Photo by Carl Warner

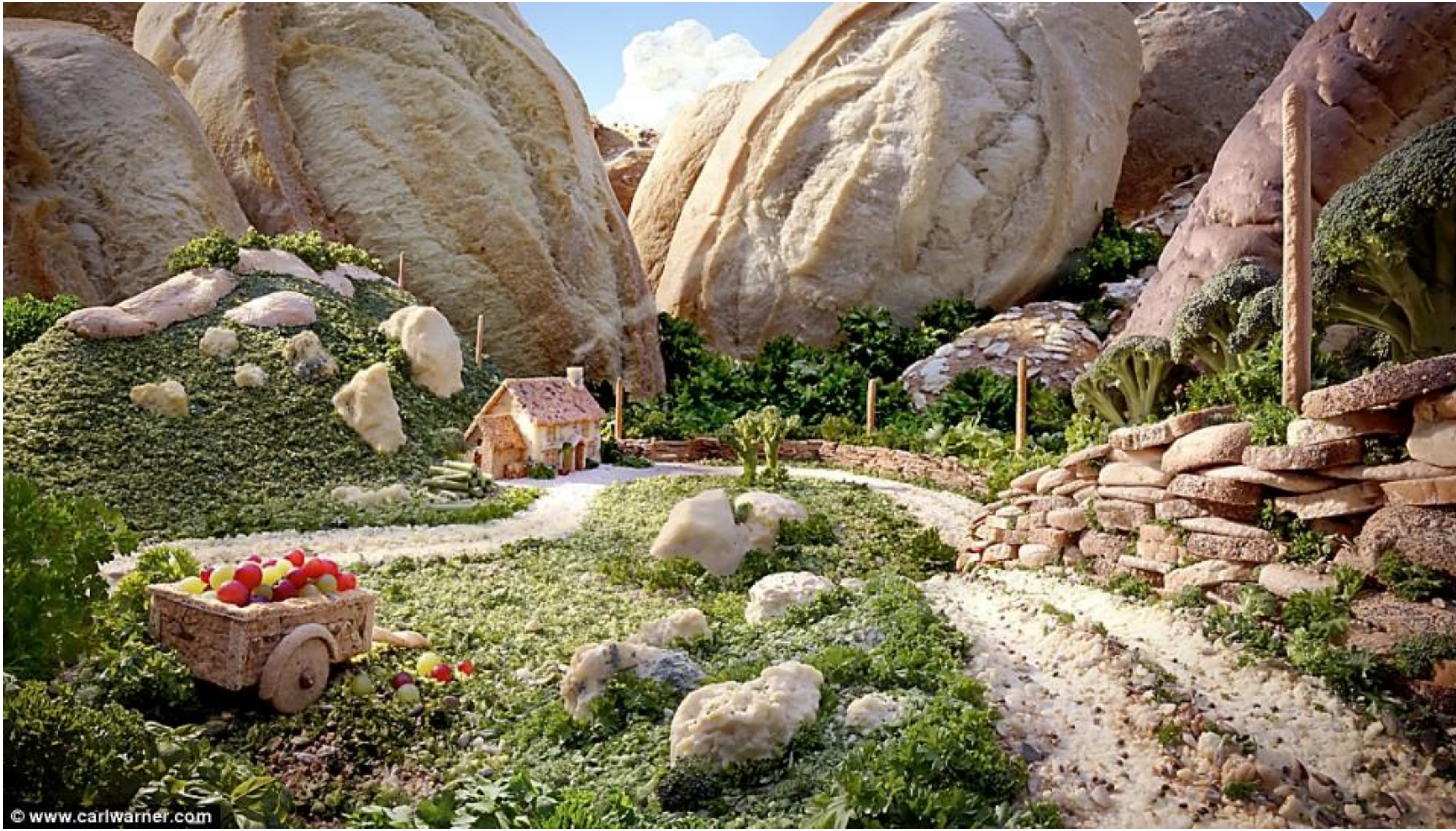


Photo by Carl Warner

Photo by Carl Warner

Feature Matching and Robust Fitting

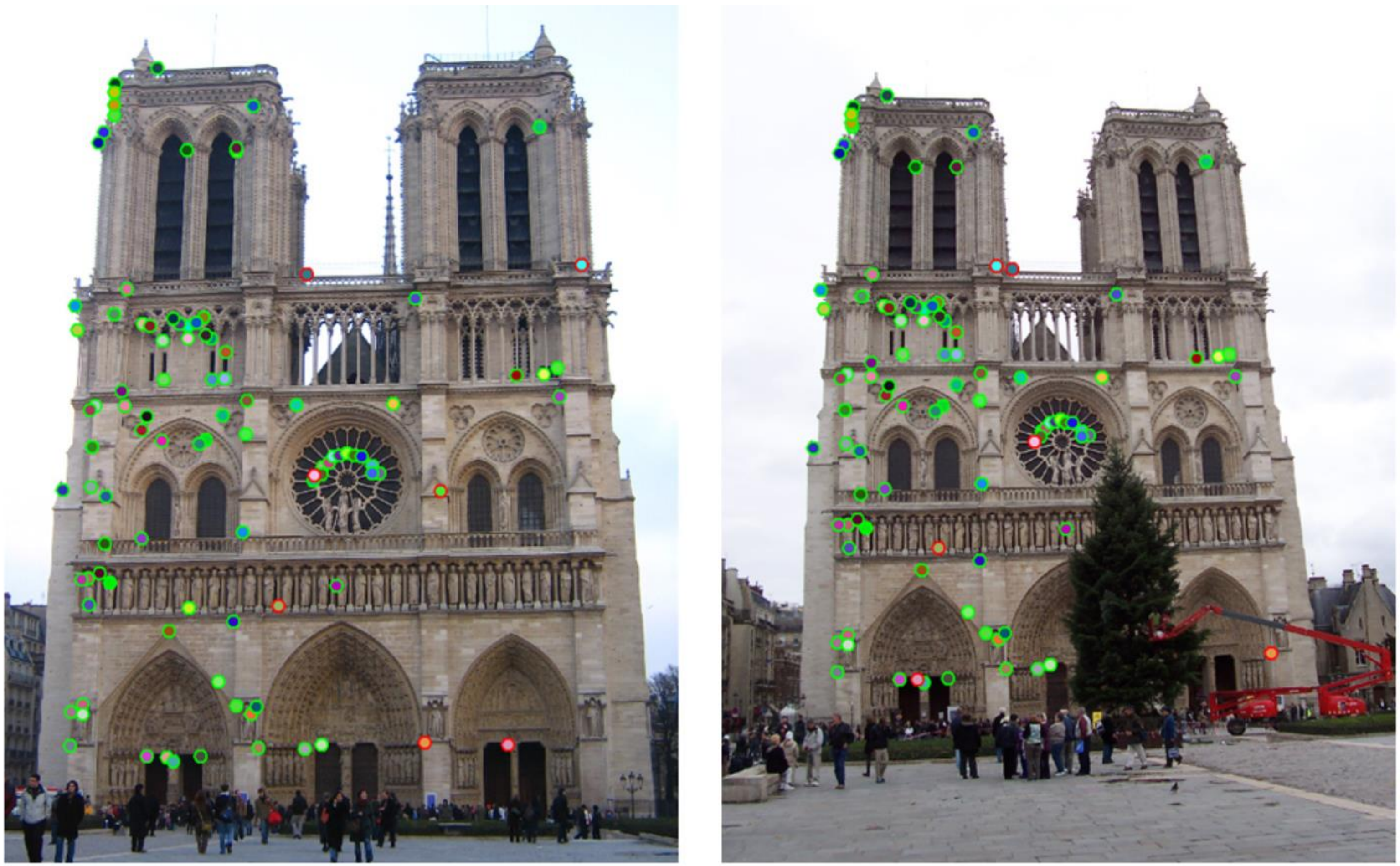
Read Szeliski 4.1

Computer Vision

James Hays

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

Project 2

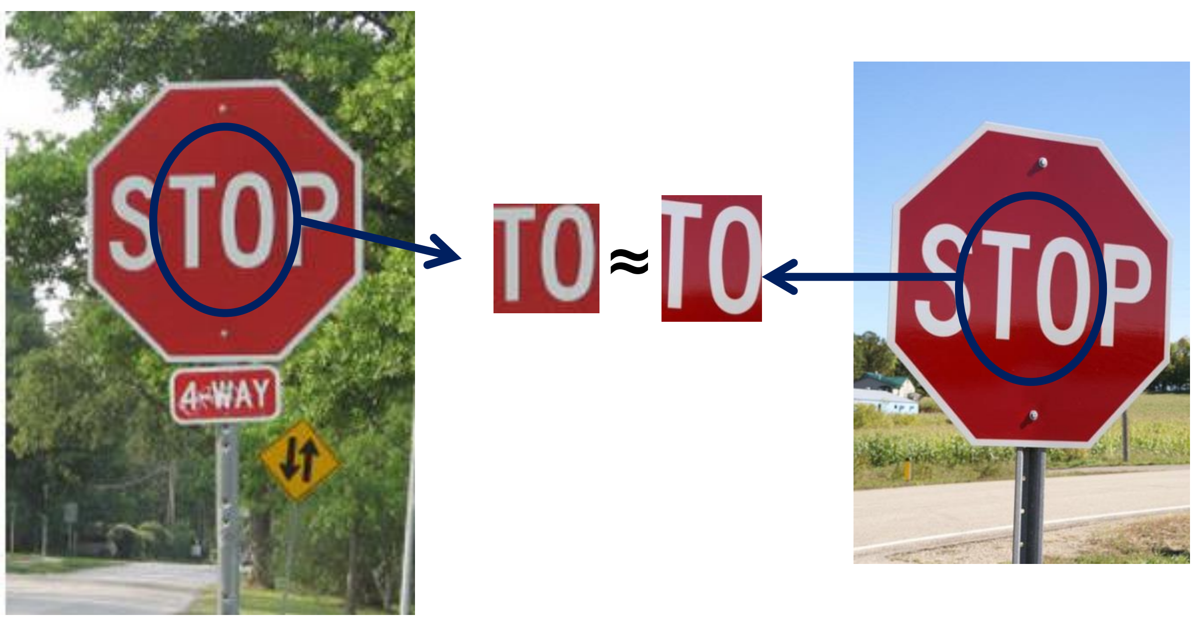


The top 100 most confident local feature matches from a baseline implementation of project 2. In this case, 93 were correct (highlighted in green) and 7 were incorrect (highlighted in red).

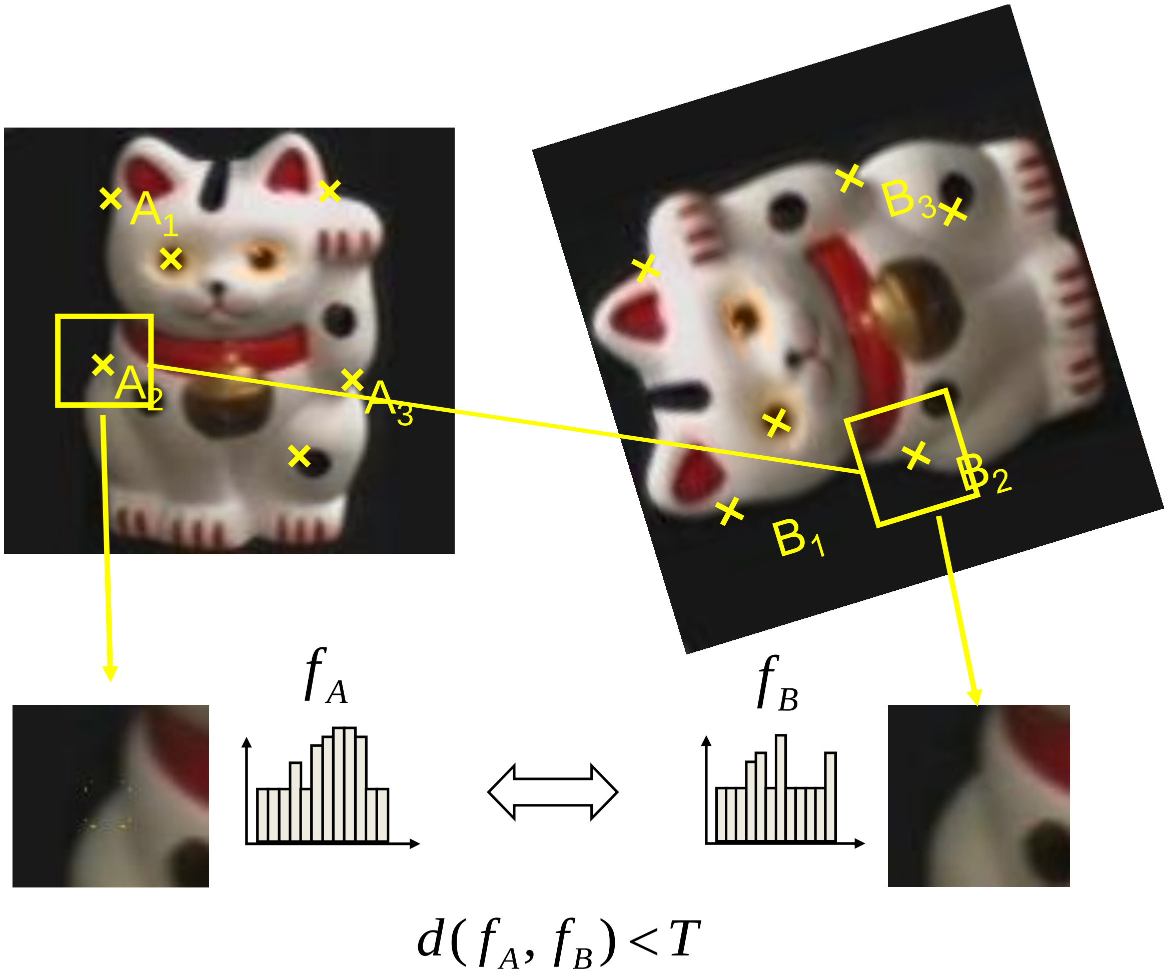
Project 2: Local Feature Matching

This section: correspondence and alignment

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



Overview of Keypoint Matching

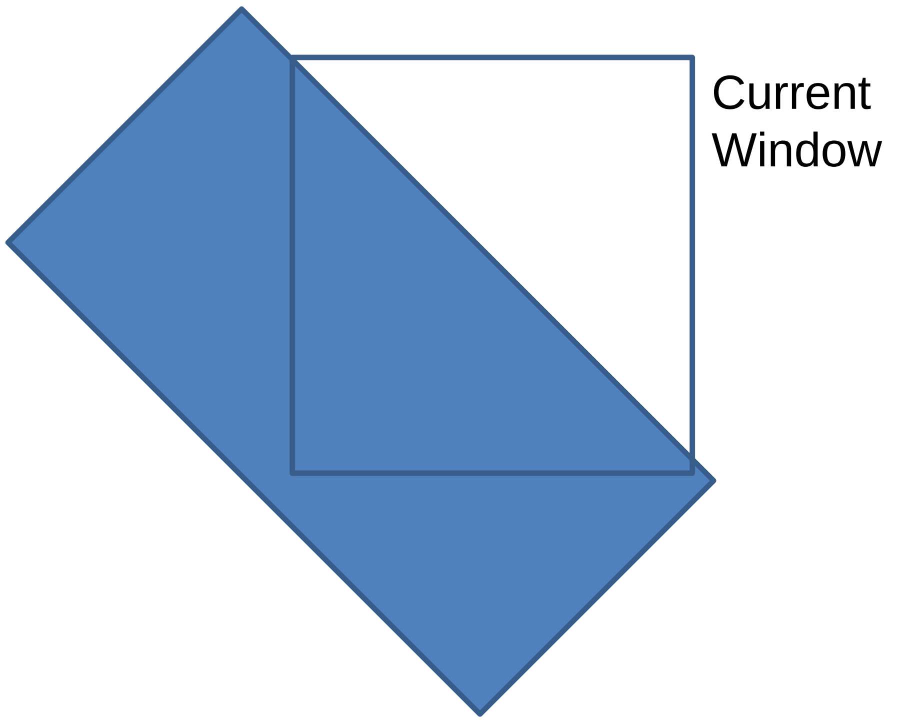


1. **Find a set of distinctive key-points**
2. **Define a region around each keypoint**
3. **Extract and normalize the region content**
4. **Compute a local descriptor from the normalized region**
5. **Match local descriptors**

K. Grauman, B. Leibe

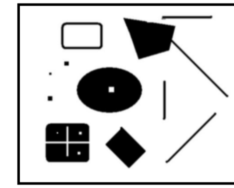
Harris Corners – Why so complicated?

- Can't we just check for regions with lots of gradients in the x and y directions?
  - No! A diagonal line would satisfy that criteria



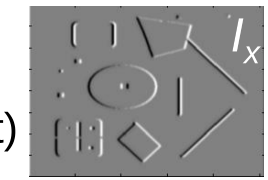
Harris Detector [Harris88]

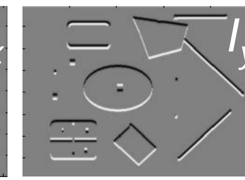
- Second moment matrix



$$\mu(\sigma_I, \sigma_D) = g(\sigma_I) * \begin{bmatrix} I_x^2(\sigma_D) & I_x I_y(\sigma_D) \\ I_x I_y(\sigma_D) & I_y^2(\sigma_D) \end{bmatrix}$$

1. Image derivatives (optionally, blur first)

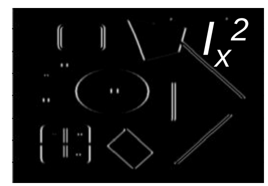


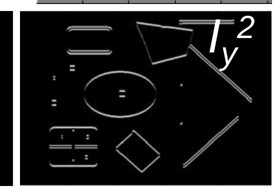


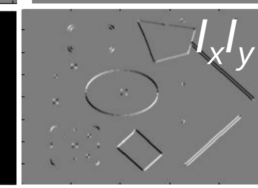
$$\det M = \lambda_1 \lambda_2$$

$$\operatorname{trace} M = \lambda_1 + \lambda_2$$

2. Square of derivatives







3. Gaussian filter $g(\sigma_I)$

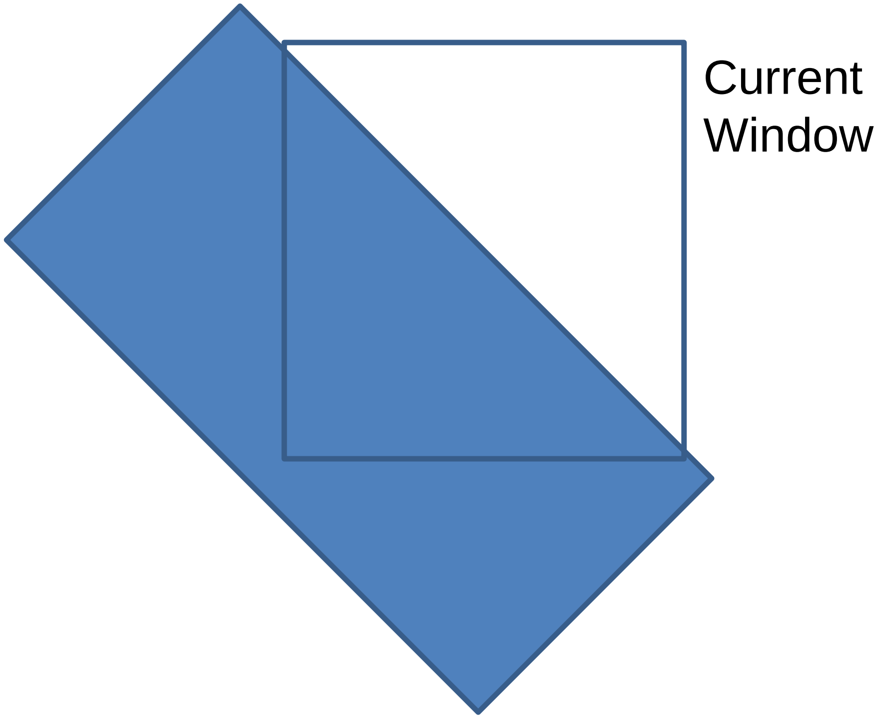
4. Cornerness function – both eigenvalues are strong

$$har = \det[\mu(\sigma_I, \sigma_D)] - \alpha[\operatorname{trace}(\mu(\sigma_I, \sigma_D))^2] =$$

$$g(I_x^2)g(I_y^2) - [g(I_xI_y)]^2 - \alpha[g(I_x^2) + g(I_y^2)]^2$$

5. Non-maxima suppression

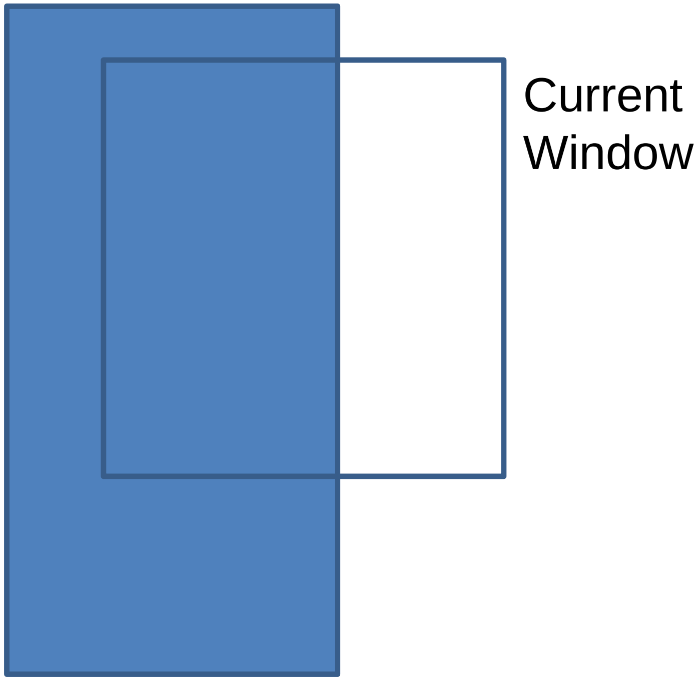
Harris Corners – Why so complicated?



- What does the structure matrix look here?

$$\begin{bmatrix} C & -C \\ -C & C \end{bmatrix}$$

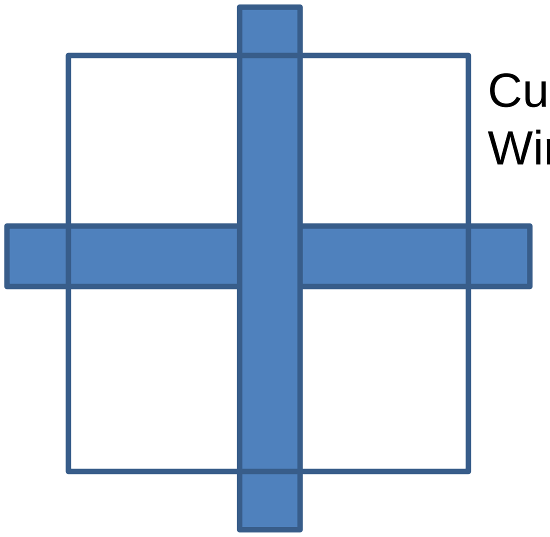
Harris Corners – Why so complicated?



- What does the structure matrix look here?

$$\begin{bmatrix} C & 0 \\ 0 & 0 \end{bmatrix}$$

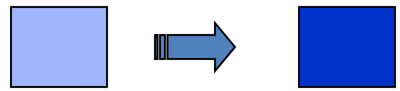
Harris Corners – Why so complicated?



- What does the structure matrix look here?

$$\begin{bmatrix} C & 0 \\ 0 & C \end{bmatrix}$$

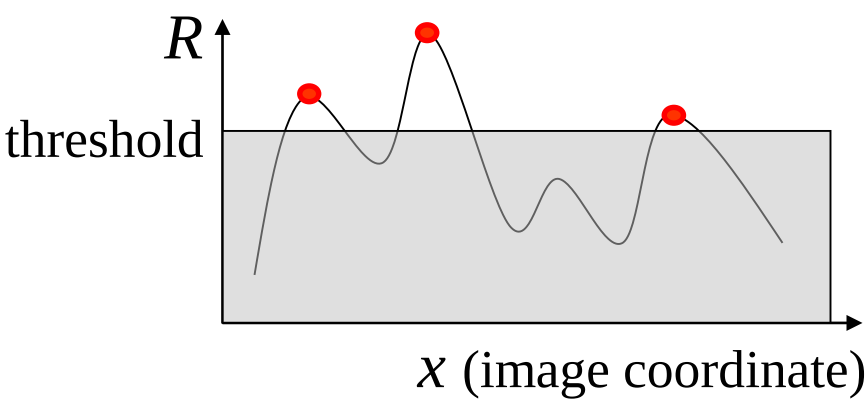
Affine intensity change

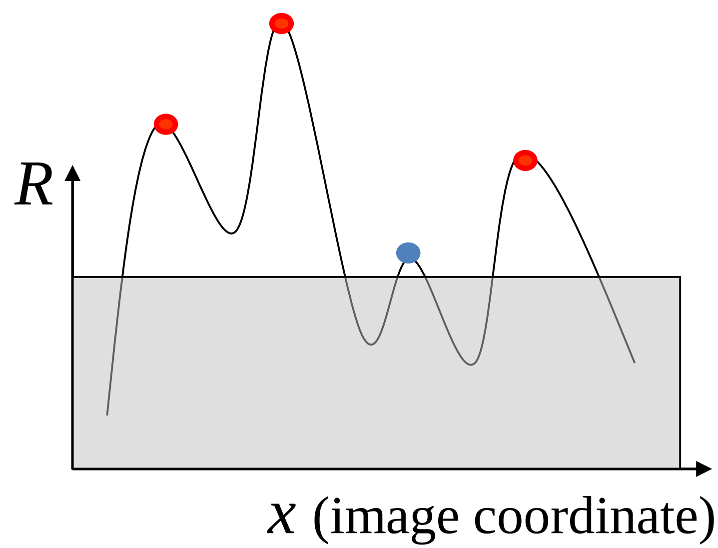


$$I \rightarrow a\,I + b$$

- Only derivatives are used => invariance to intensity shift $I \rightarrow I + b$

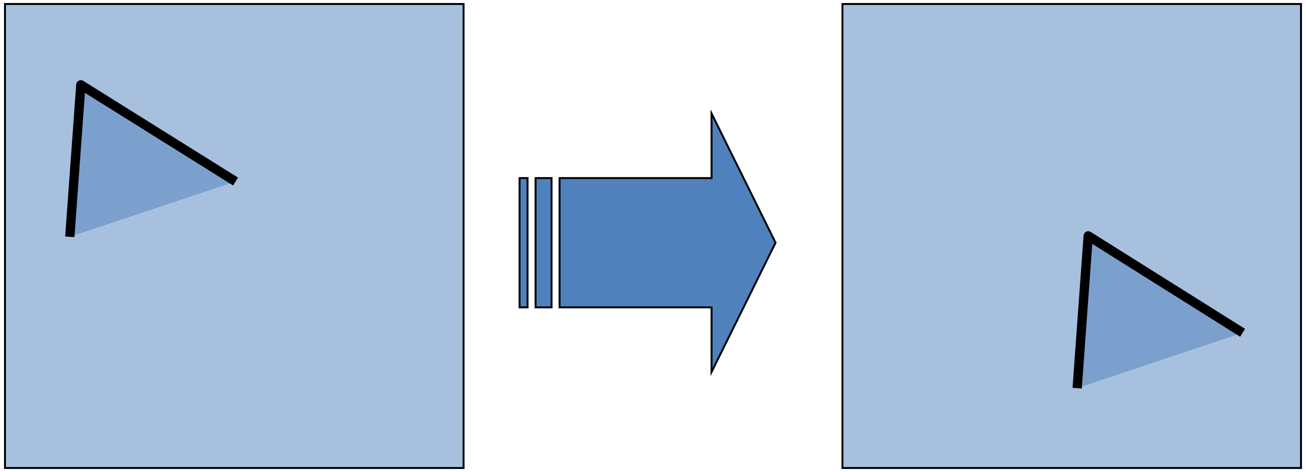
- Intensity scaling: $I \rightarrow a\,I$





Partially invariant to affine intensity change

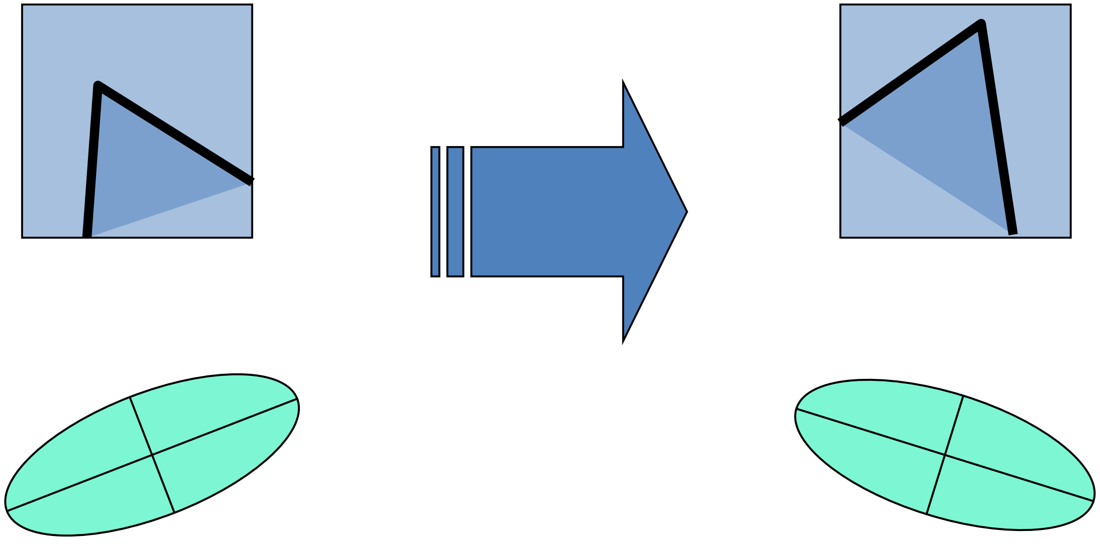
Image translation



- Derivatives and window function are shift-invariant

Corner location is covariant w.r.t. translation

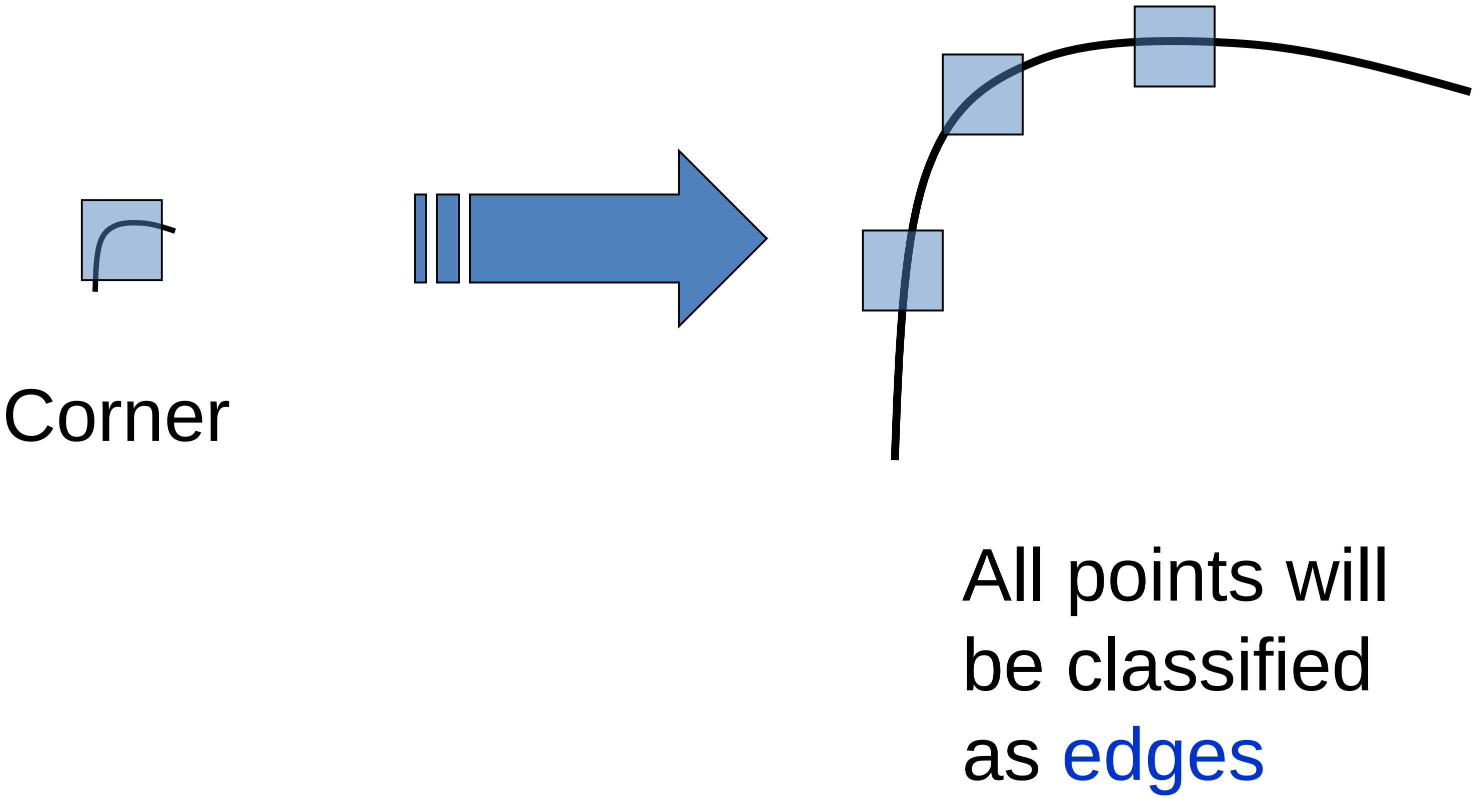
Image rotation



Second moment ellipse rotates but its shape (i.e. eigenvalues) remains the same

Corner location is covariant w.r.t. rotation

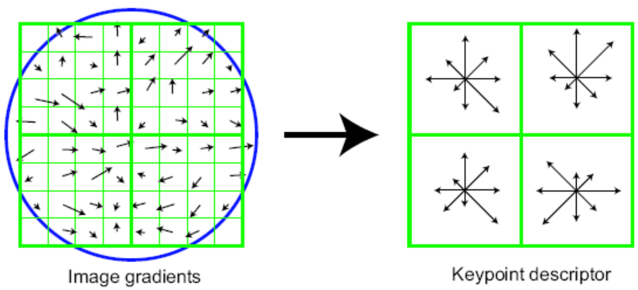
Scaling



Corner location is not covariant to scaling!

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



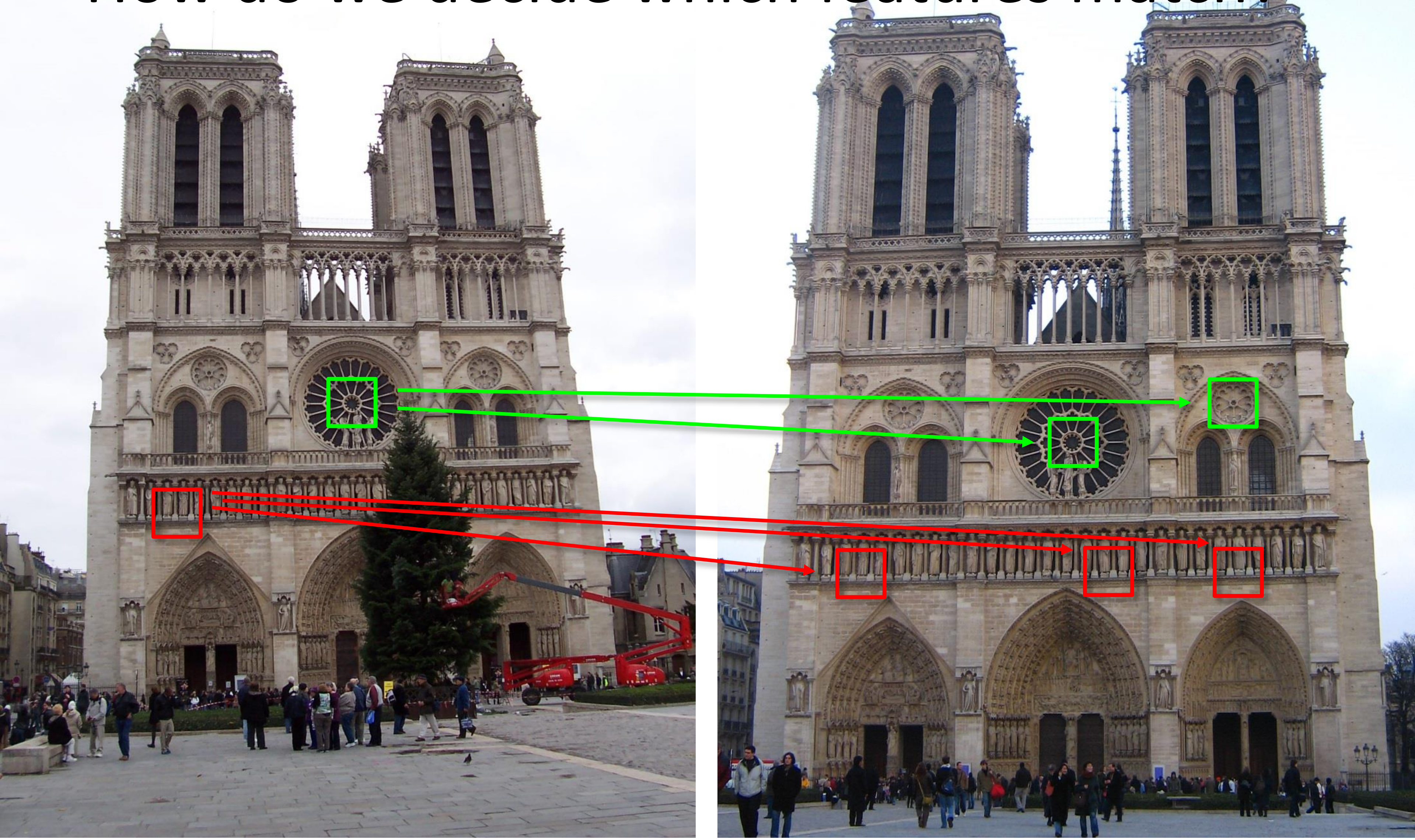
- Most available descriptors focus on edge/gradient information
  - Capture texture information
  - Color rarely used

K. Grauman, B. Leibe

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

How do we decide which features match?



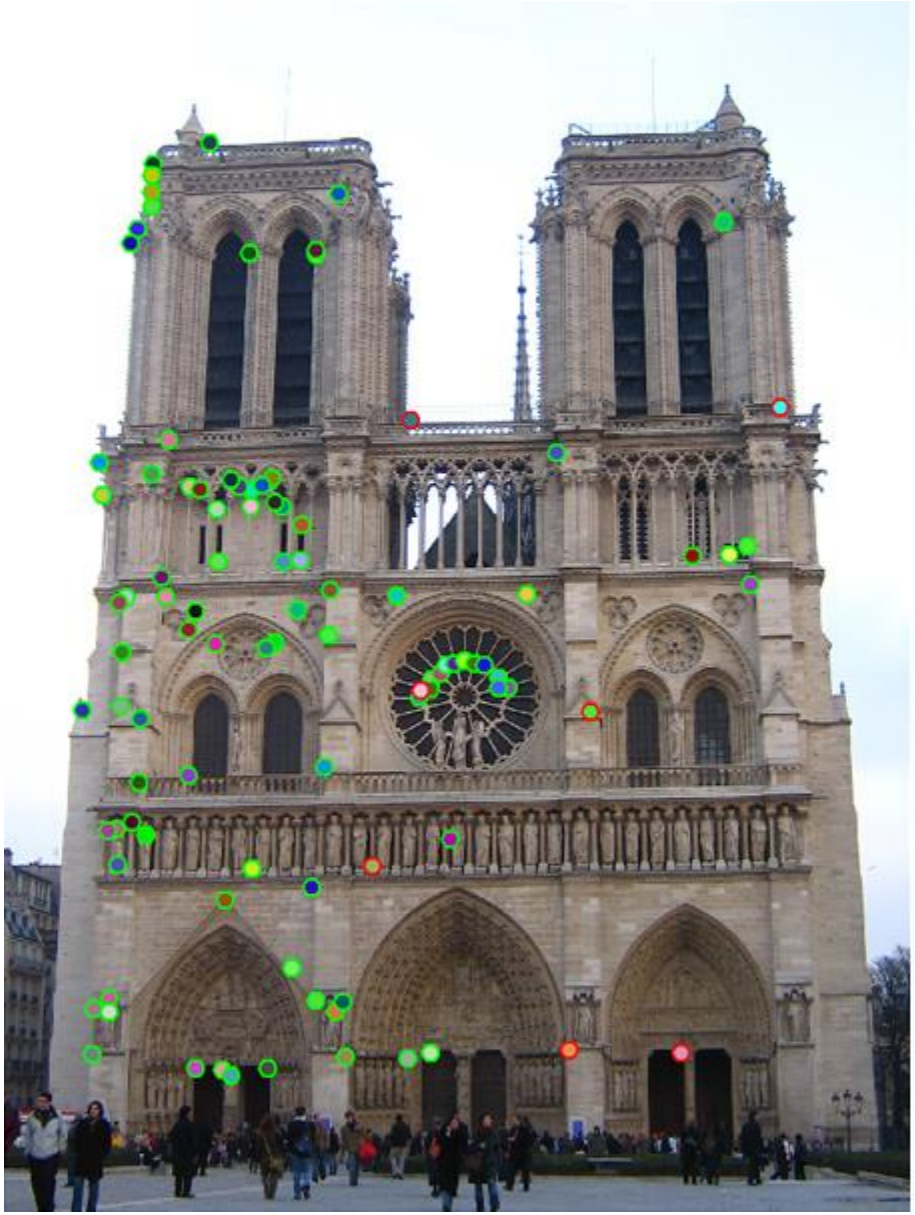
Distance: 0.34, 0.30, 0.40

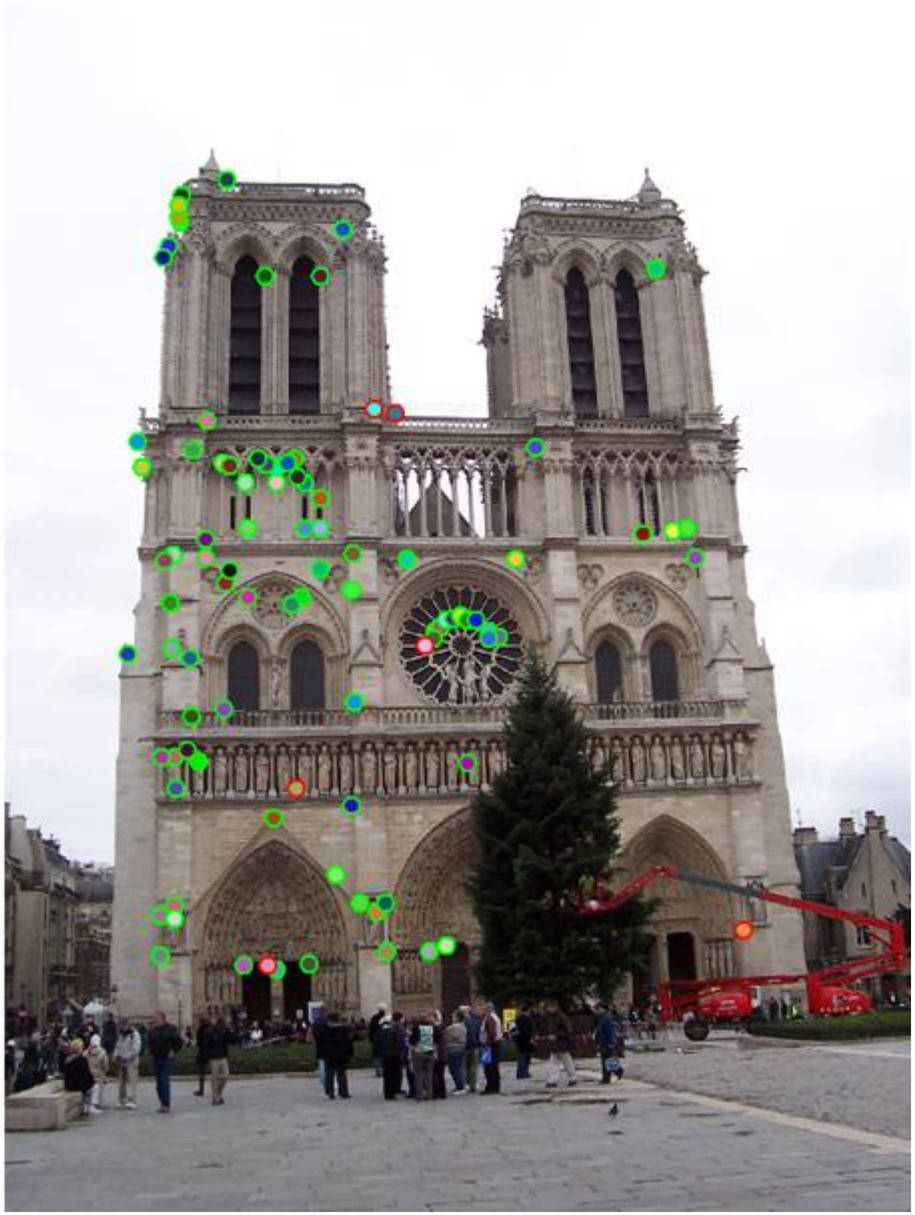
Distance: 0.61, 1.22

Nearest Neighbor Distance Ratio

- $\frac{NN1}{NN2}$ where NN1 is the distance to the first nearest neighbor and NN2 is the distance to the second nearest neighbor.
- Sorting by this ratio puts matches in order of confidence.

Can we refine this further?





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

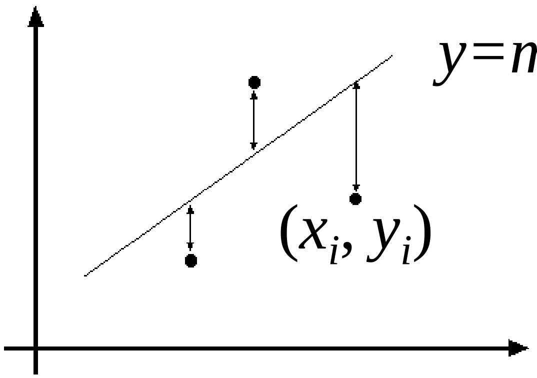
- Global optimization / Search for parameters
  - Least squares fit
  - Robust least squares
  - Iterative closest point (ICP)
- Hypothesize and test
  - Generalized Hough transform
  - RANSAC

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

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



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

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

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

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

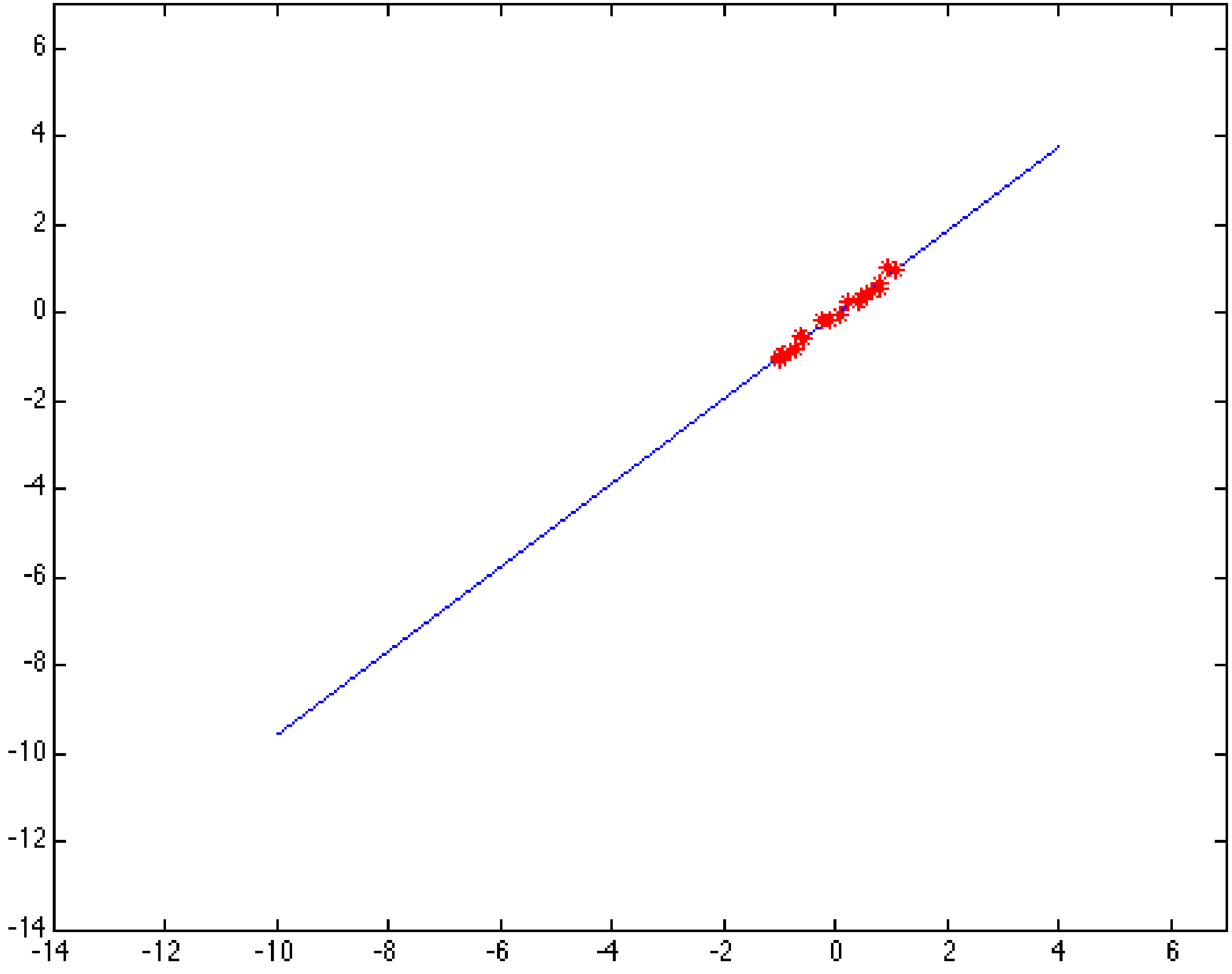
- Clearly specified objective
- Optimization is easy

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.

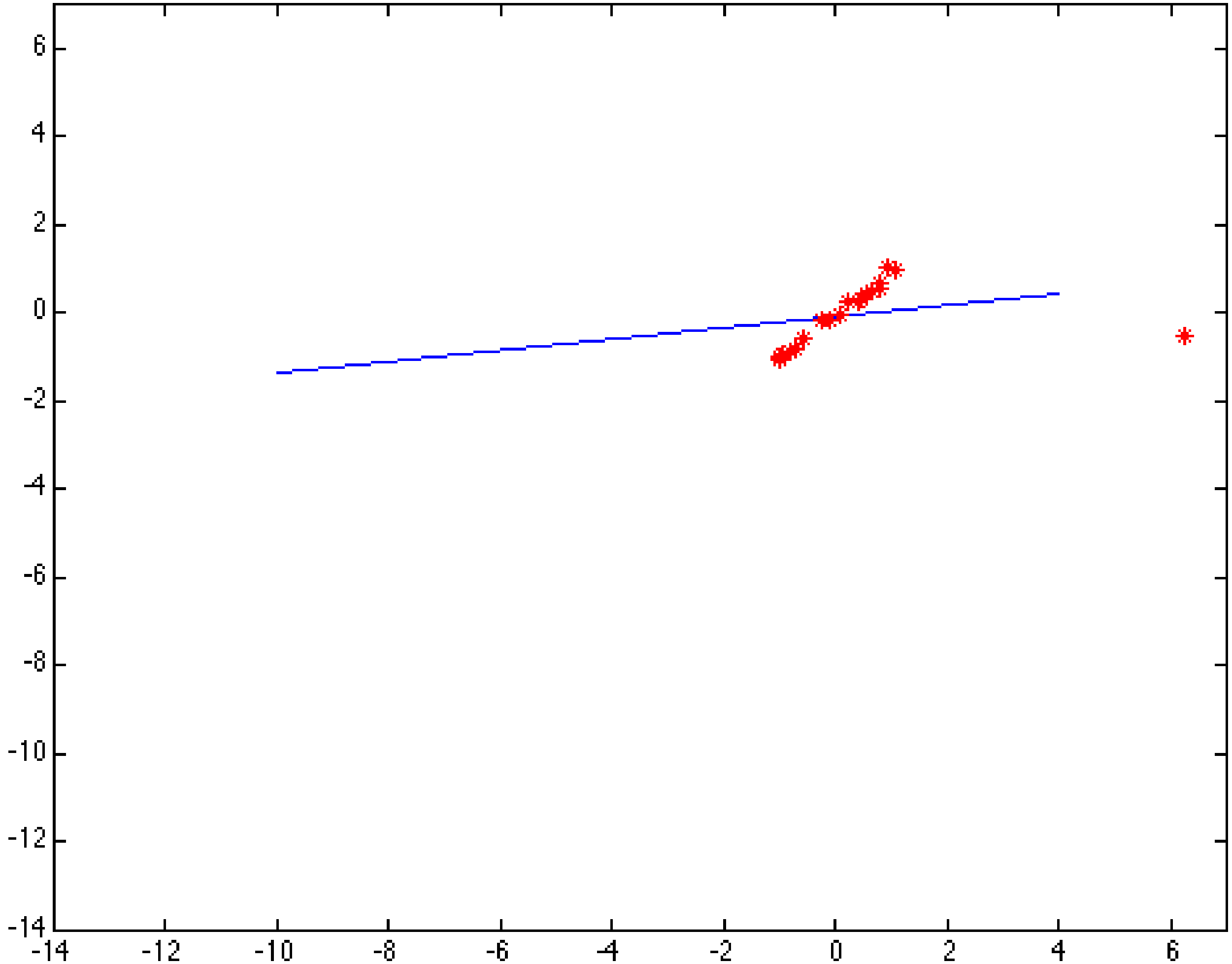
Least squares: Robustness to noise

- Least squares fit to the red points:



Least squares: Robustness to noise

- Least squares fit with an outlier:



Problem: squared error heavily penalizes outliers

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

Robust least squares (to deal with outliers)

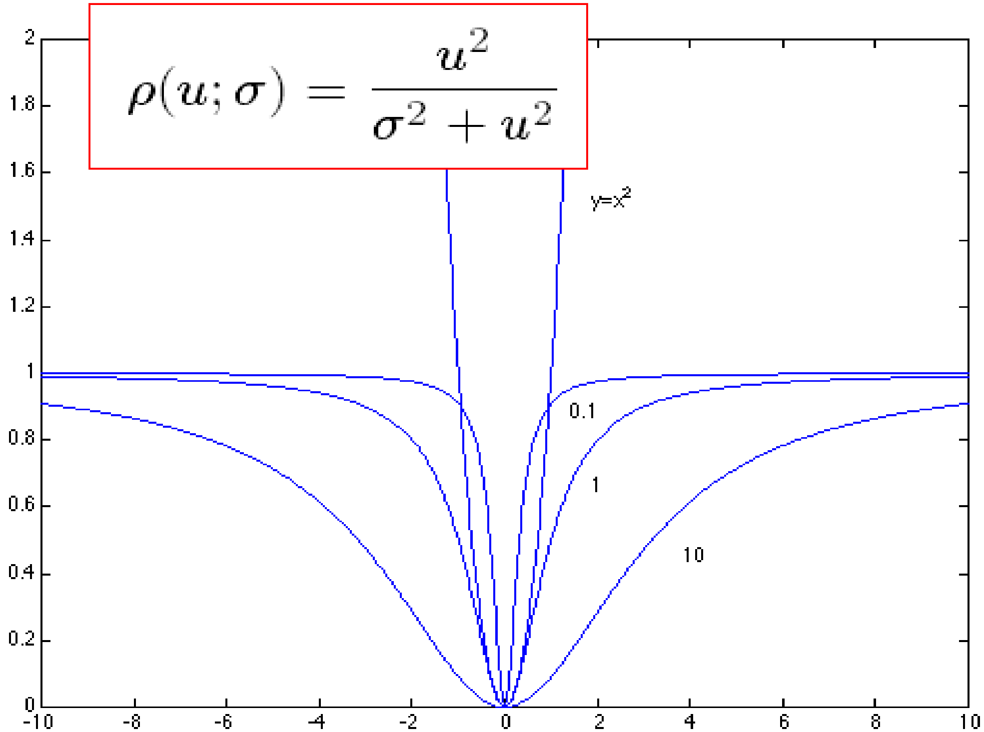
General approach:

minimize

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

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

ρ – robust function with scale parameter σ

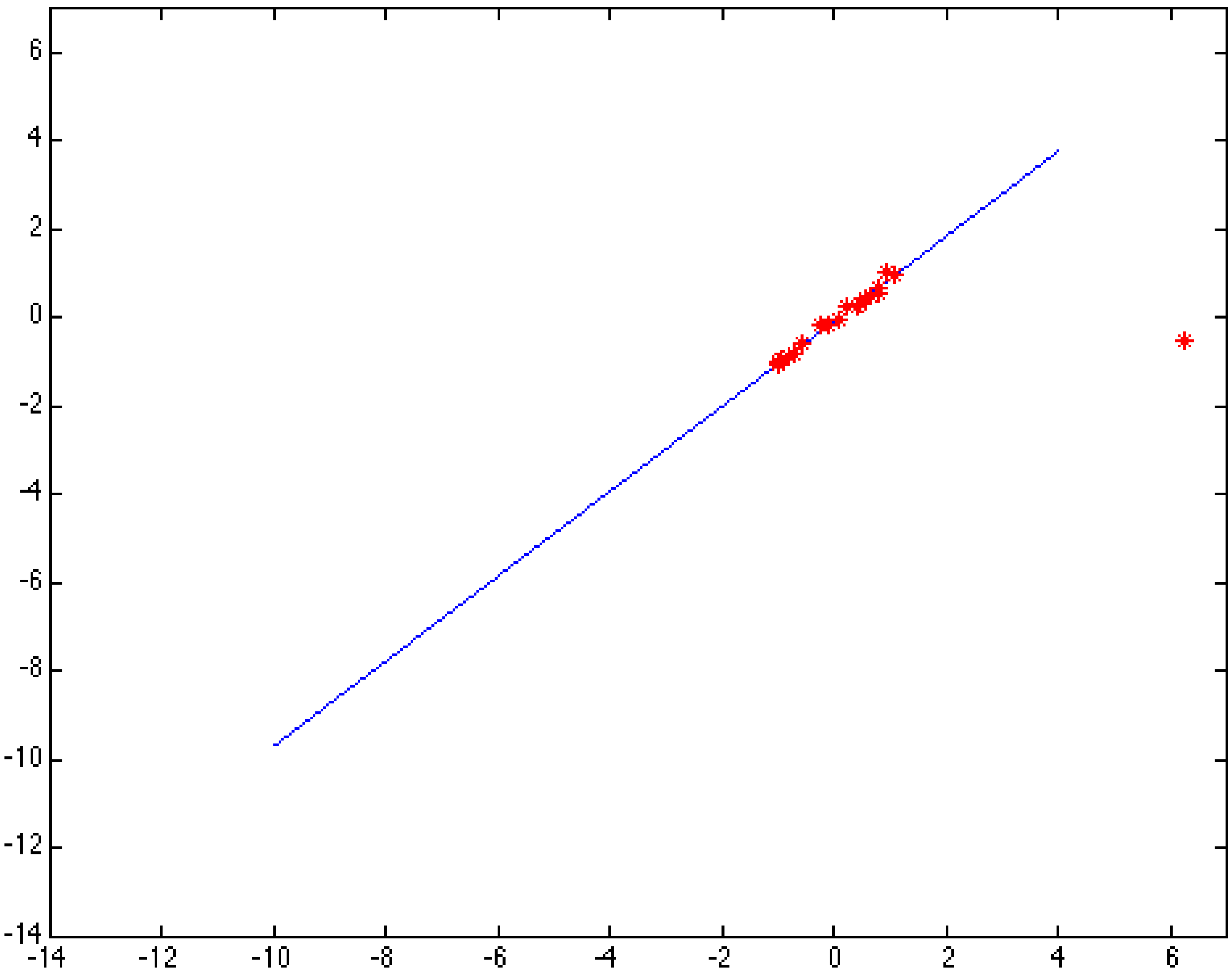


The robust function ρ

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

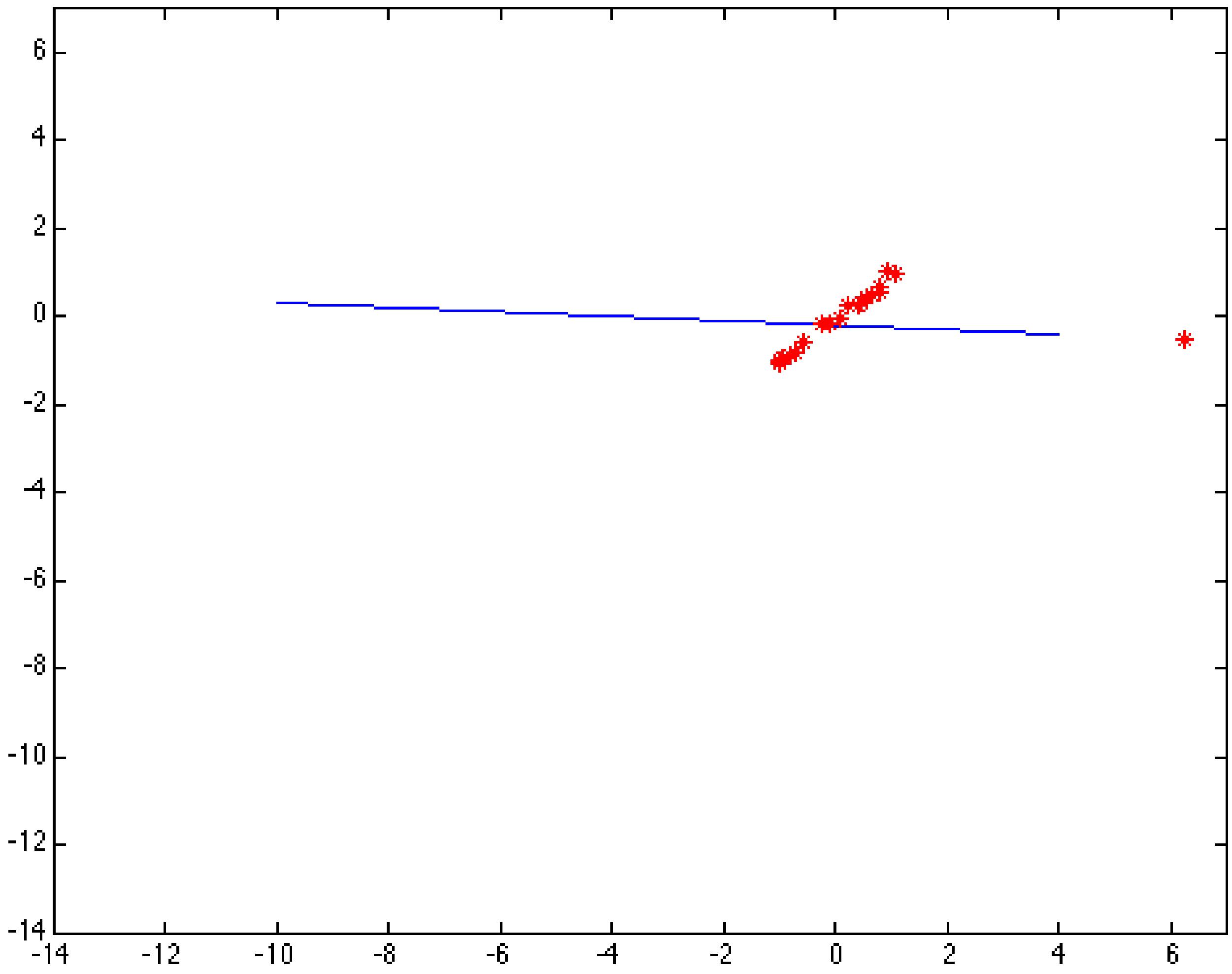
Slide from S. Savarese

Choosing the scale: Just right



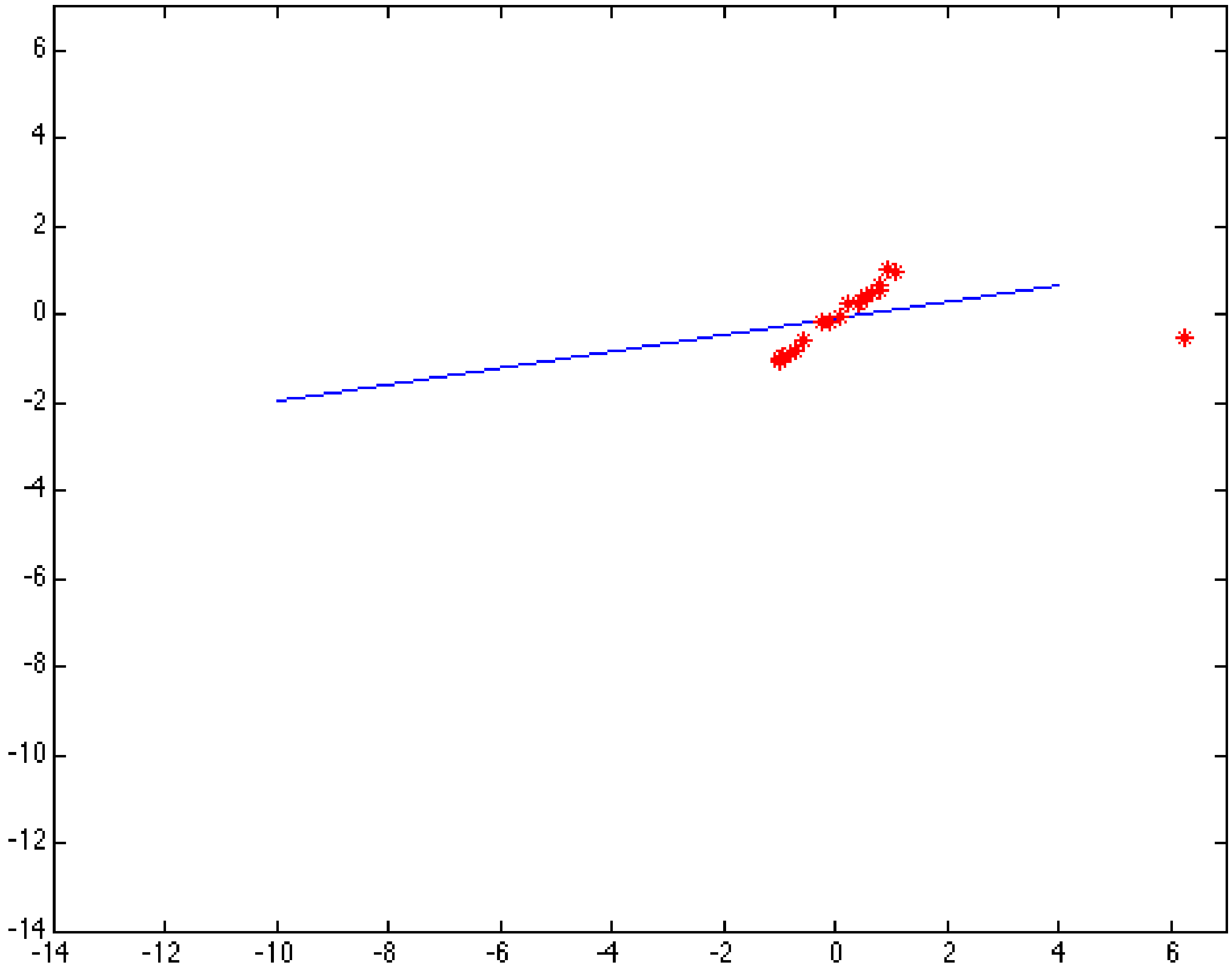
The effect of the outlier is minimized

Choosing the scale: Too small



The error value is almost the same for every point and the fit is very poor

Choosing the scale: Too large



Behaves much the same as least squares

Robust estimation: Details

- Robust fitting is a nonlinear optimization problem that must be solved iteratively
- Least squares solution can be used for initialization
- Scale of robust function should be chosen adaptively based on median residual

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

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

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

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

Hough Transform: Outline

1. Create a grid of parameter values

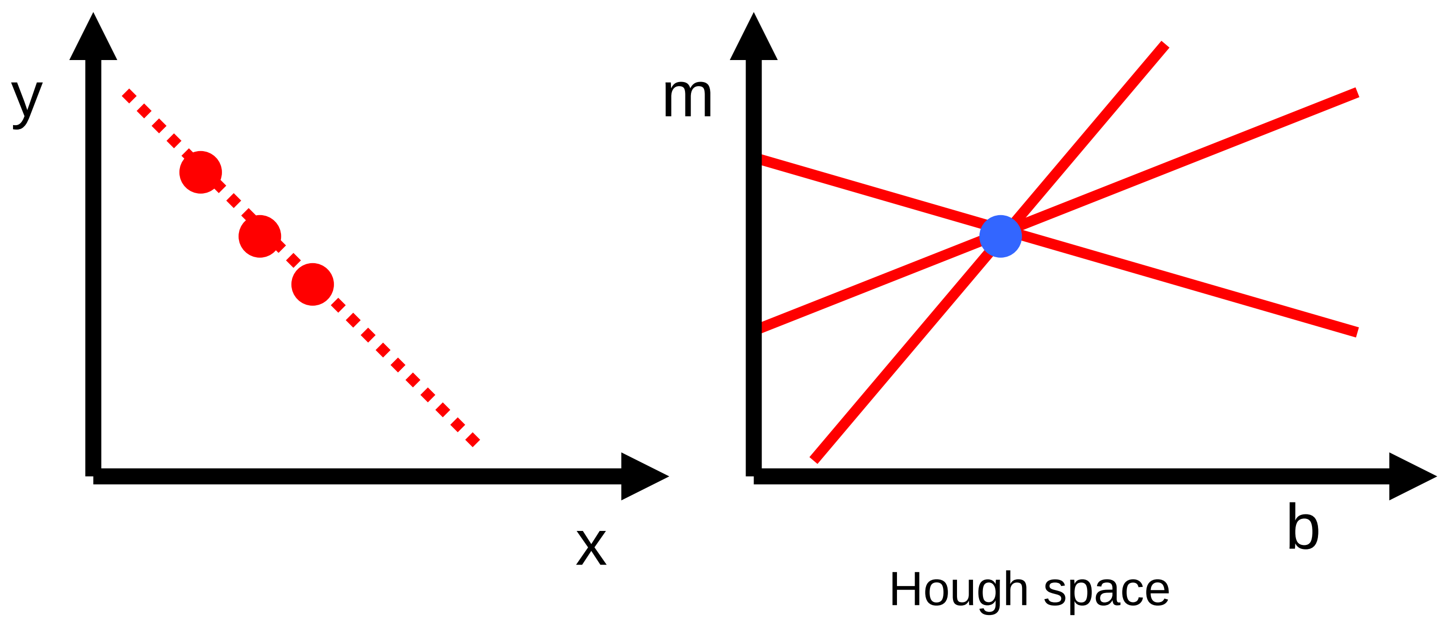
2. Each point votes for a set of parameters, incrementing those values in grid

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

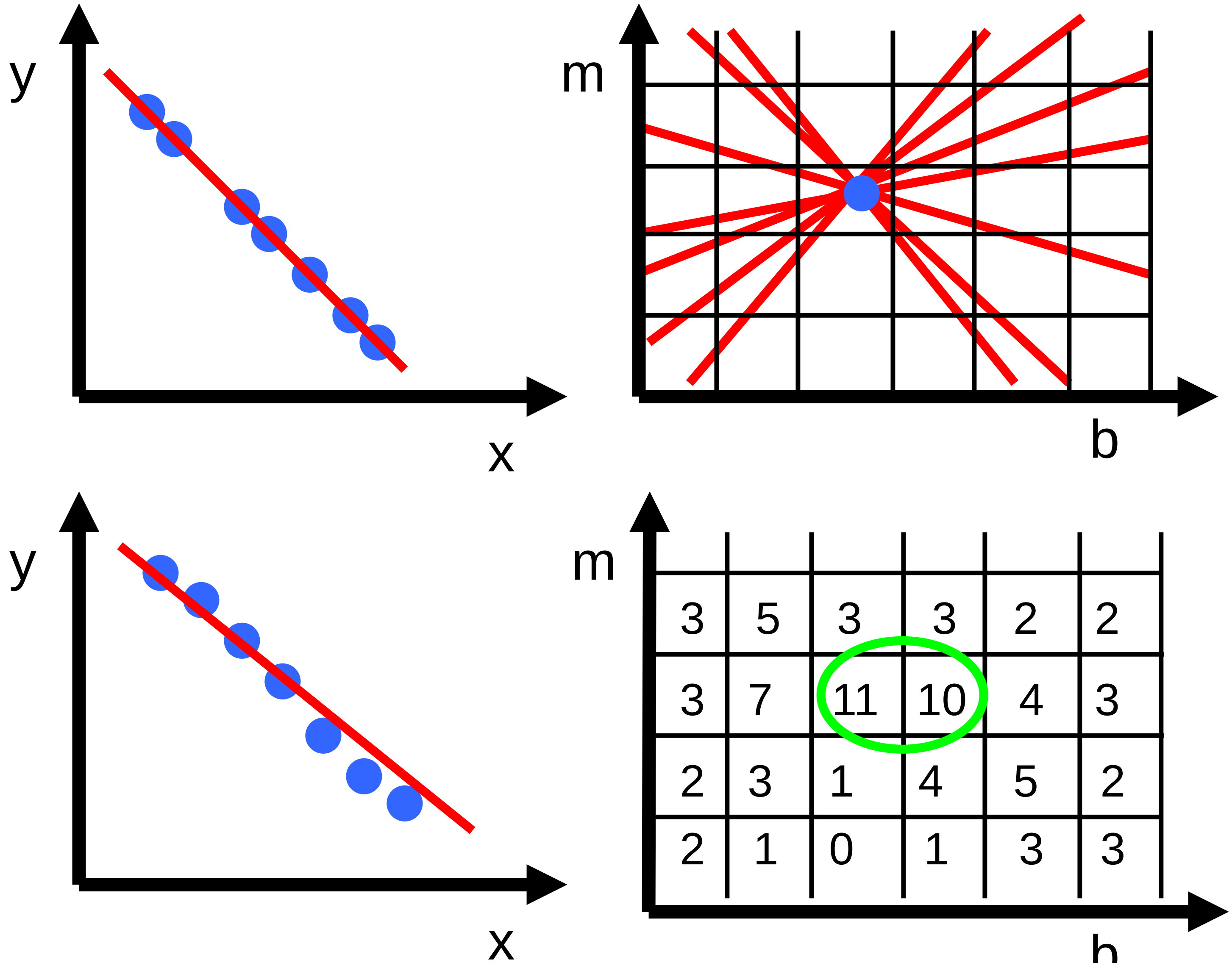
Given a set of points, find the curve or line that explains the data points best



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

Slide from S. Savarese

Hough transform



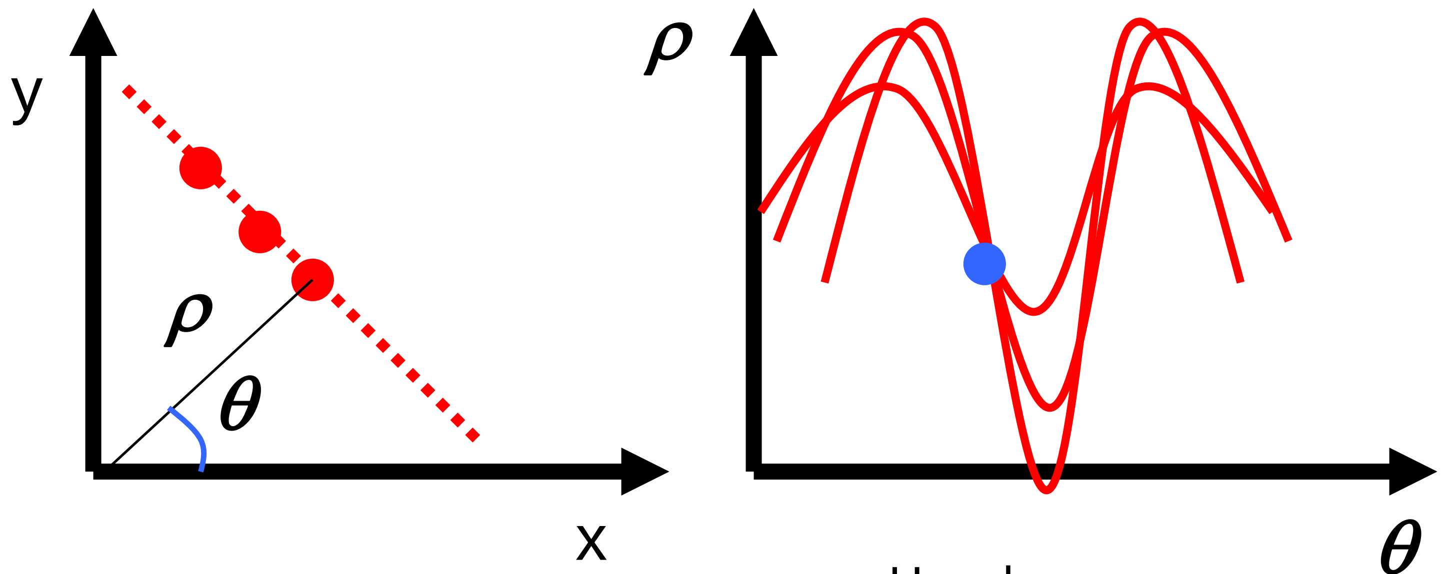
Slide from S. Savarese

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

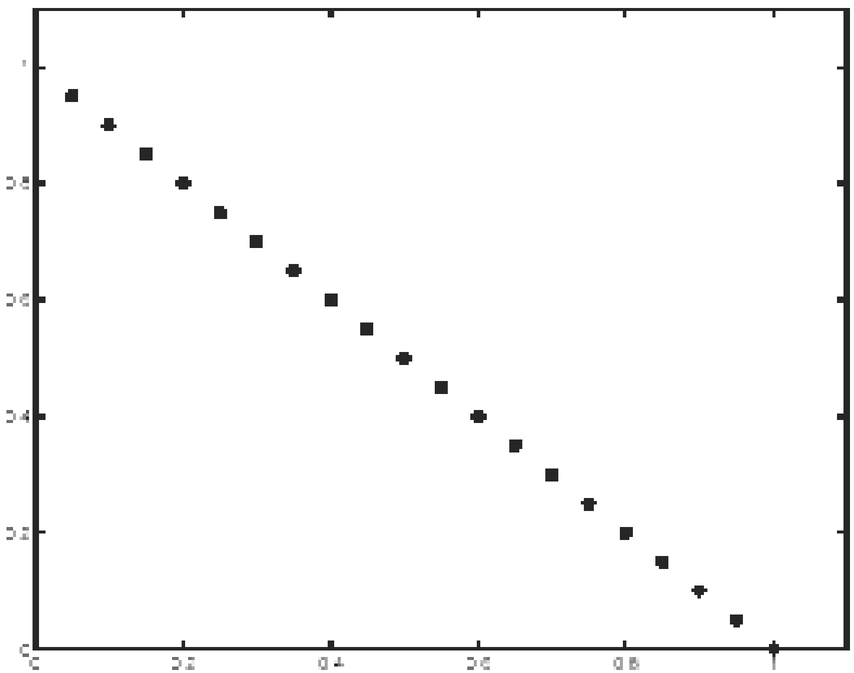


Hough space

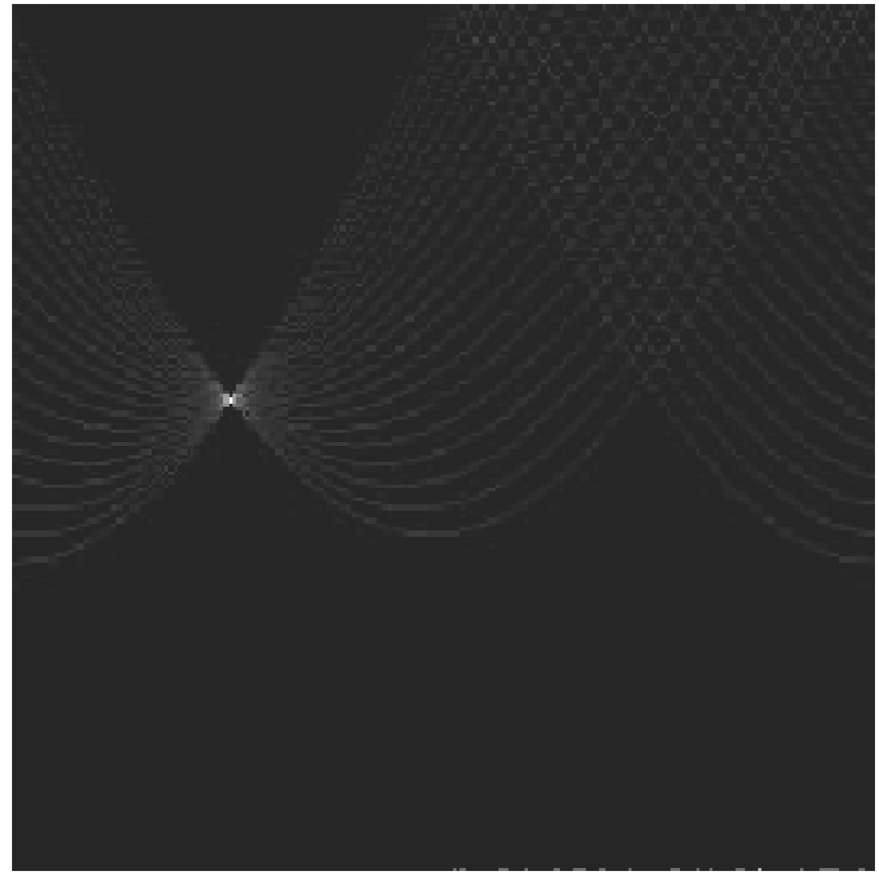
$$x\cos\theta + y\sin\theta = \rho$$

Slide from S. Savarese

Hough transform - experiments



features

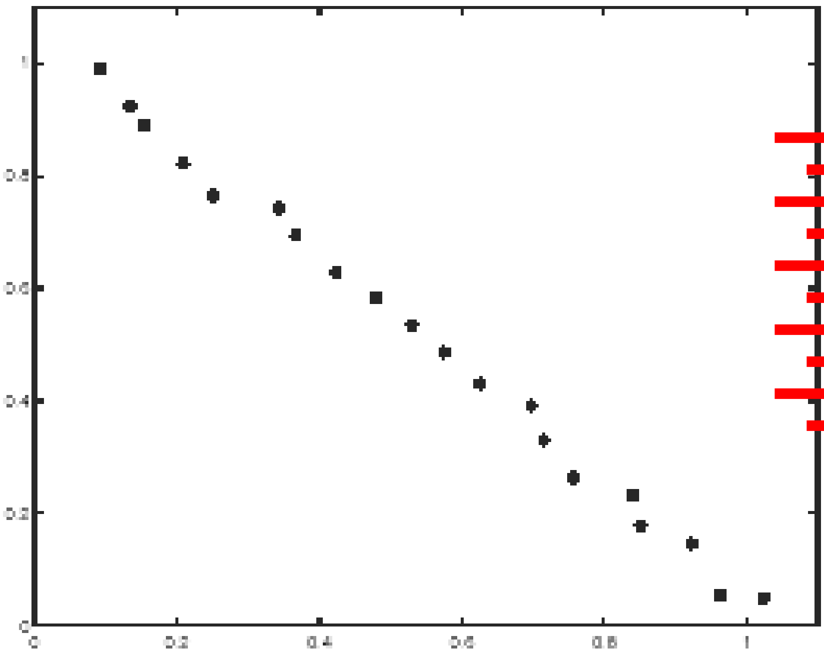


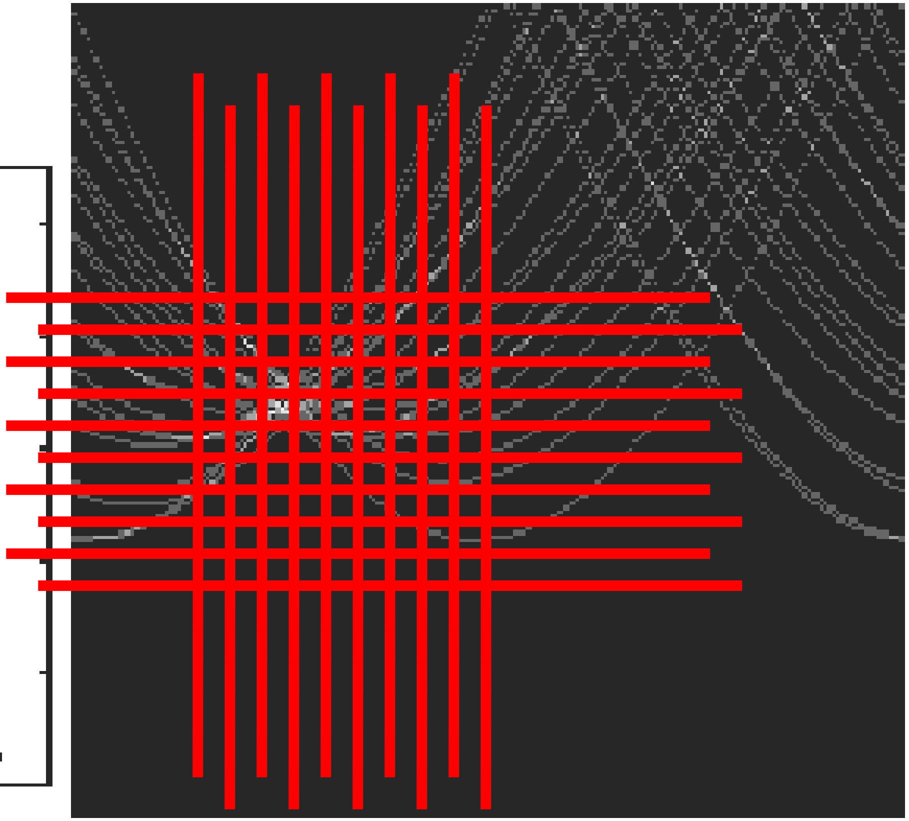
votes

Slide from S. Savarese

Hough transform - experiments

Noisy data





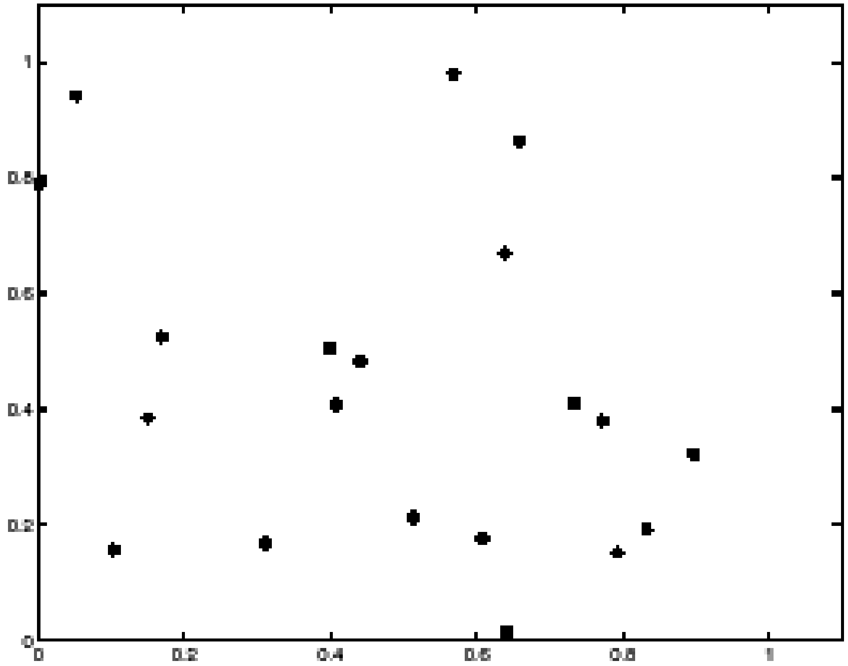
features

votes

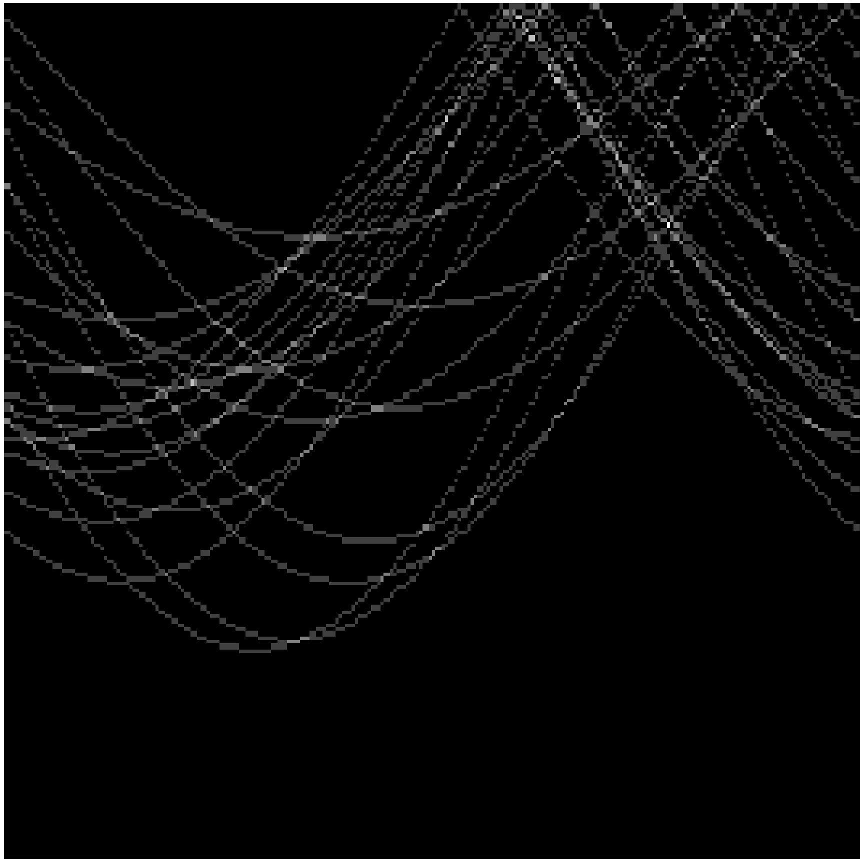
Need to adjust grid size or smooth

Slide from S. Savarese

Hough transform - experiments



features

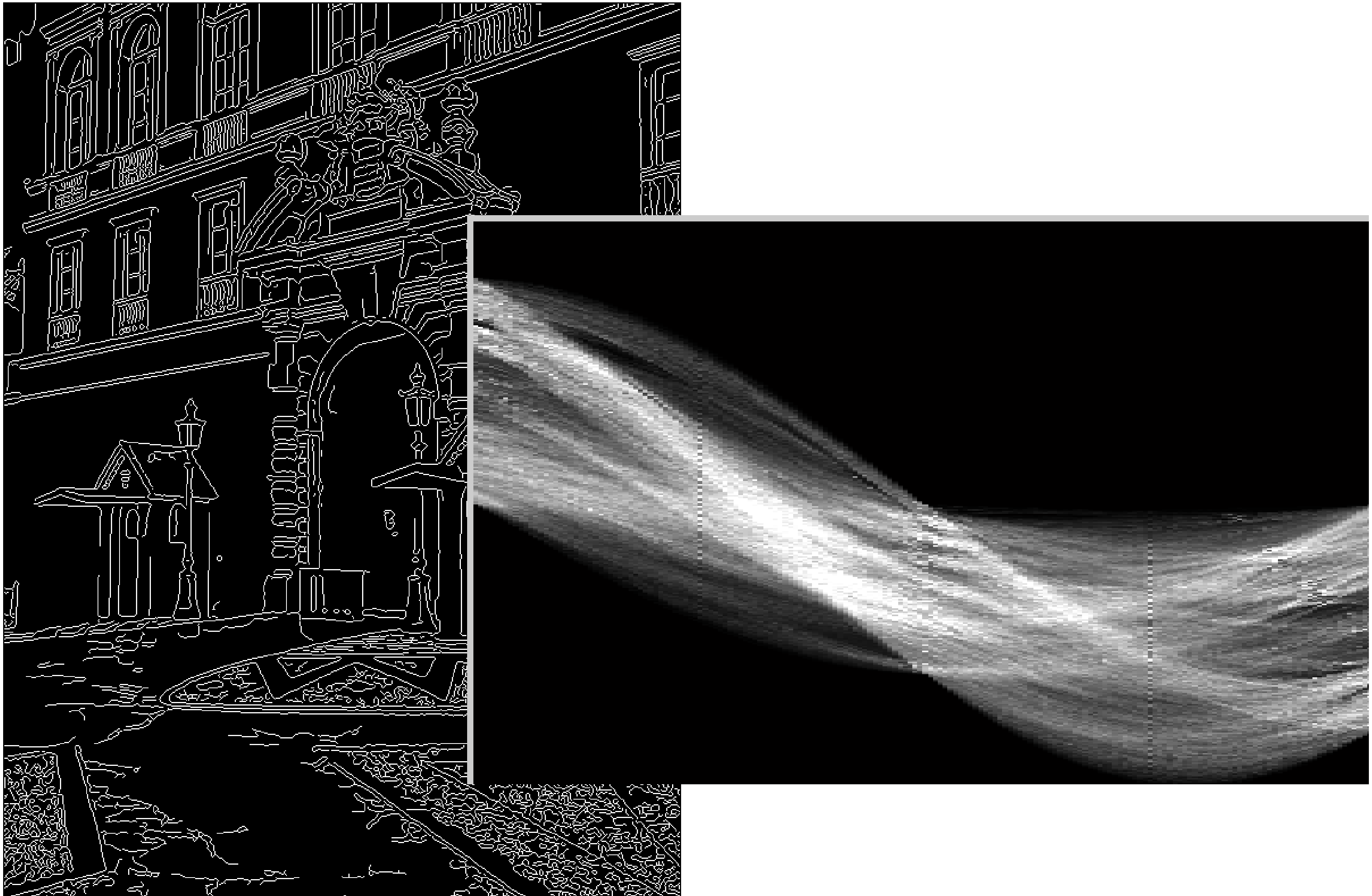

votes

Issue: spurious peaks due to uniform noise

Slide from S. Savarese

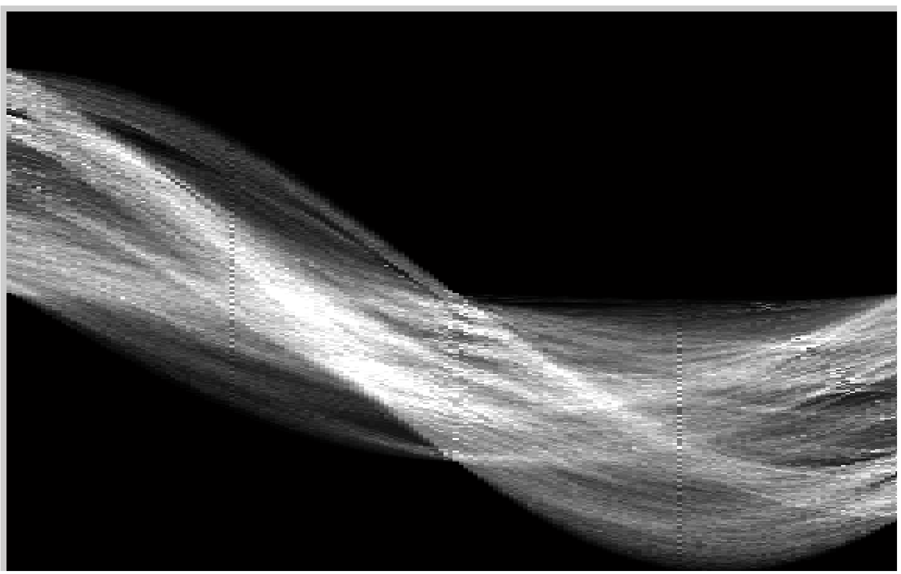
1. Image → Canny

2. Canny → Hough votes

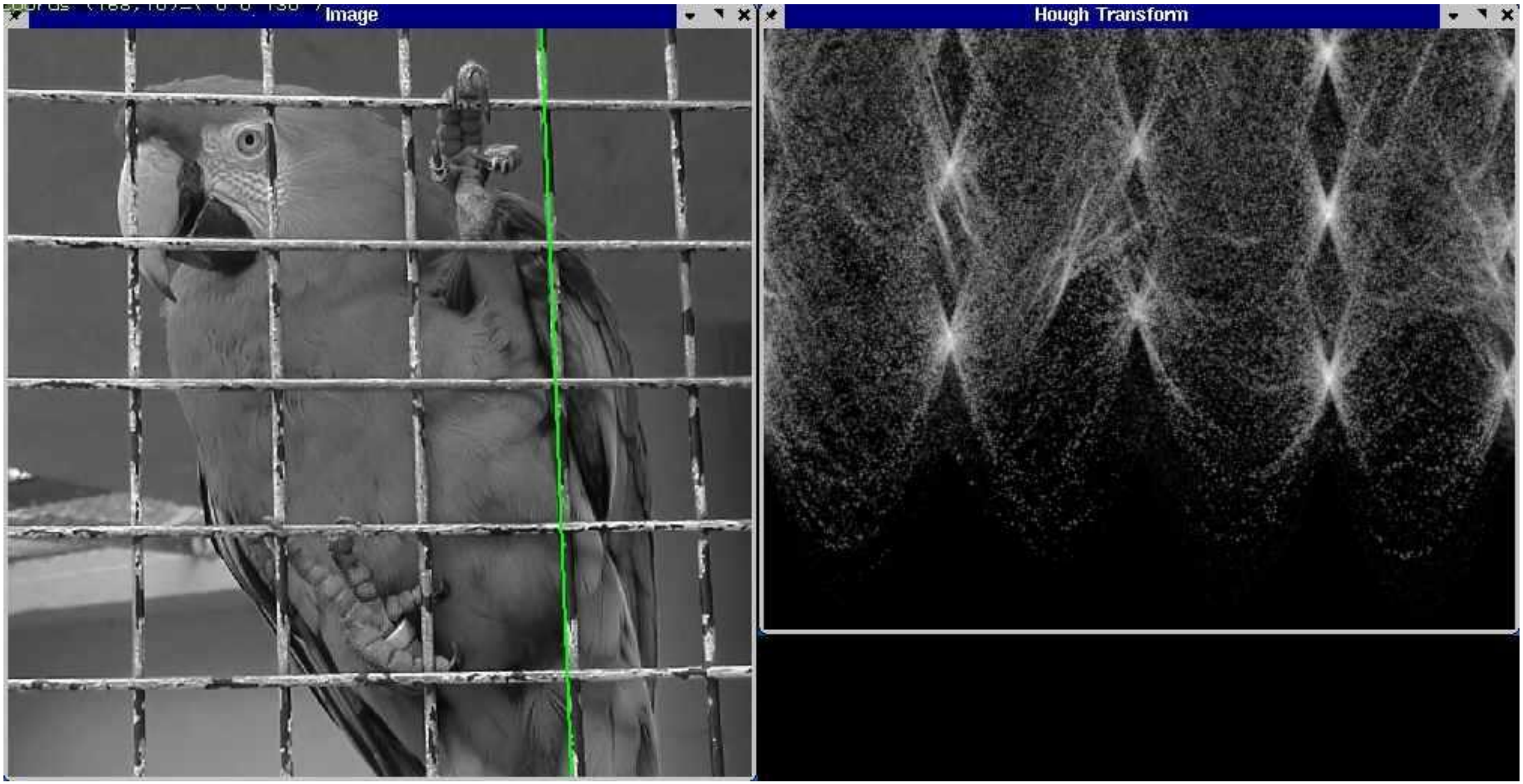


3. Hough votes → Edges

Find peaks and post-process



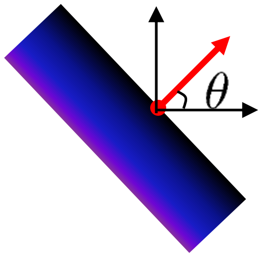
Hough transform example



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

Incorporating image gradients

- Recall: when we detect an edge point, we also know its gradient direction
- But this means that the line is uniquely determined!



$$\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$$

$$\theta = \tan^{-1}\left(\frac{\partial f}{\partial y} / \frac{\partial f}{\partial x}\right)$$

- Modified Hough transform:

- For each edge point (x,y)
  - θ = gradient orientation at (x,y)
  - $\rho = x \cos \theta + y \sin \theta$
  - $H(\theta, \rho) = H(\theta, \rho) + 1$

end

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

Hough Transform

- How would we find circles?
  - Of fixed radius
  - Of unknown radius
  - Of unknown radius but with known edge orientation

Next lecture

- RANSAC
- Connecting model fitting with feature matching