + a_5 x + a_6 y$$

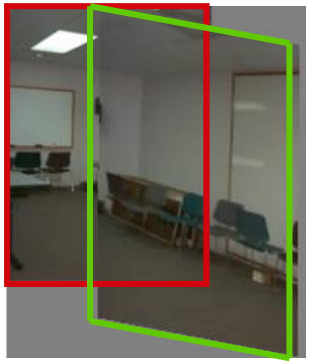


Substituting into the brightness constancy equation:

$$\boxed{I_x \cdot u + I_y \cdot v + I_t \approx 0}$$

Affine motion

$$u(x, y) = a_1 + a_2 x + a_3 y$$
$$v(x, y) = a_4 + a_5 x + a_6 y$$



Substituting into the brightness constancy equation:

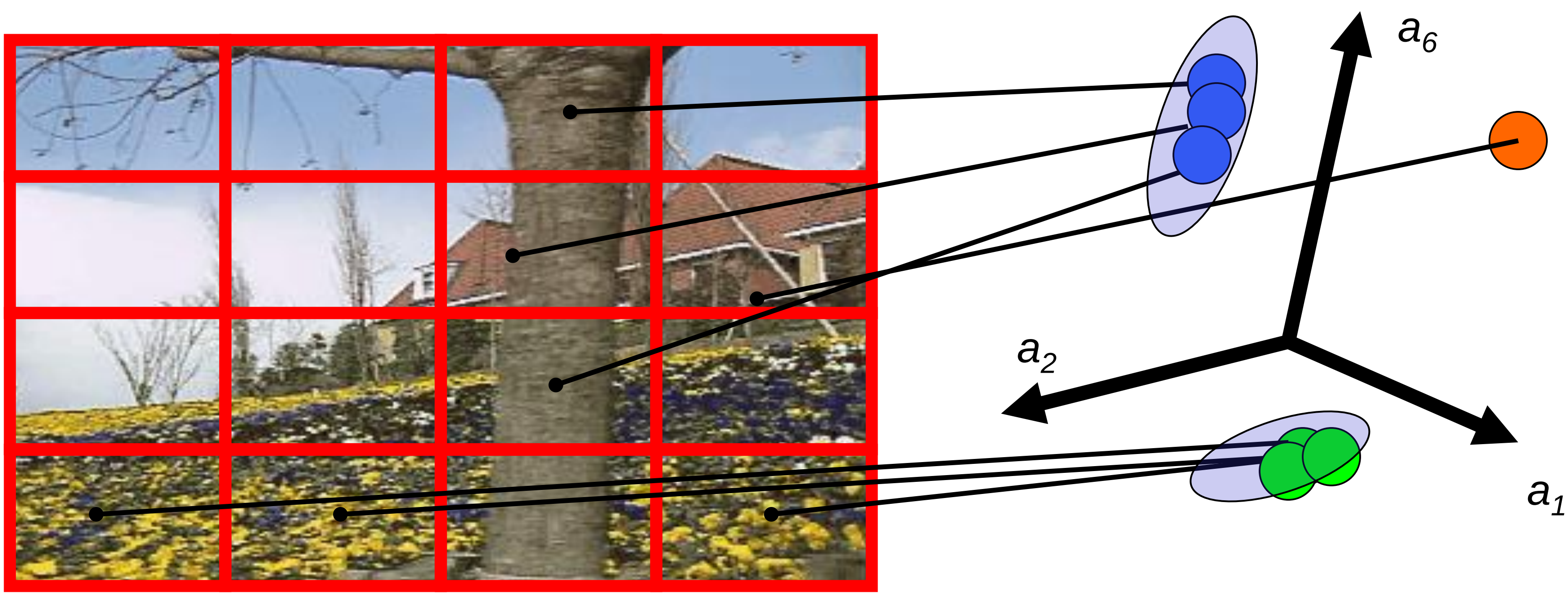
$$\boxed{I_x(a_1 + a_2 x + a_3 y) + I_y(a_4 + a_5 x + a_6 y) + I_t \approx 0}$$

- Each pixel provides 1 linear constraint in 6 unknowns
- If we have at least 6 pixels in a neighborhood, $a_1 \ldots a_6$ can be found by least squares minimization:

$$\boxed{Err(\vec{a}) = \sum \left[I_x(a_1 + a_2 x + a_3 y) + I_y(a_4 + a_5 x + a_6 y) + I_t \right]^2}$$

How do we estimate the layers?

1. Obtain a set of initial affine motion hypotheses
   - Divide the image into blocks and estimate affine motion parameters in each block by least squares
     - Eliminate hypotheses with high residual error
2. Map into motion parameter space
3. Perform k-means clustering on affine motion parameters
   –Merge clusters that are close and retain the largest clusters to obtain a smaller set of hypotheses to describe all the motions in the scene



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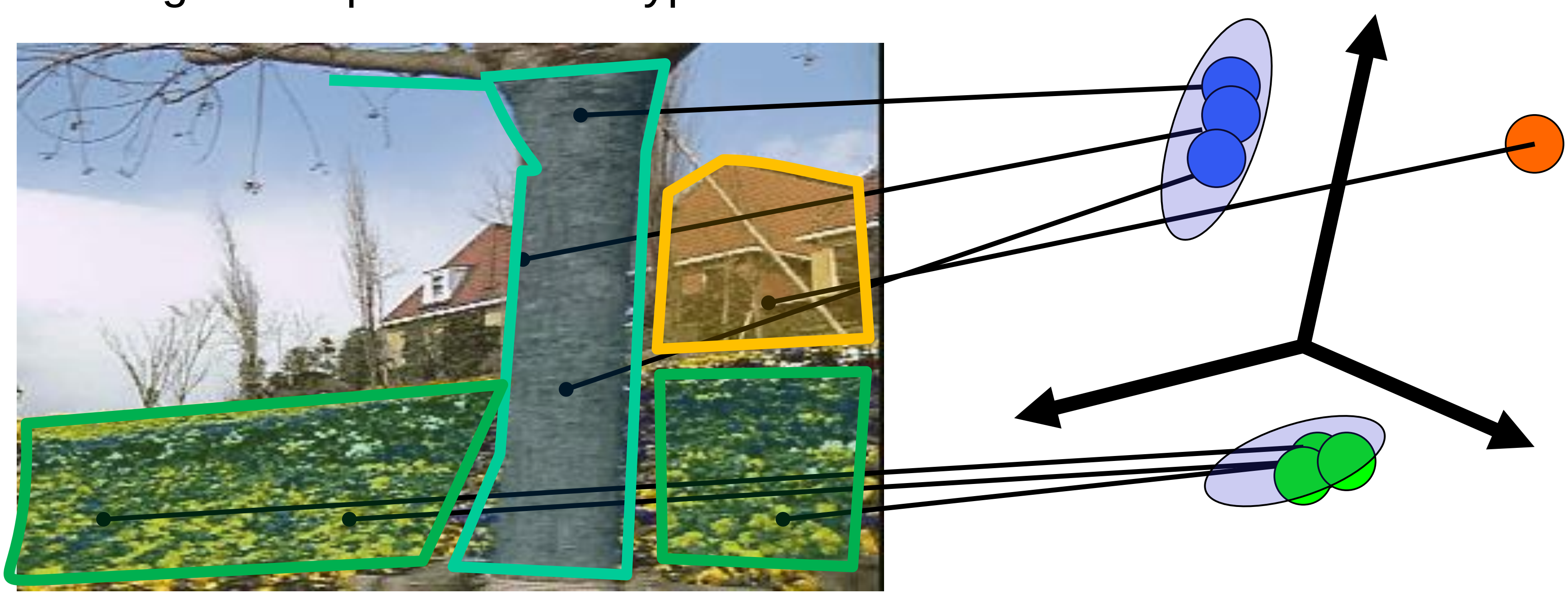
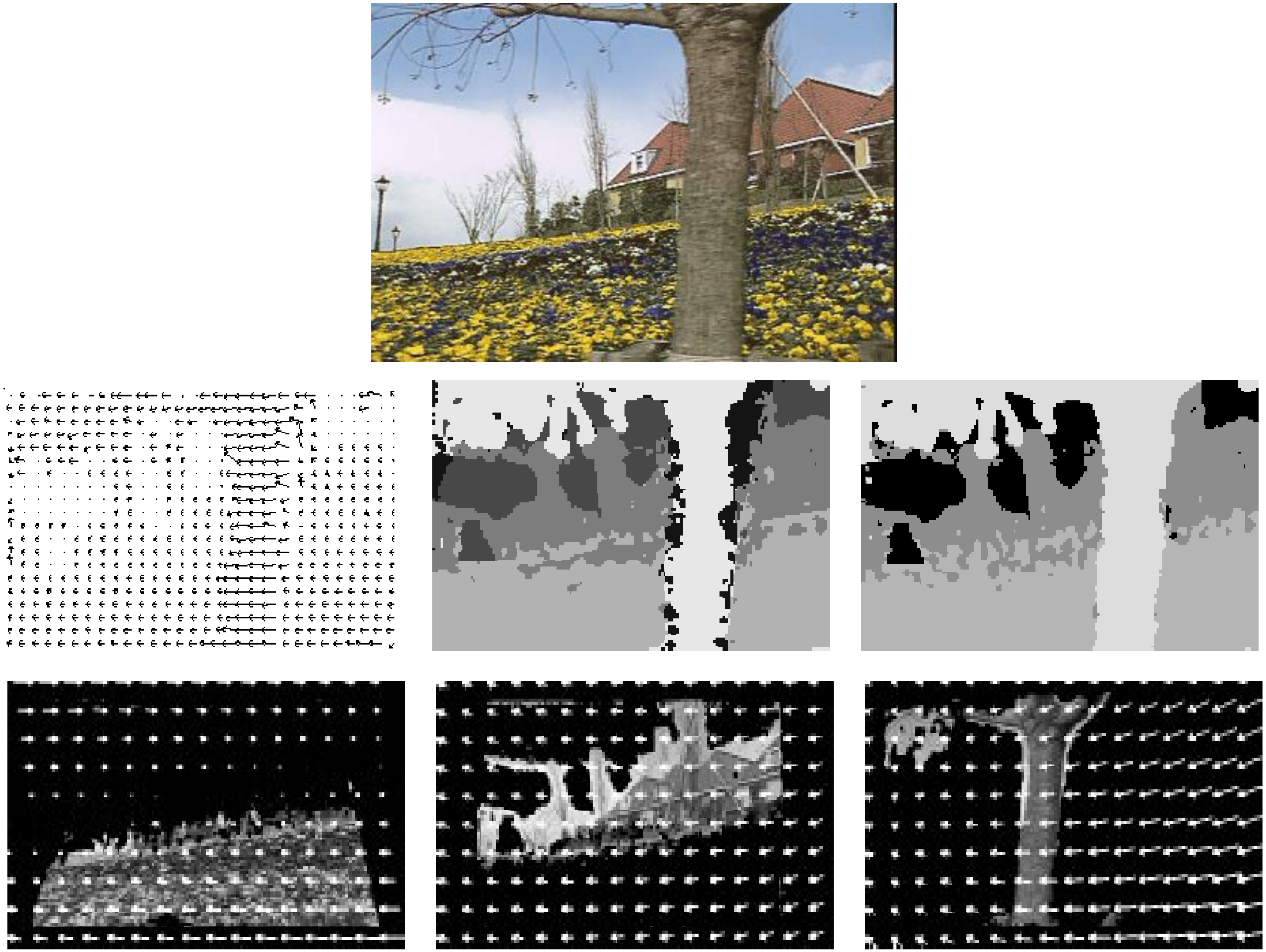
4. Assign each pixel to best hypothesis --- iterate



Example result



J. Wang and E. Adelson. [Layered Representation for Motion Analysis.](#) *CVPR 1993*.

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Next lecture:

Recognition & classification