Feature Matching and Robust Fitting

Read Szeliski 4.1

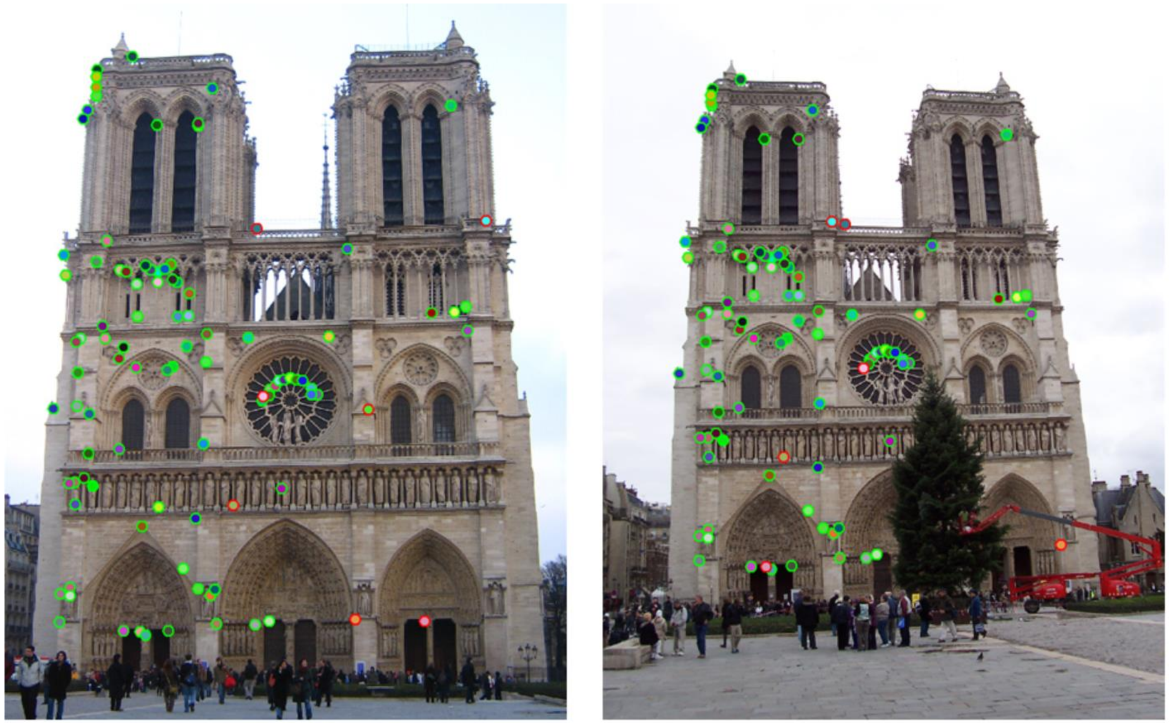
Computer Vision

CS 143, Brown

James Hays

Acknowledgment: Many slides from Derek Hoiem and Grauman&Leibe 2008 AAAI Tutorial

Project 2 questions?



The top 100 most confident local feature matches from a baseline implementation of project 2. In this case, 93 were correct (highlighted in green) and 7 were incorrect (highlighted in red).

Project 2: Local Feature Matching

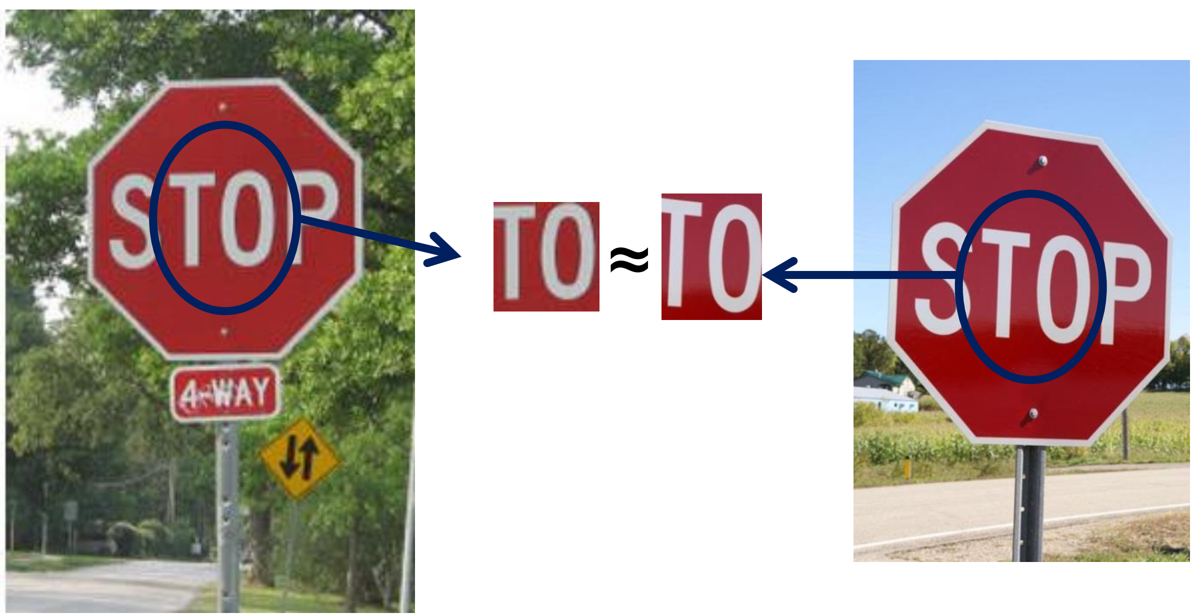
CS 143: Introduction to Computer Vision

Brief

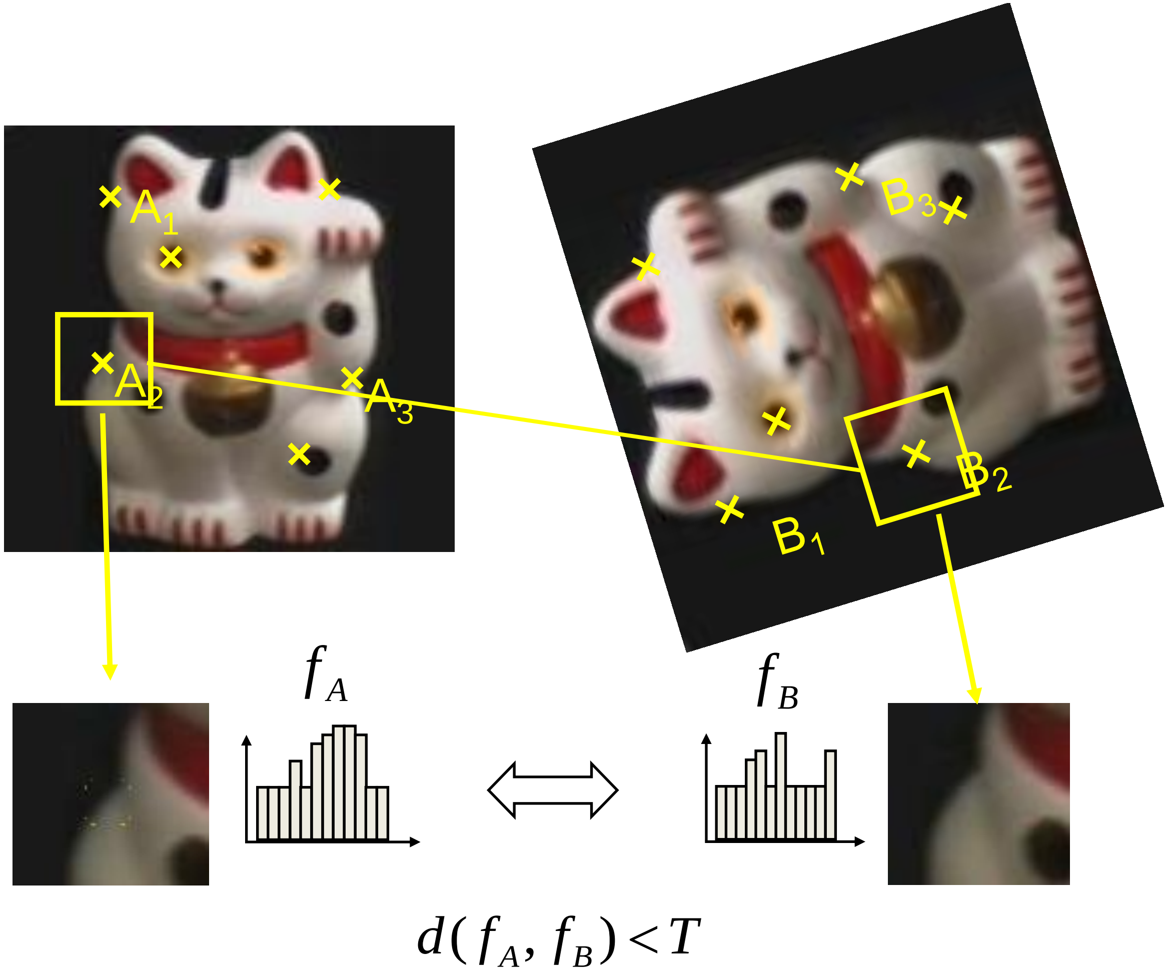
- Due: 11:59pm on Monday, October 7th, 2013
- Stencil code: `/course/cs143/asgn/proj2/code/`
- Data: `/course/cs143/asgn/proj2/data/` includes 93 images from 9 different outdoor scenes.
- Html writeup template: `/course/cs143/asgn/proj2/html/`
- *Partial* project materials are also available in **proj2.zip (1.7 MB)**. Includes only the two test images shown above.
- Handin: `cs143_handin proj2`
- Required files: README, code/, html/, html/index.html

This section: correspondence and alignment

- Correspondence: matching points, patches, edges, or regions across images



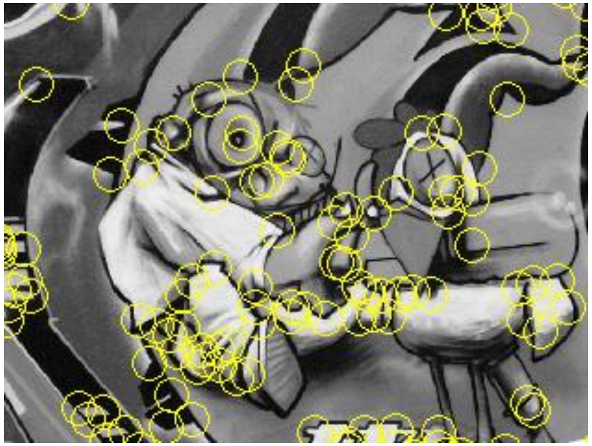
Overview of Keypoint Matching



1. **Find a set of distinctive key-points**
2. **Define a region around each keypoint**
3. **Extract and normalize the region content**
4. **Compute a local descriptor from the normalized region**
5. **Match local descriptors**

Review: Interest points

- Keypoint detection: repeatable and distinctive
  - Corners, blobs, stable regions
  - Harris, DoG, MSER



Review: Choosing an interest point detector

- What do you want it for?
  - Precise localization in x-y: Harris
  - Good localization in scale: Difference of Gaussian
  - Flexible region shape: MSER

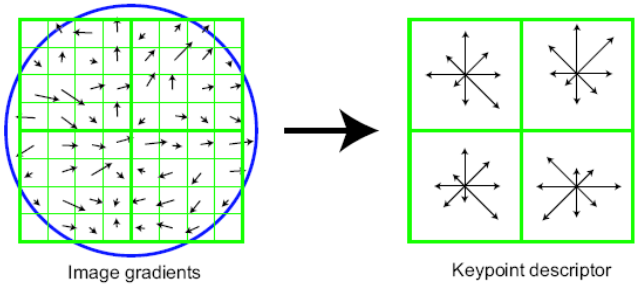
- Best choice often application dependent
  - Harris-/Hessian-Laplace/DoG work well for many natural categories
  - MSER works well for buildings and printed things

- Why choose?
  - Get more points with more detectors

- There have been extensive evaluations/comparisons
  - [Mikolajczyk et al., IJCV’05, PAMI’05]
  - All detectors/descriptors shown here work well

Review: Local Descriptors

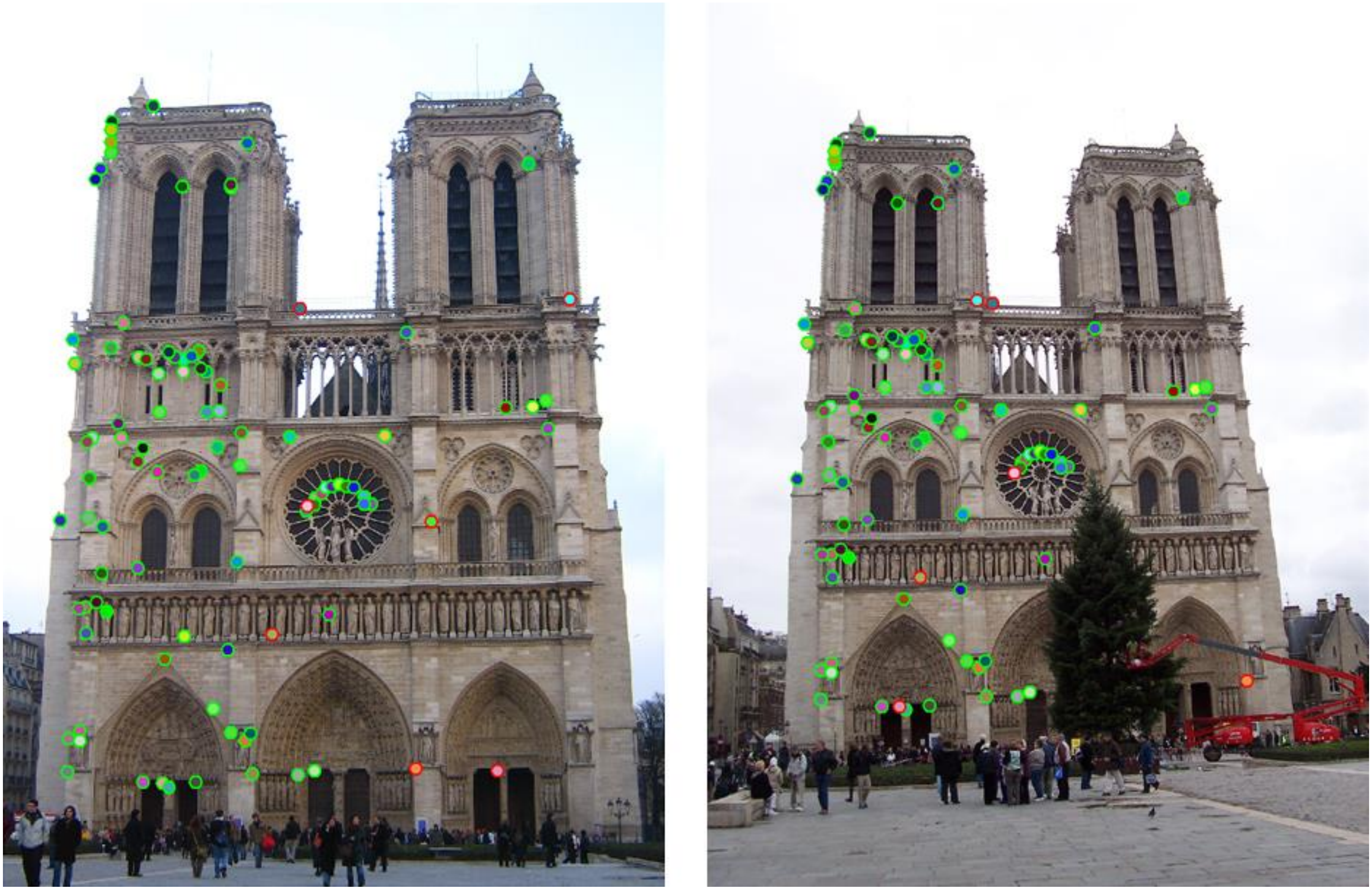
- Most features can be thought of as templates, histograms (counts), or combinations
- The ideal descriptor should be
  - Robust and Distinctive
  - Compact and Efficient



- Most available descriptors focus on edge/gradient information
  - Capture texture information
  - Color rarely used

K. Grauman, B. Leibe

How do we decide which features match?



Feature Matching

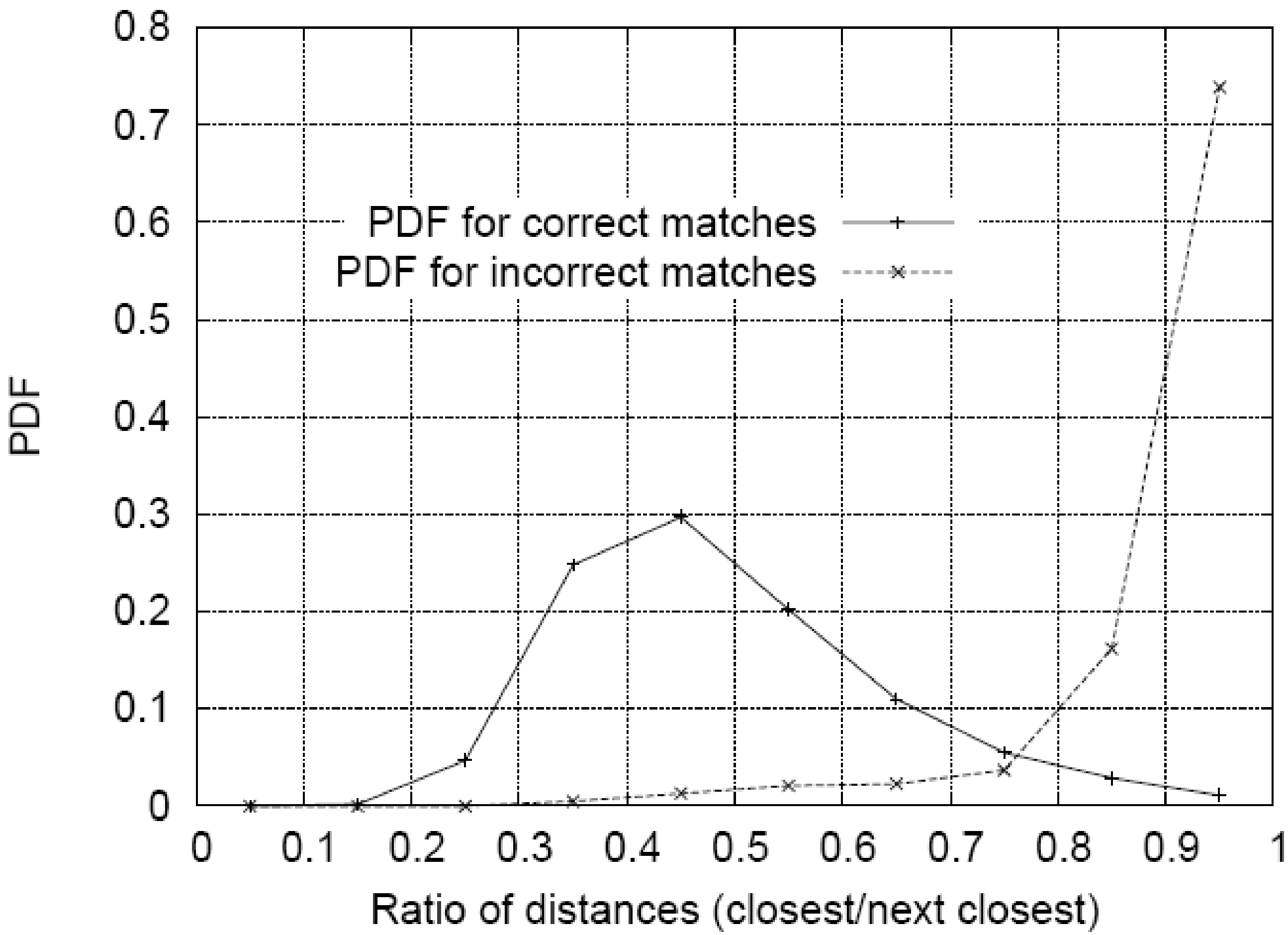
- Szeliski 4.1.3
  - Simple feature-space methods
  - Evaluation methods
  - Acceleration methods
  - Geometric verification (Chapter 6)

Feature Matching

- Simple criteria: One feature matches to another if those features are nearest neighbors and their distance is below some threshold.
- Problems:
  - Threshold is difficult to set
  - Non-distinctive features could have lots of close matches, only one of which is correct

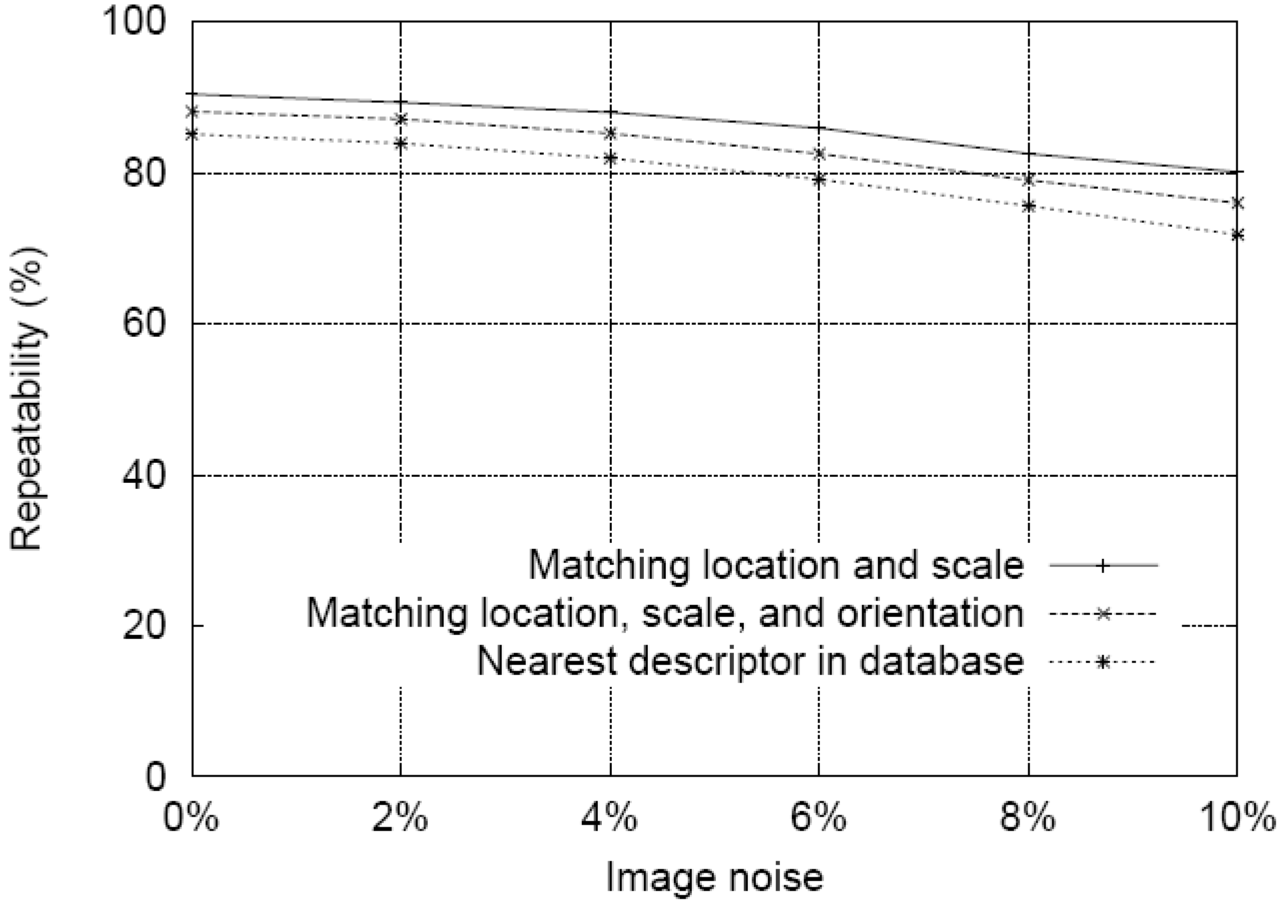
Matching Local Features

- Threshold based on the ratio of 1st nearest neighbor to 2nd nearest neighbor distance.



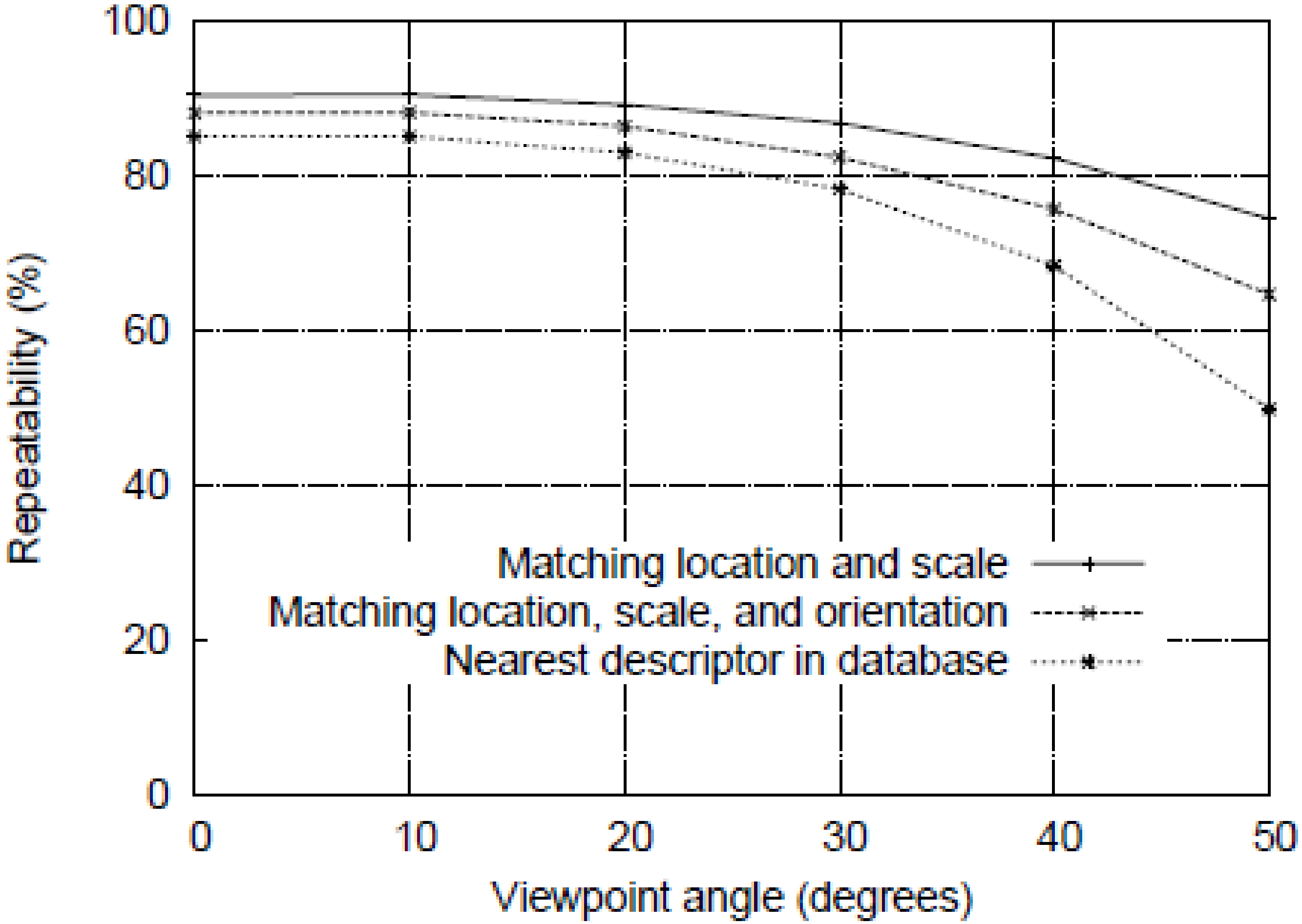
Lowe IJCV 2004

SIFT Repeatability

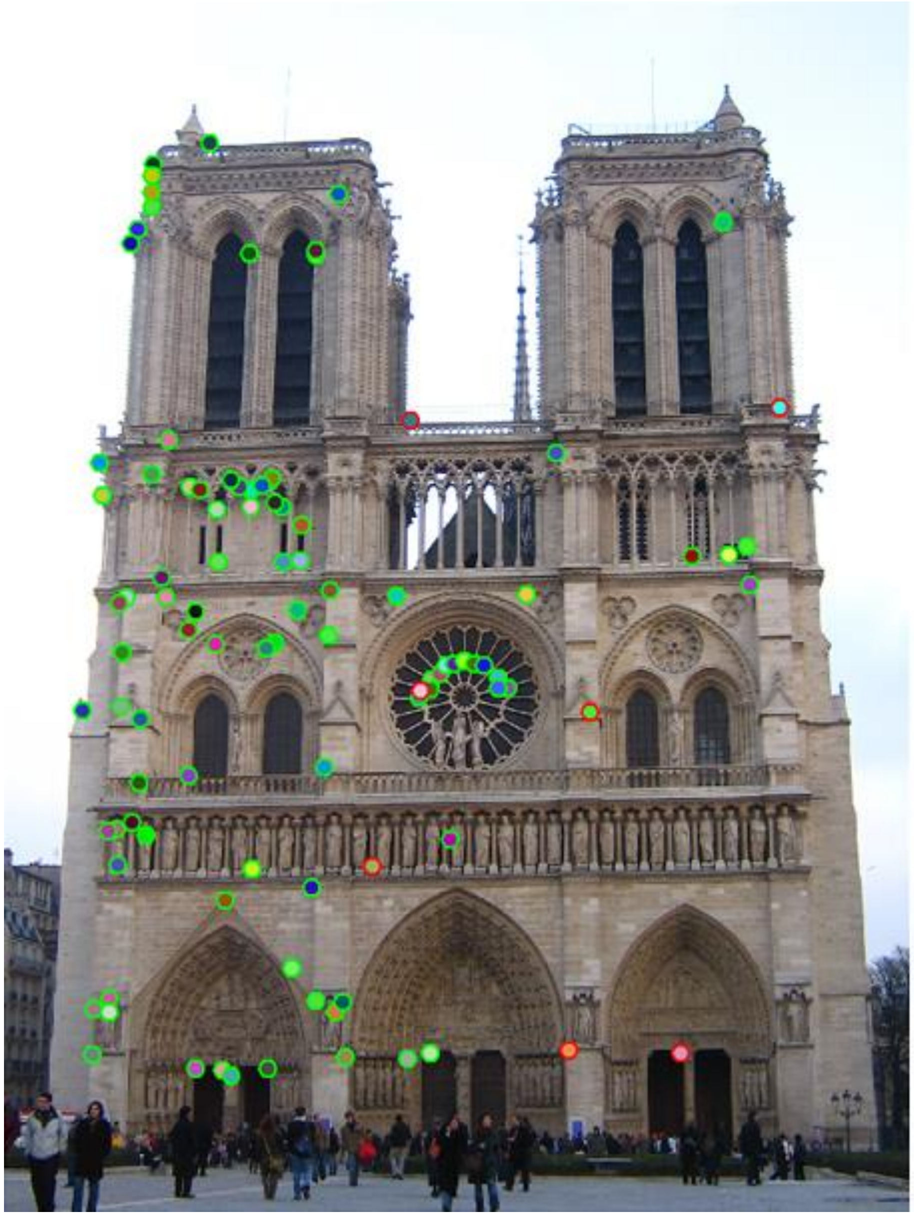


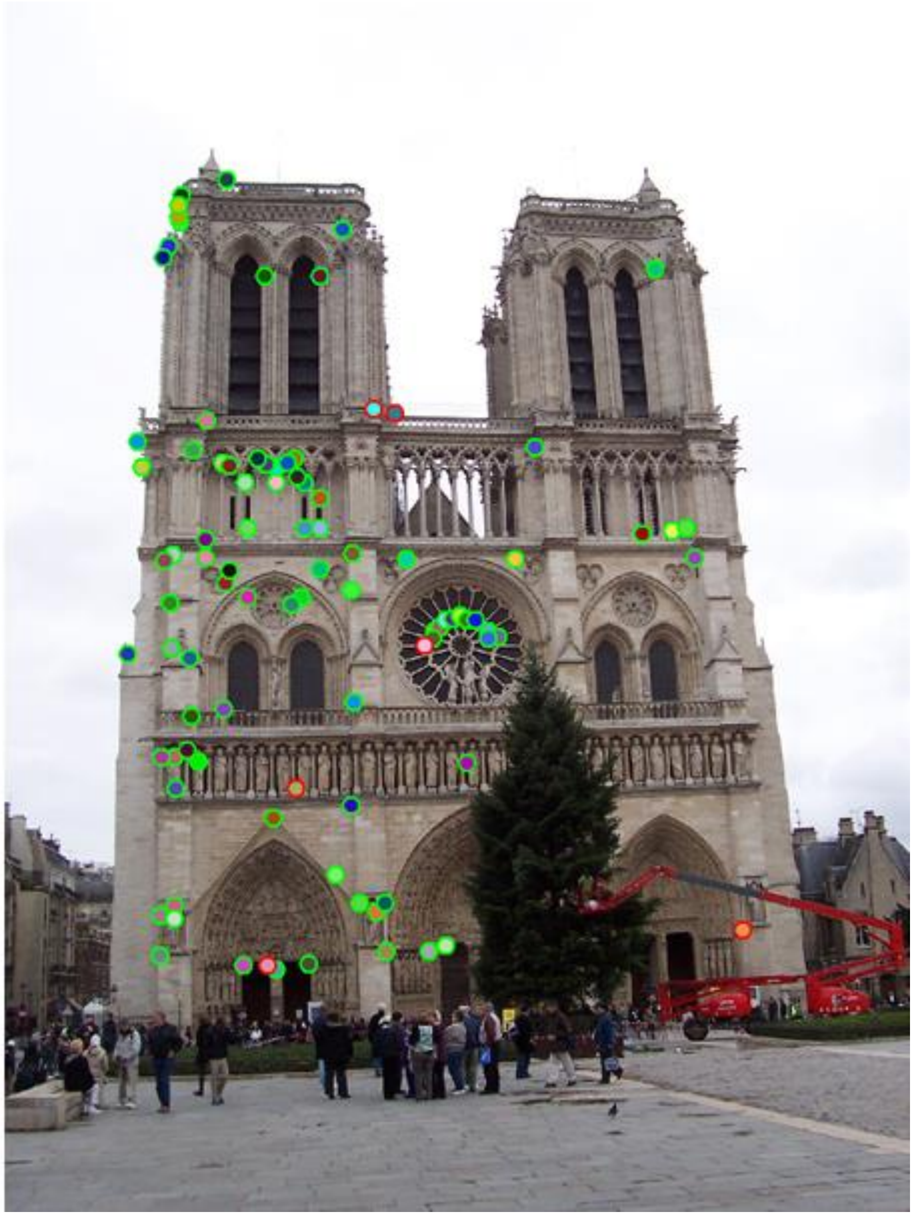
Lowe IJCV 2004

SIFT Repeatability



How do we decide which features match?





Fitting: find the parameters of a model that best fit the data

Alignment: find the parameters of the transformation that best align matched points

Fitting and Alignment

- Design challenges
  - Design a suitable **goodness of fit** measure
    - Similarity should reflect application goals
    - Encode robustness to outliers and noise
  - Design an **optimization** method
    - Avoid local optima
    - Find best parameters quickly

Fitting and Alignment: Methods

- Global optimization / Search for parameters
  - Least squares fit
  - Robust least squares
  - Iterative closest point (ICP)

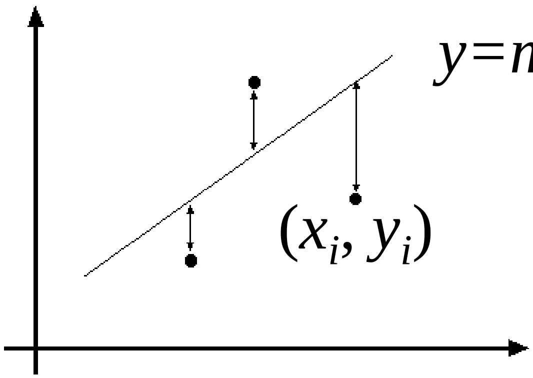
- Hypothesize and test
  - Generalized Hough transform
  - RANSAC

Simple example: Fitting a line

Least squares line fitting

- Data: $(x_1, y_1), \ldots, (x_n, y_n)$
- Line equation: $y_i = m\,x_i + b$
- Find (m, b) to minimize

$$\boxed{E = \sum_{i=1}^{n} (y_i - m x_i - b)^2}$$



$$E = \sum_{i=1}^{n}\left(\begin{bmatrix} x_i & 1 \end{bmatrix}\begin{bmatrix} m \\ b \end{bmatrix} - y_i\right)^2 = \left\|\begin{bmatrix} x_1 & 1 \\ \vdots & \vdots \\ x_n & 1 \end{bmatrix}\begin{bmatrix} m \\ b \end{bmatrix} - \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix}\right\|^2 = \|\mathbf{Ap} - \mathbf{y}\|^2$$

$$= \mathbf{y}^T\mathbf{y} - 2(\mathbf{Ap})^T\mathbf{y} + (\mathbf{Ap})^T(\mathbf{Ap})$$

$$\frac{dE}{dp} = 2\mathbf{A}^T\mathbf{Ap} - 2\mathbf{A}^T\mathbf{y} = 0$$

Matlab: `p = A \ y;`

$$\mathbf{A}^T\mathbf{Ap} = \mathbf{A}^T\mathbf{y} \Rightarrow \mathbf{p} = \left(\mathbf{A}^T\mathbf{A}\right)^{-1}\mathbf{A}^T\mathbf{y}$$

Modified from S. Lazebnik

Least squares (global) optimization

Good

- Clearly specified objective
- Optimization is easy

Bad

- May not be what you want to optimize
- Sensitive to outliers
  - Bad matches, extra points
- Doesn’t allow you to get multiple good fits
  - Detecting multiple objects, lines, etc.

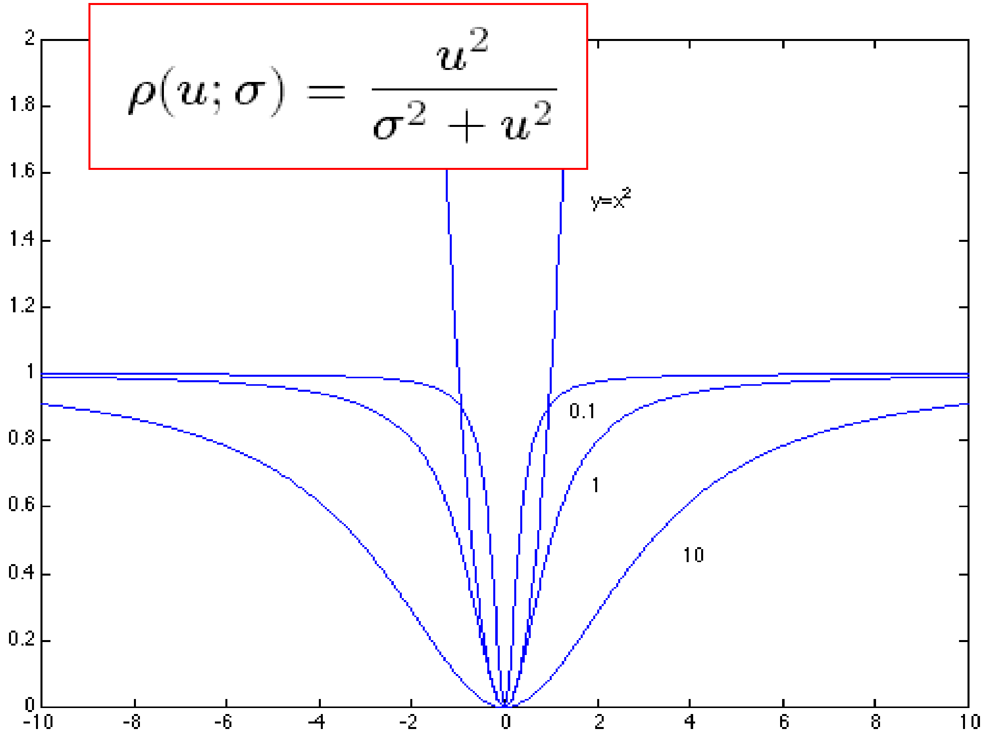
Robust least squares (to deal with outliers)

General approach:

minimize $$\sum_{i} \rho\left(u_i\left(x_i, \theta\right); \sigma\right) \qquad u^2 = \sum_{i=1}^{n} (y_i - mx_i - b)^2$$

$u_i\,(x_i,\,\theta)$ – residual of i^{th} point w.r.t. model parameters ϑ

ρ – robust function with scale parameter σ



The robust function ρ

- Favors a configuration with small residuals
- Constant penalty for large residuals

Robust Estimator

1. Initialize: e.g., choose θ by least squares fit and $\sigma = 1.5 \cdot \mathrm{median}(error)$

2. Choose params to minimize: $\sum_i \frac{error(\theta, data_i)^2}{\sigma^2 + error(\theta, data_i)^2}$
   – E.g., numerical optimization

3. Compute new $\sigma = 1.5 \cdot \mathrm{median}(error)$

4. Repeat (2) and (3) until convergence

Other ways to search for parameters (for when no closed form solution exists)

- Line search
  1. For each parameter, step through values and choose value that gives best fit
  2. Repeat (1) until no parameter changes

- Grid search
  1. Propose several sets of parameters, evenly sampled in the joint set
  2. Choose best (or top few) and sample joint parameters around the current best; repeat

- Gradient descent
  1. Provide initial position (e.g., random)
  2. Locally search for better parameters by following gradient

Hypothesize and test

1. Propose parameters
   - Try all possible
   - Each point votes for all consistent parameters
   - Repeatedly sample enough points to solve for parameters

2. Score the given parameters
   - Number of consistent points, possibly weighted by distance

3. Choose from among the set of parameters
   - Global or local maximum of scores

4. Possibly refine parameters using inliers

Hough Transform: Outline

1. Create a grid of parameter values

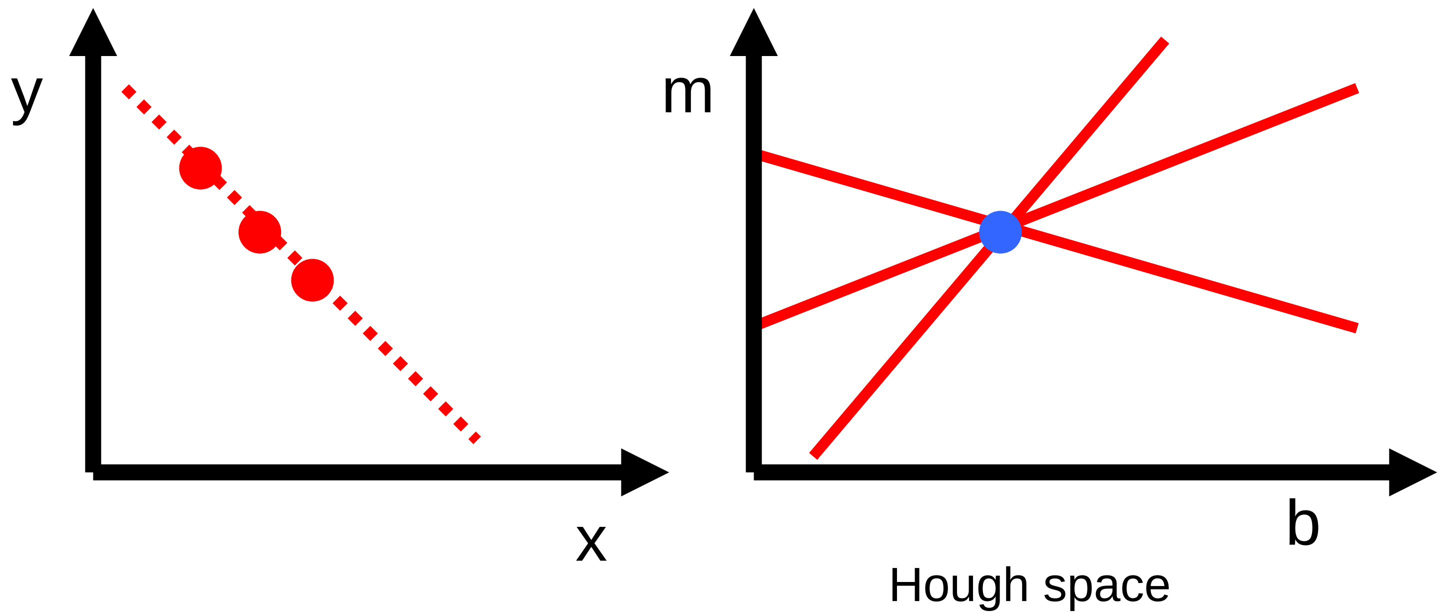
2. Each point votes for a set of parameters, incrementing those values in grid

3. Find maximum or local maxima in grid

Hough transform

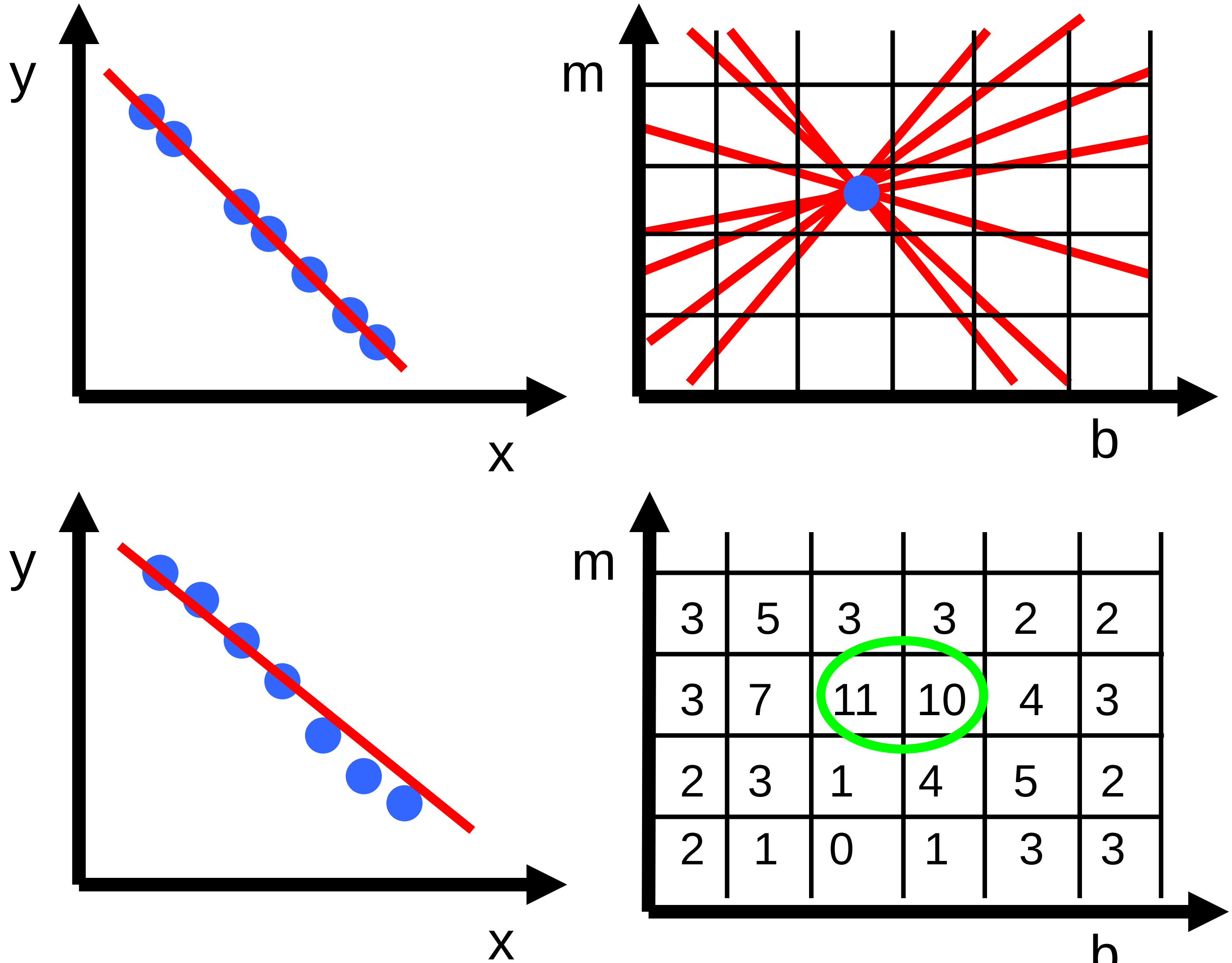
P.V.C. Hough, *Machine Analysis of Bubble Chamber Pictures,* Proc. Int. Conf. High Energy Accelerators and Instrumentation, 1959

Given a set of points, find the curve or line that explains the data points best



$$y = m\,x + b$$

Hough transform

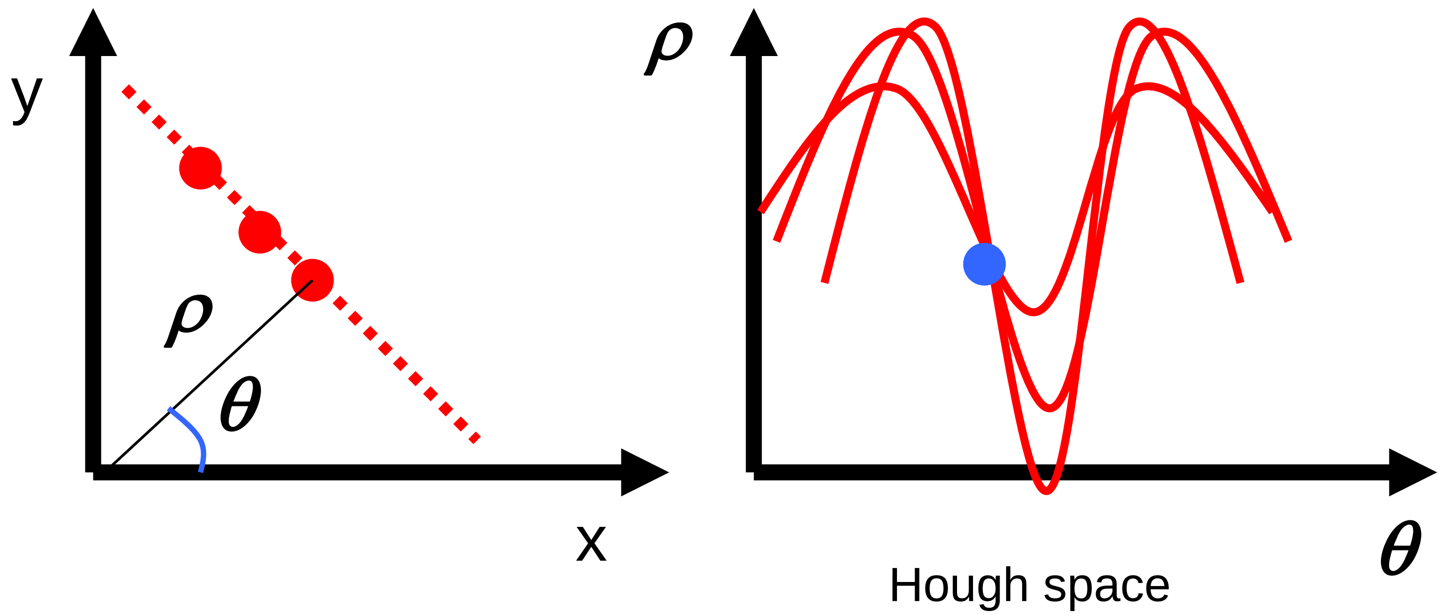


Hough transform

P.V.C. Hough, *Machine Analysis of Bubble Chamber Pictures,* Proc. Int. Conf. High Energy Accelerators and Instrumentation, 1959

Issue : parameter space [m,b] is unbounded…

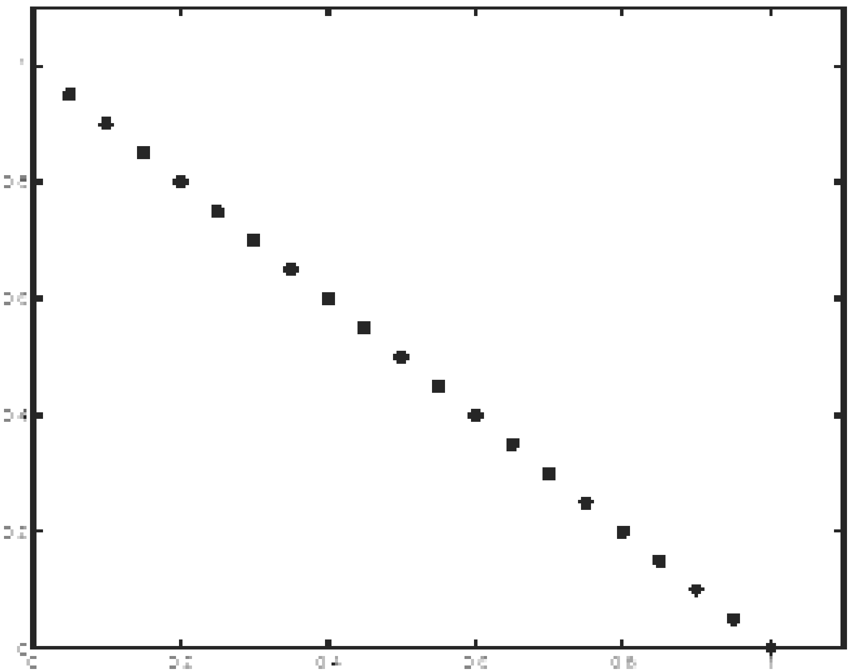
Use a polar representation for the parameter space



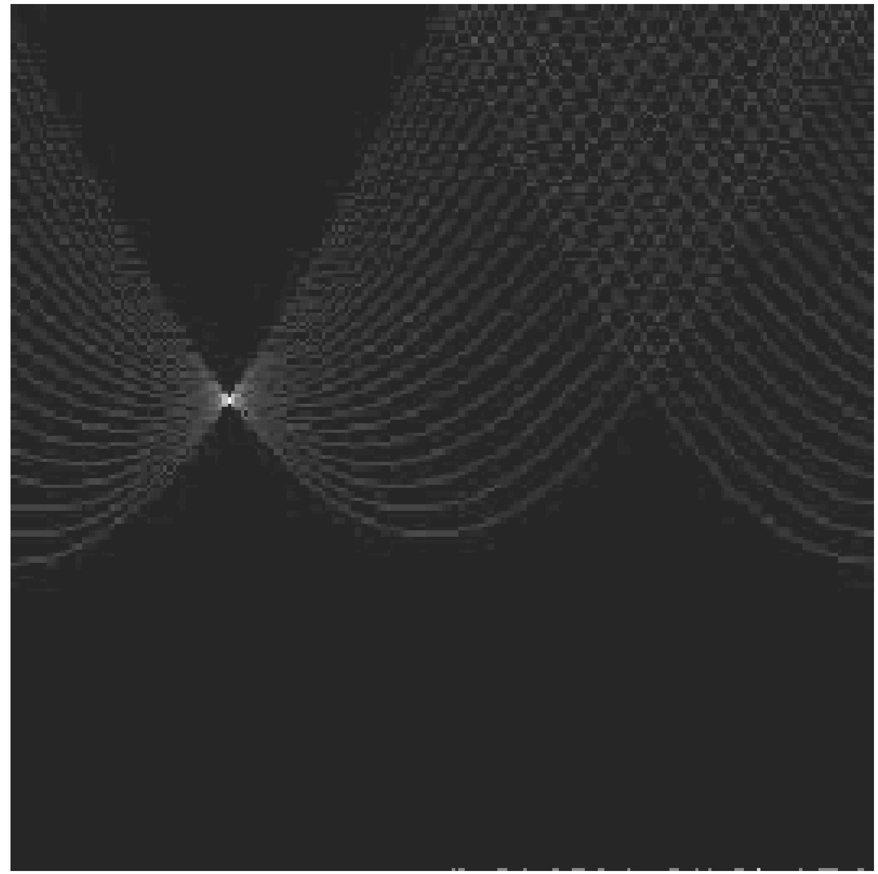
$$x\cos\theta + y\sin\theta = \rho$$

Slide from S. Savarese

Hough transform - experiments



features

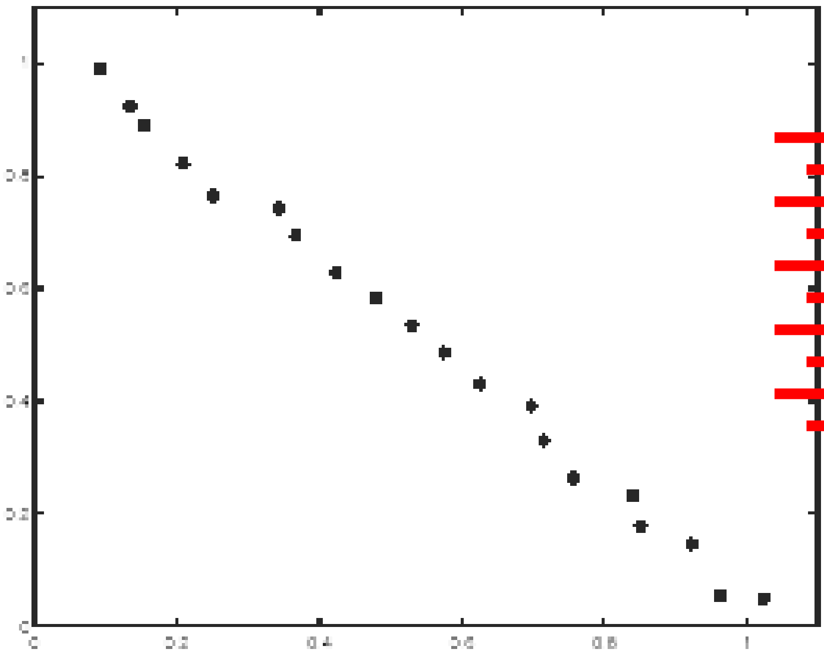


votes

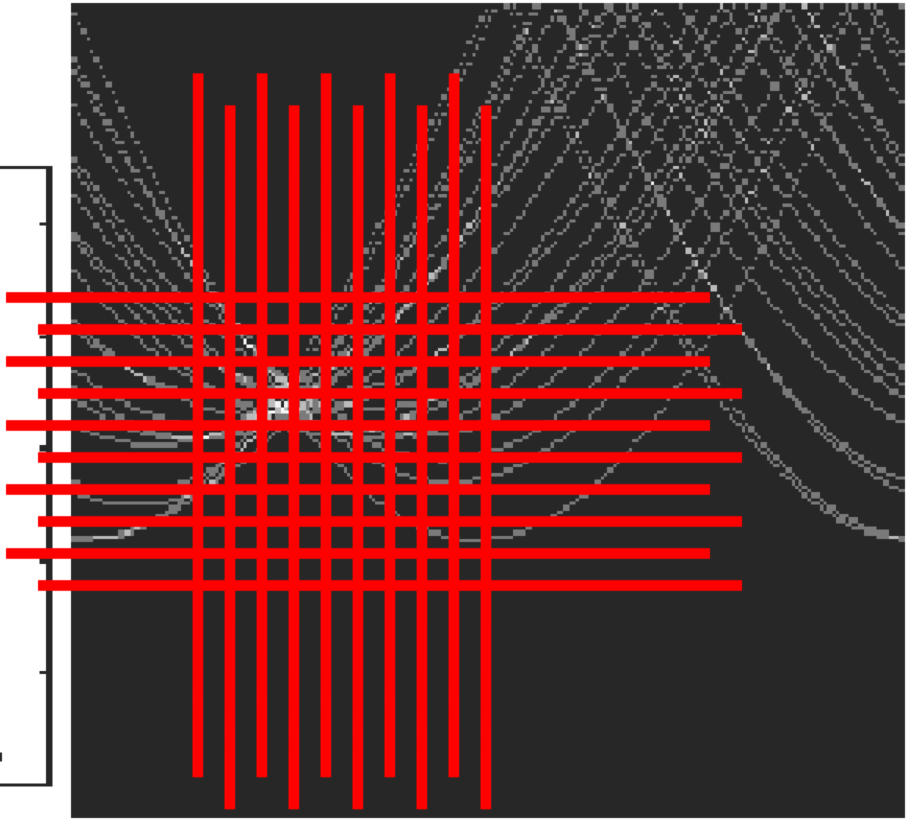
Slide from S. Savarese

Hough transform - experiments

Noisy data



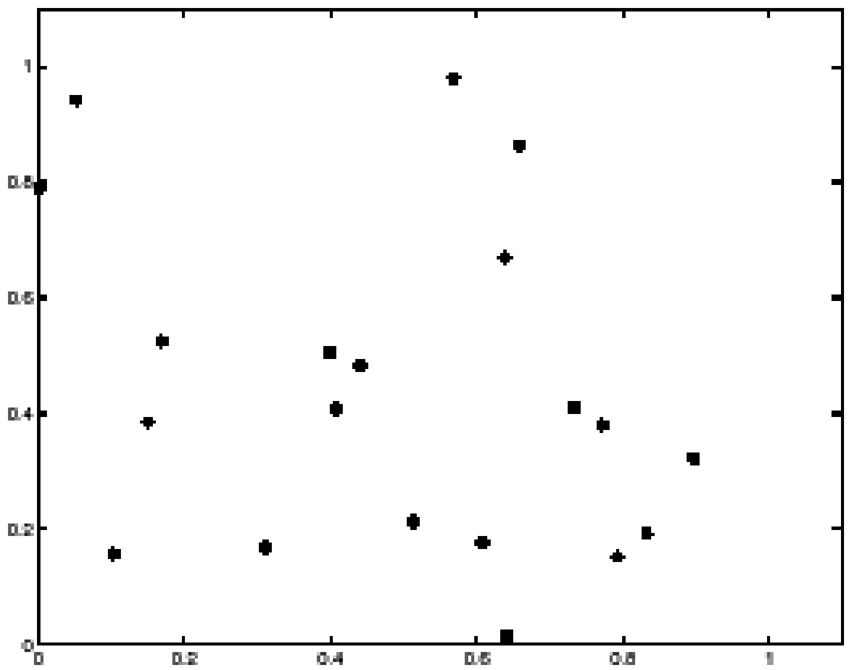
features



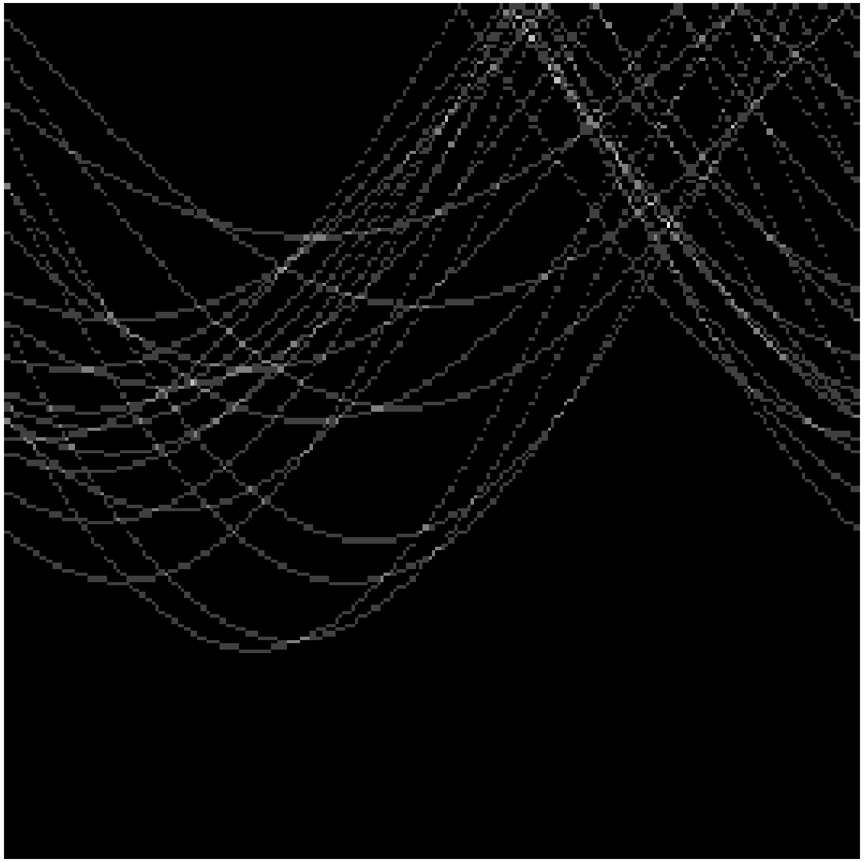
votes

Need to adjust grid size or smooth

Hough transform - experiments



features



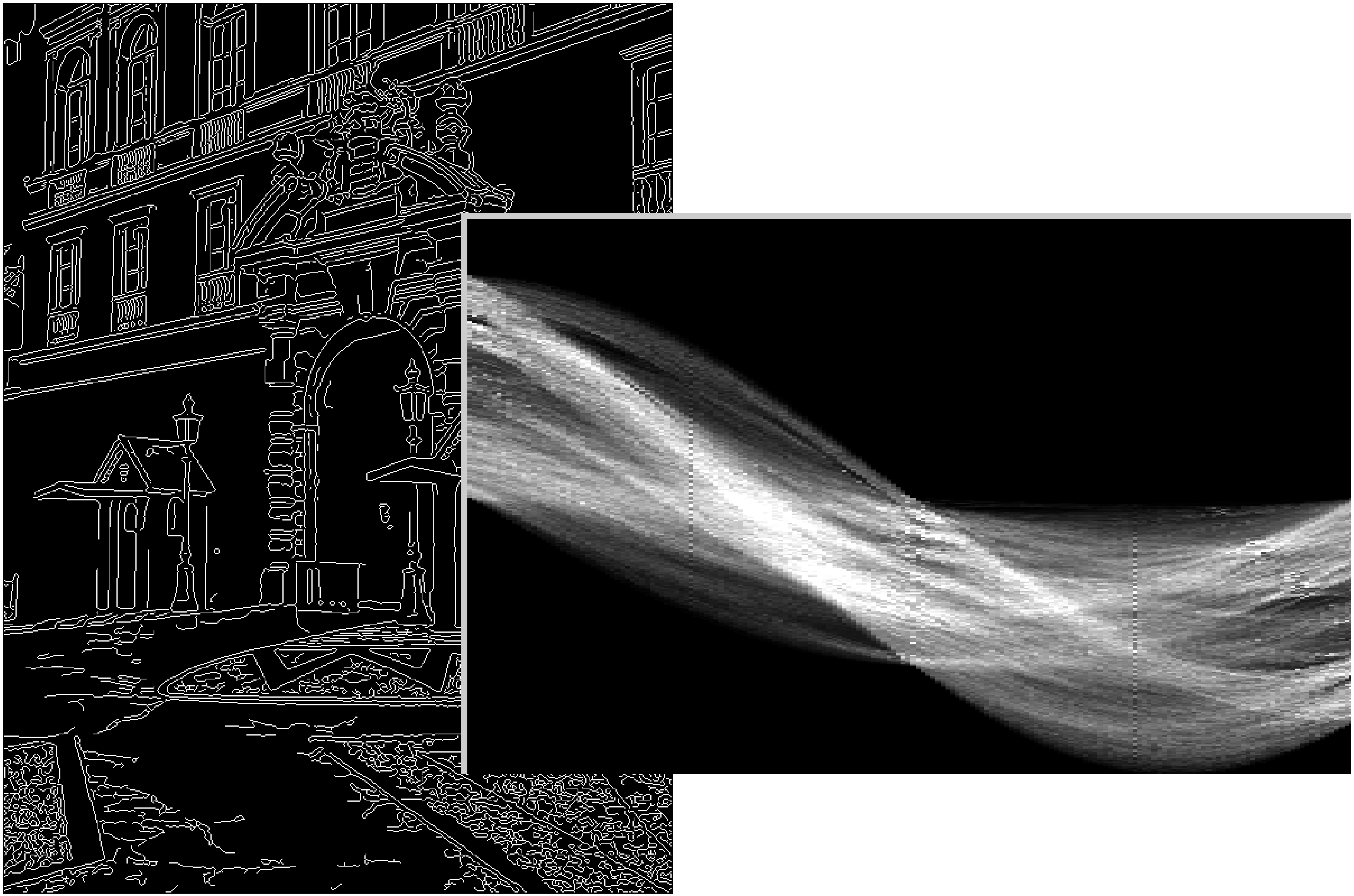
votes

Issue: spurious peaks due to uniform noise

Slide from S. Savarese

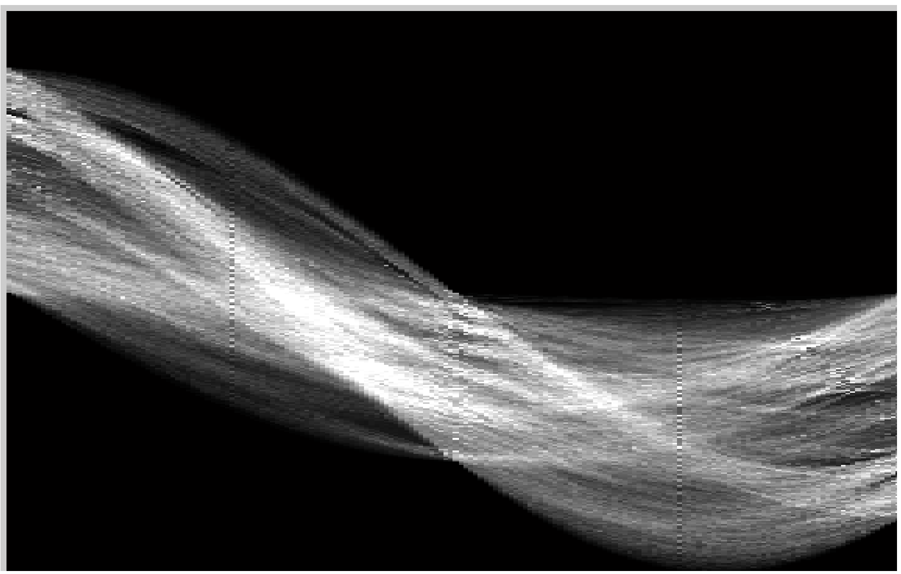
1. Image → Canny

2. Canny → Hough votes

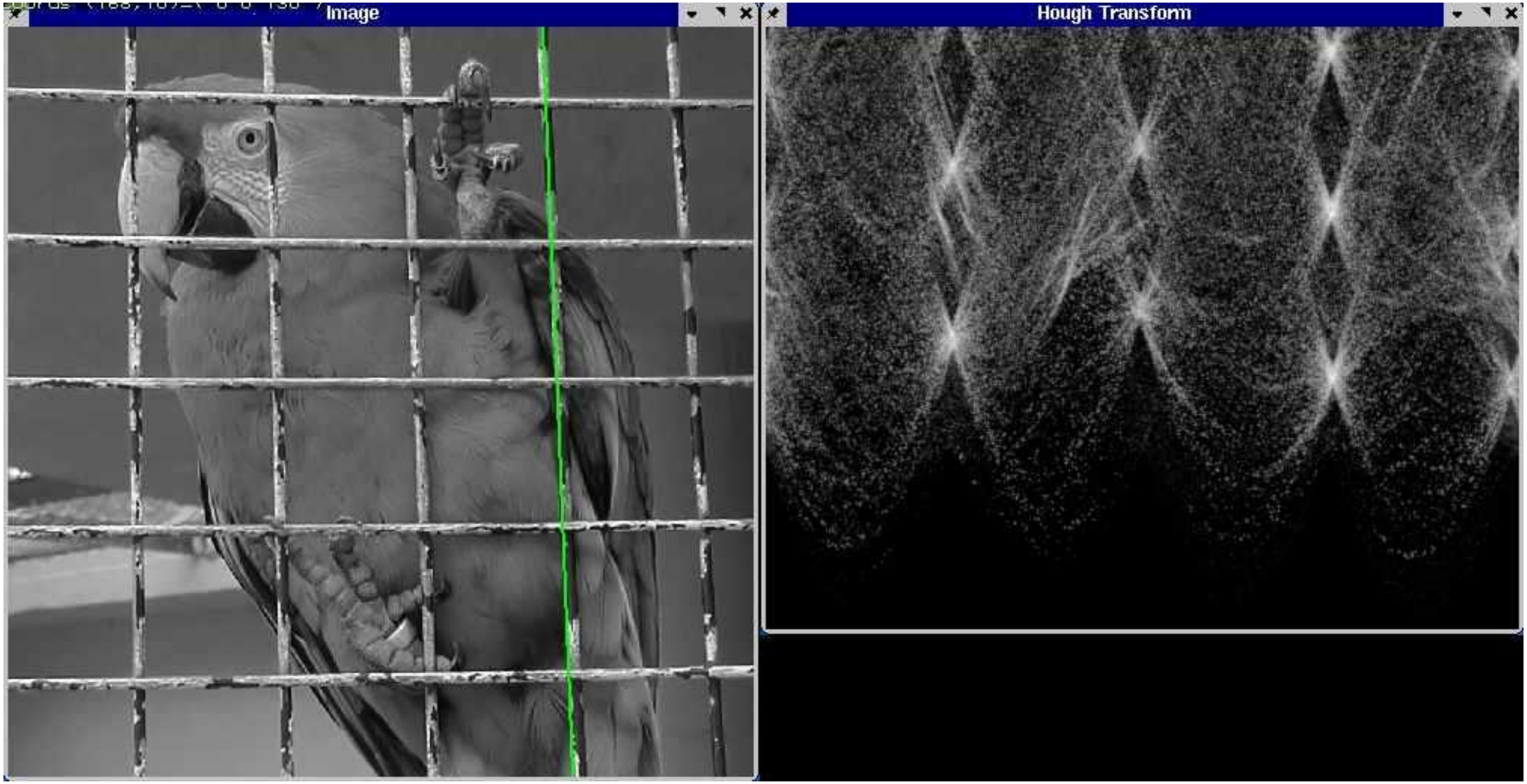


3. Hough votes → Edges

Find peaks and post-process



Hough transform example



http://ostatic.com/files/images/ss_hough.jpg

Finding lines using Hough transform

- Using m,b parameterization
- Using r, theta parameterization
  - Using oriented gradients
- Practical considerations
  - Bin size
  - Smoothing
  - Finding multiple lines
  - Finding line segments

Next lecture

- RANSAC
- Connecting model fitting with feature matching