

EEE-6512: Image Processing and Computer Vision

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Lecture #11: Model-Fitting

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Outline

- Overview
- **Fitting Lines**
- Fitting Curves
- Addressing Noise
- Fitting Multiple Models

Line Fitting

Fitting: Methods

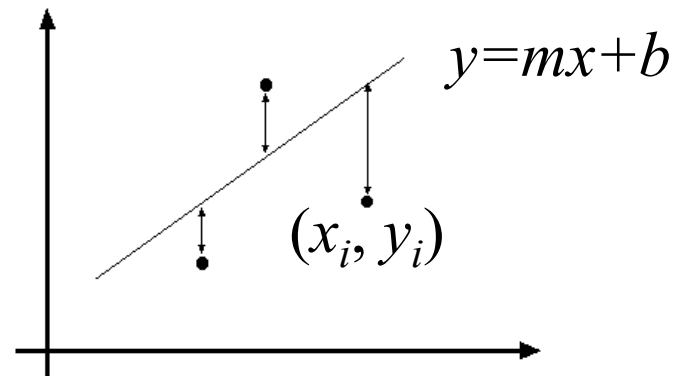
- Global optimization / Search for parameters
 - Ordinary Least Squares
 - Total Least Squares
- Hypothesize and test
 - Generalized Hough transform
 - RANSAC

Ordinary Least Squares / Total Least Squares

Least squares line fitting

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

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



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

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

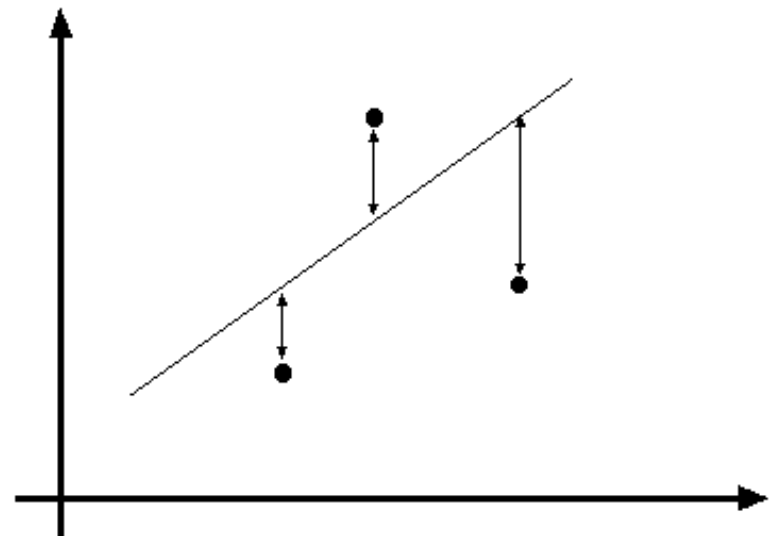
$$\frac{dE}{dp} = 2\mathbf{A}^T \mathbf{A}\mathbf{p} - 2\mathbf{A}^T \mathbf{y} = 0$$

Matlab: `p = A \ y;`

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

Problem with “vertical” least squares

- Not rotation-invariant
- Fails completely for vertical lines



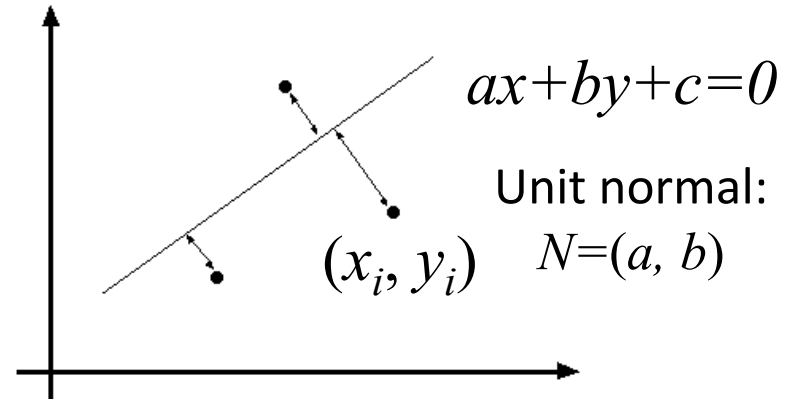
Total least squares

If $(a^2+b^2=1)$ then

Distance between point (x_i, y_i) and line $ax+by+c=0$ is $|ax_i + by_i + c|$

Find (a, b, c) to minimize the sum of squared perpendicular distances

$$E = \sum_{i=1}^n (ax_i + by_i + c)^2$$



Total least squares

Find (a, b, c) to minimize the sum of squared perpendicular distances

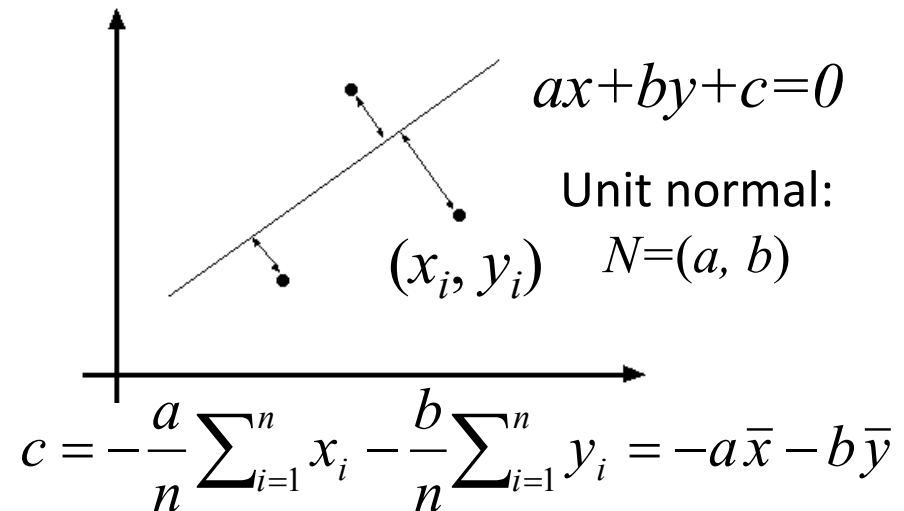
$$E = \sum_{i=1}^n (ax_i + by_i + c)^2$$

$$\frac{\partial E}{\partial c} = \sum_{i=1}^n 2(ax_i + by_i + c) = 0$$

$$E = \sum_{i=1}^n (a(x_i - \bar{x}) + b(y_i - \bar{y}))^2 = \left\| \begin{bmatrix} x_1 - \bar{x} & y_1 - \bar{y} \\ \vdots & \vdots \\ x_n - \bar{x} & y_n - \bar{y} \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} \right\|^2 = \mathbf{p}^T \mathbf{A}^T \mathbf{A} \mathbf{p}$$

$$\text{minimize } \mathbf{p}^T \mathbf{A}^T \mathbf{A} \mathbf{p} \quad \text{s.t. } \mathbf{p}^T \mathbf{p} = 1 \quad \Rightarrow \quad \text{minimize } \frac{\mathbf{p}^T \mathbf{A}^T \mathbf{A} \mathbf{p}}{\mathbf{p}^T \mathbf{p}}$$

Solution is eigenvector corresponding to smallest eigenvalue of $\mathbf{A}^T \mathbf{A}$



Recap: Two Common Optimization Problems

Problem statement

$$\text{minimize } \|\mathbf{Ax} - \mathbf{b}\|^2$$

least squares solution to $\mathbf{Ax} = \mathbf{b}$

Solution

$$\mathbf{x} = (\mathbf{A}^T \mathbf{A})^{-1} \mathbf{A}^T \mathbf{b}$$

$$\mathbf{x} = \mathbf{A} \setminus \mathbf{b} \quad (\text{matlab})$$

Problem statement

$$\text{minimize } \mathbf{x}^T \mathbf{A}^T \mathbf{Ax} \quad \text{s.t. } \mathbf{x}^T \mathbf{x} = 1$$

$$\text{minimize } \frac{\mathbf{x}^T \mathbf{A}^T \mathbf{Ax}}{\mathbf{x}^T \mathbf{x}}$$

non - trivial lsq solution to $\mathbf{Ax} = 0$

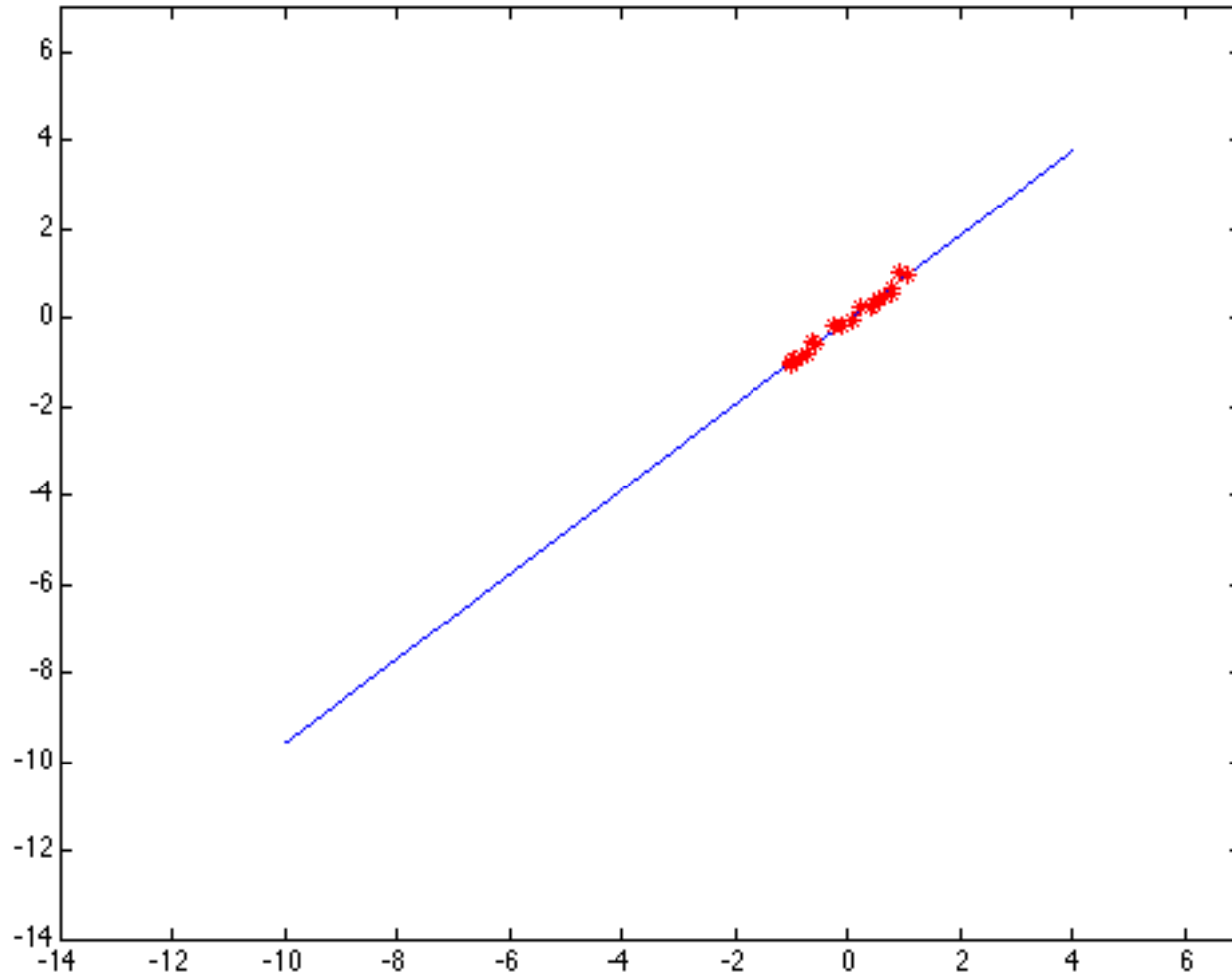
Solution

$$[\mathbf{v}, \lambda] = \text{eig}(\mathbf{A}^T \mathbf{A})$$

$$\lambda_1 < \lambda_{2..n} : \mathbf{x} = \mathbf{v}_1$$

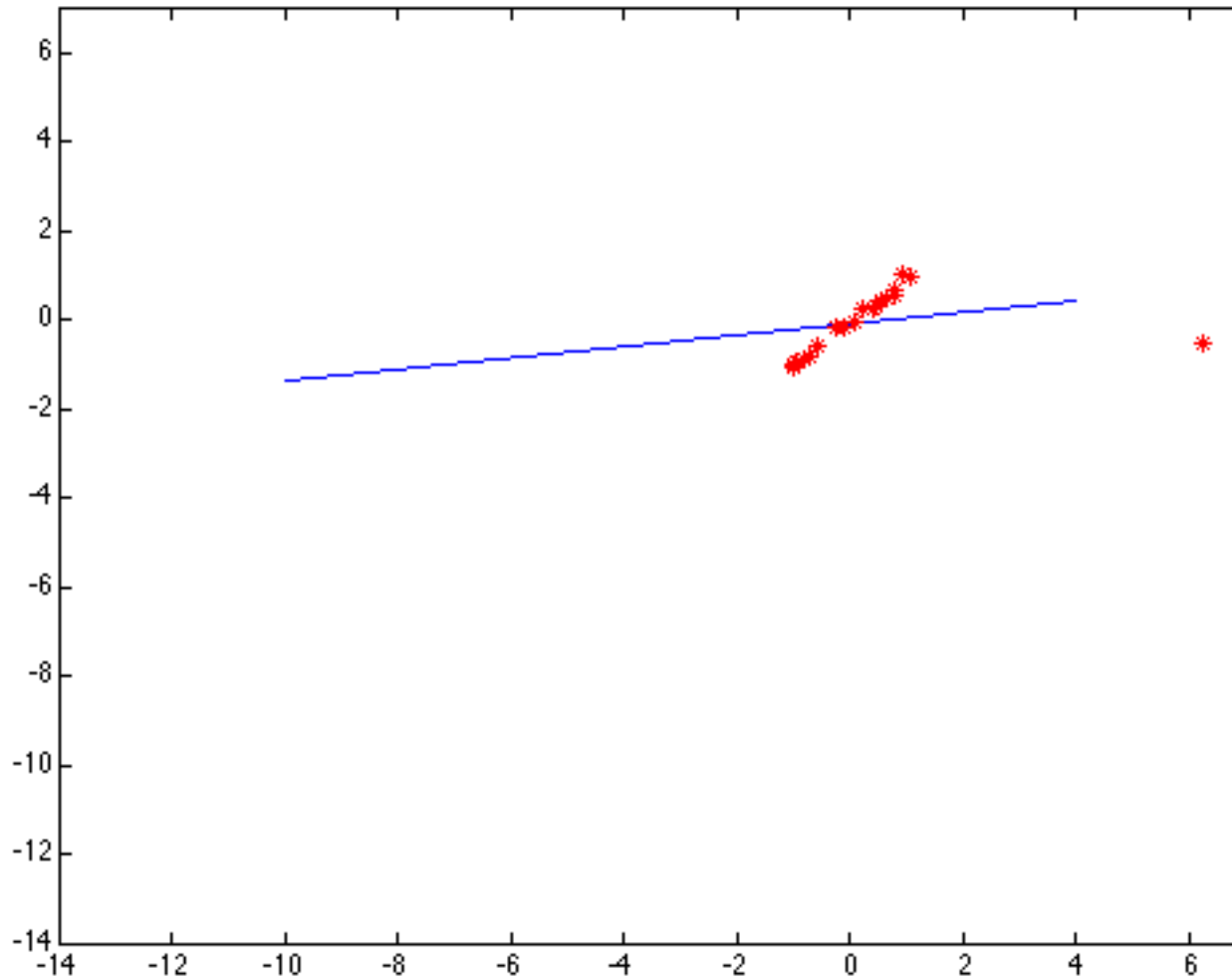
Least squares: Robustness to noise

Least squares fit to the red points:



Least squares: Robustness to noise

Least squares fit with an outlier:



Problem: squared error heavily penalizes outliers

Least squares (global) optimization

Good

- Clearly specified objective
- Optimization is easy

Bad

- Sensitive to outliers
 - Bad matches, extra points
- Doesn't allow you to get multiple good fits
 - Detecting multiple objects, lines, etc.

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

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

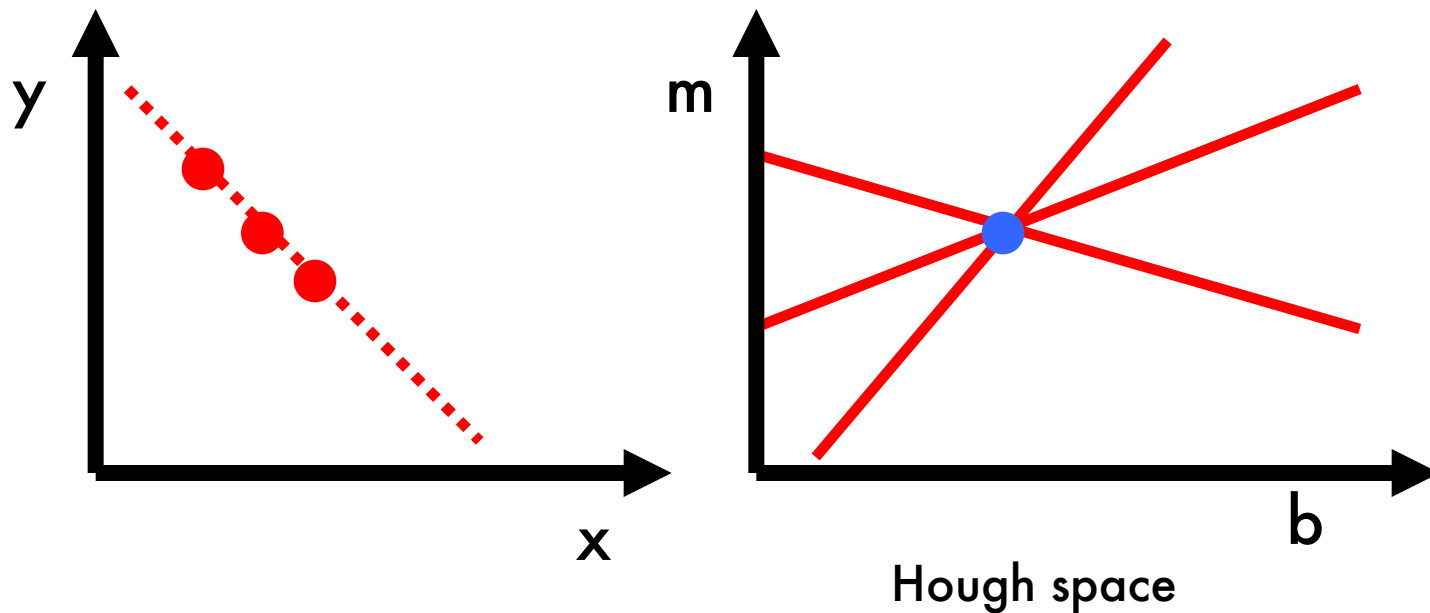
4. Possibly refine parameters using inliers

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

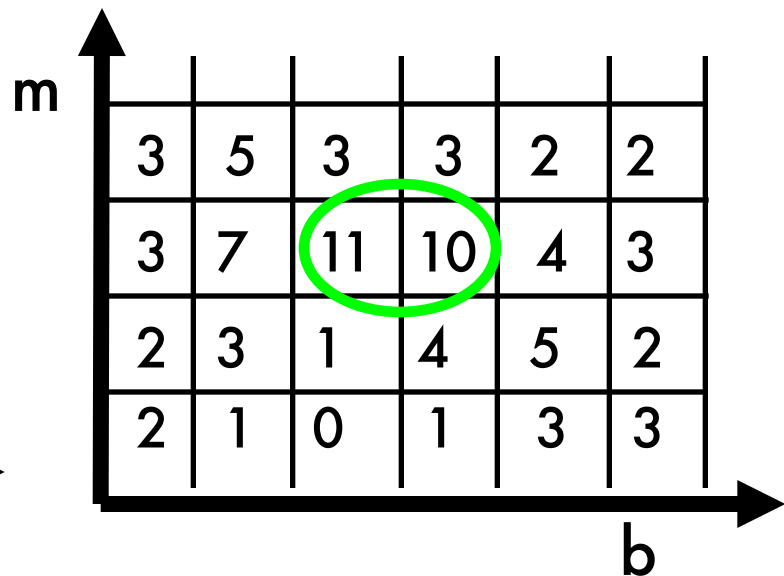
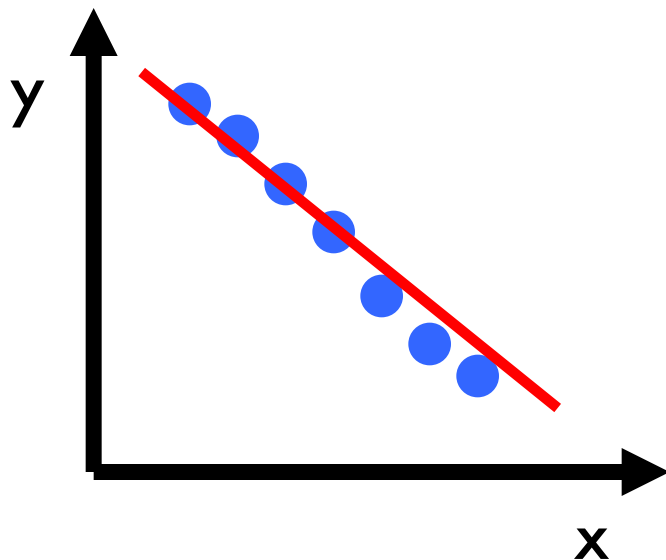
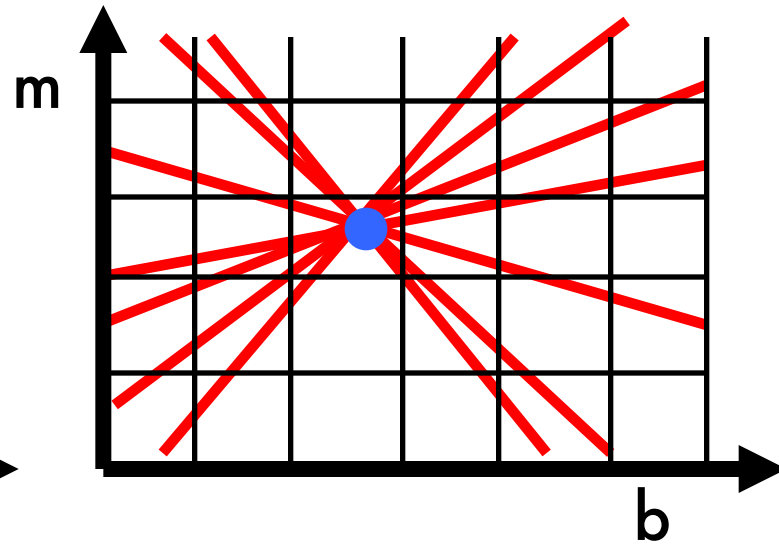
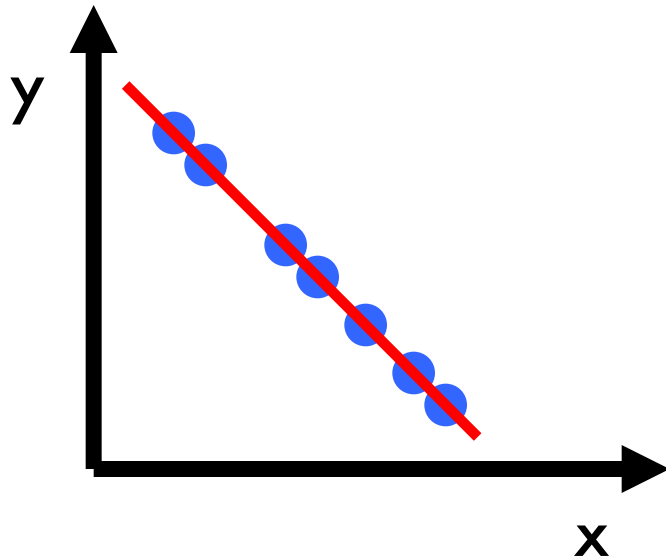
Given a set of points, find the curve or line that explains the data points best



$$y = m x + b$$

Connection Between Image and Hough Spaces

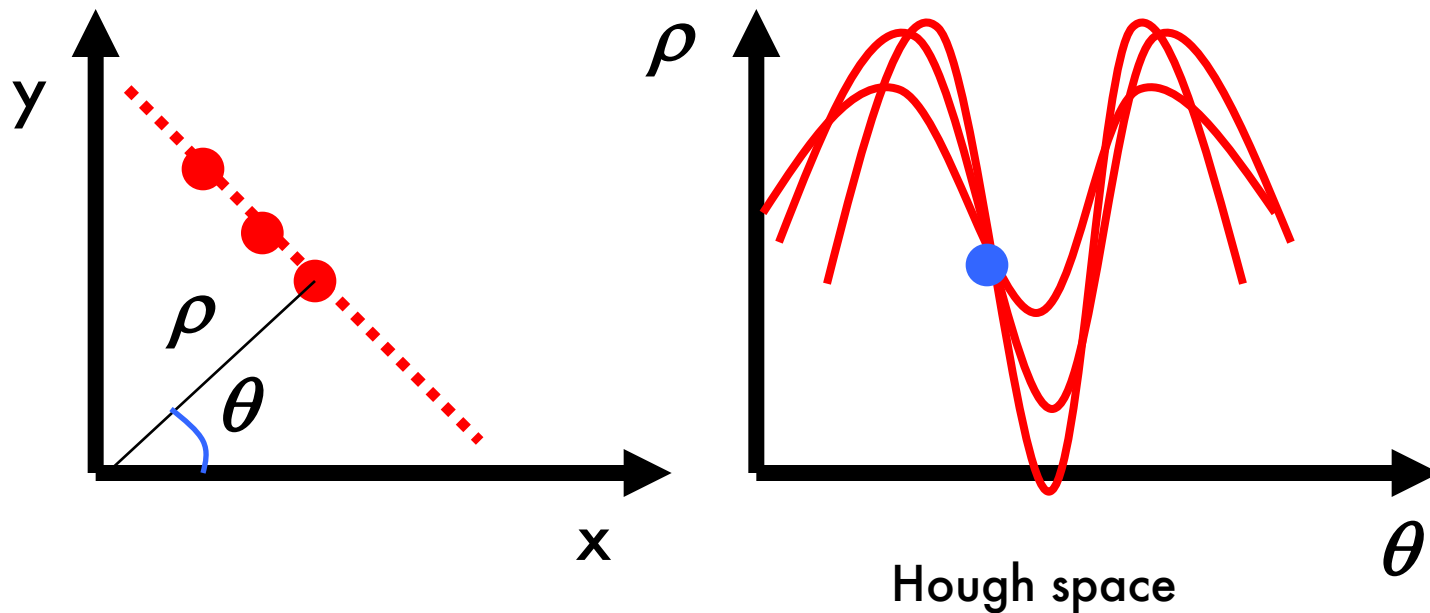
Hough transform



Hough transform

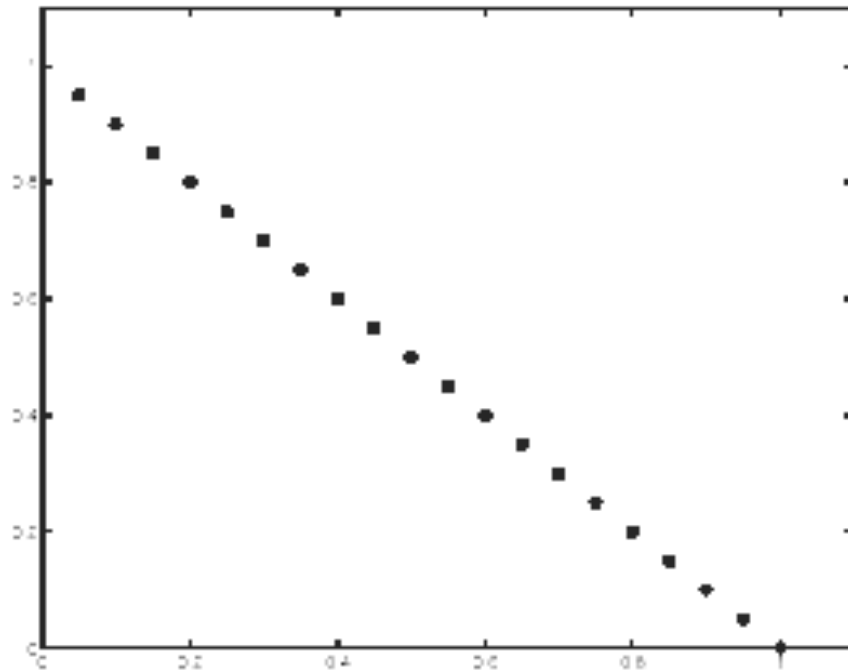
Issue : parameter space $[m,b]$ is unbounded...

Use a polar representation for the parameter space

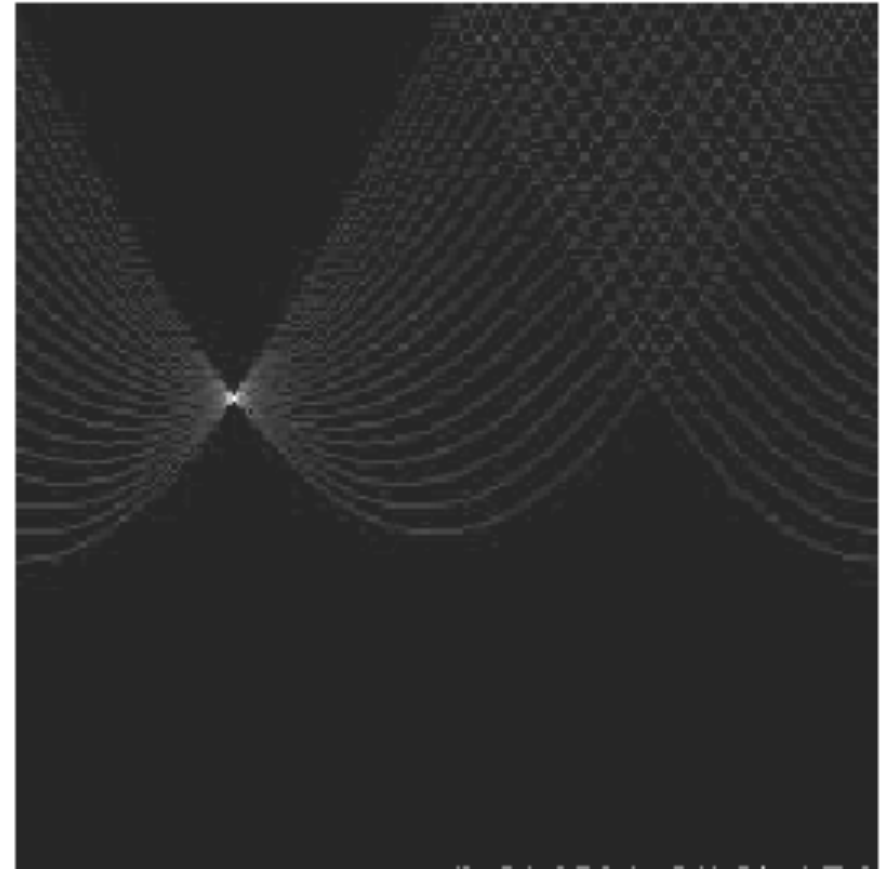


$$x \cos \theta + y \sin \theta = \rho$$

Hough transform - experiments

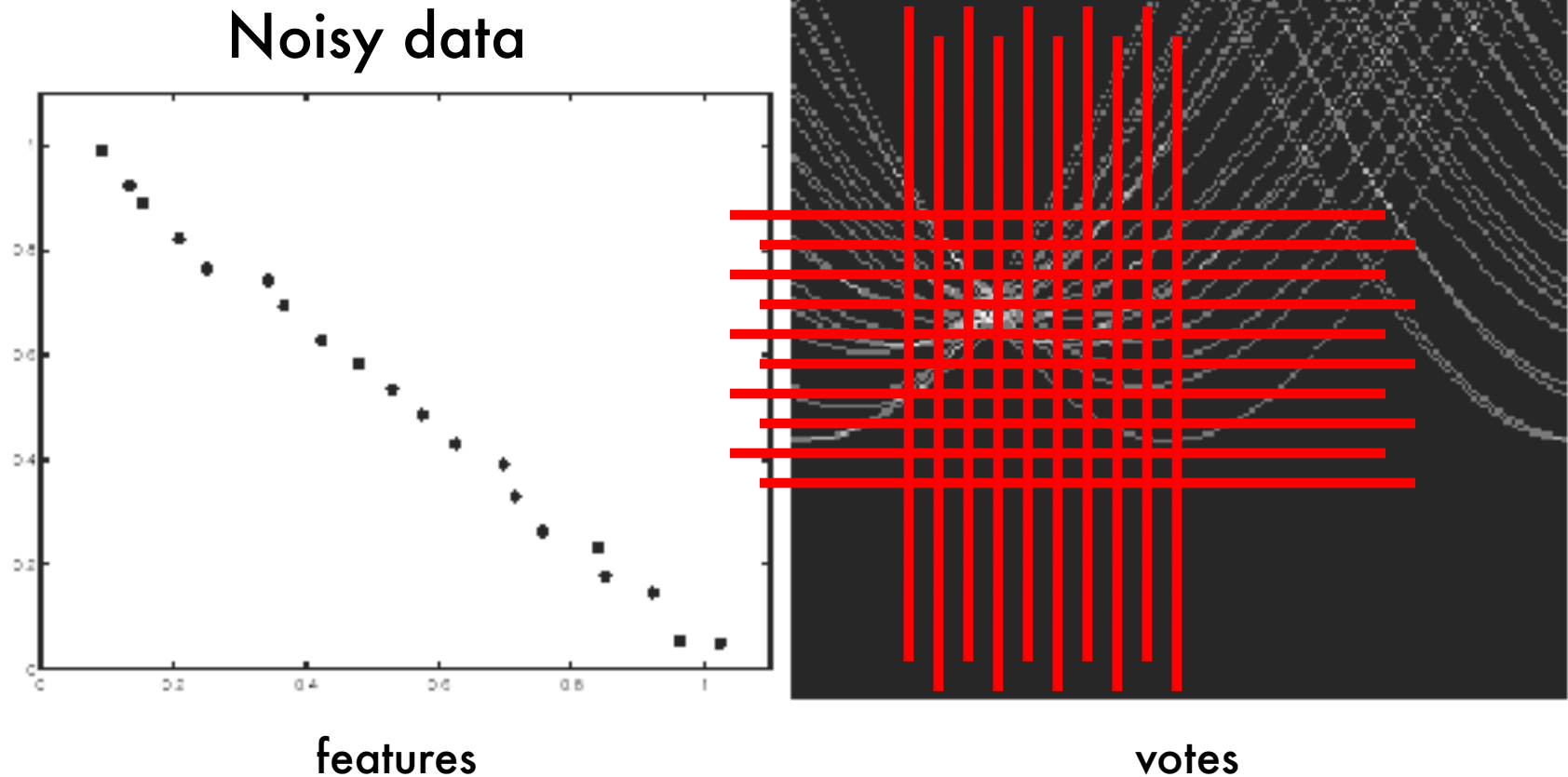


features



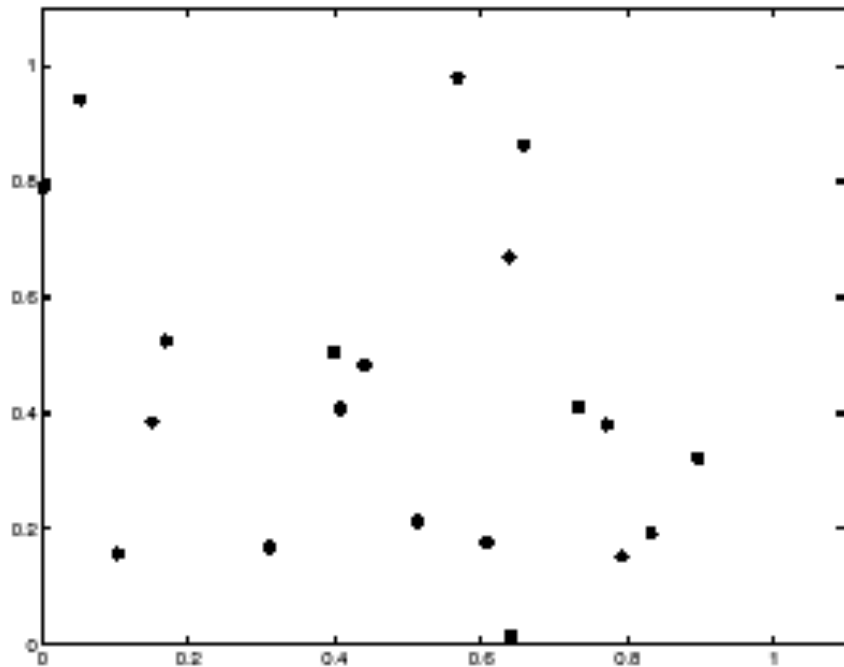
votes

Hough transform - experiments

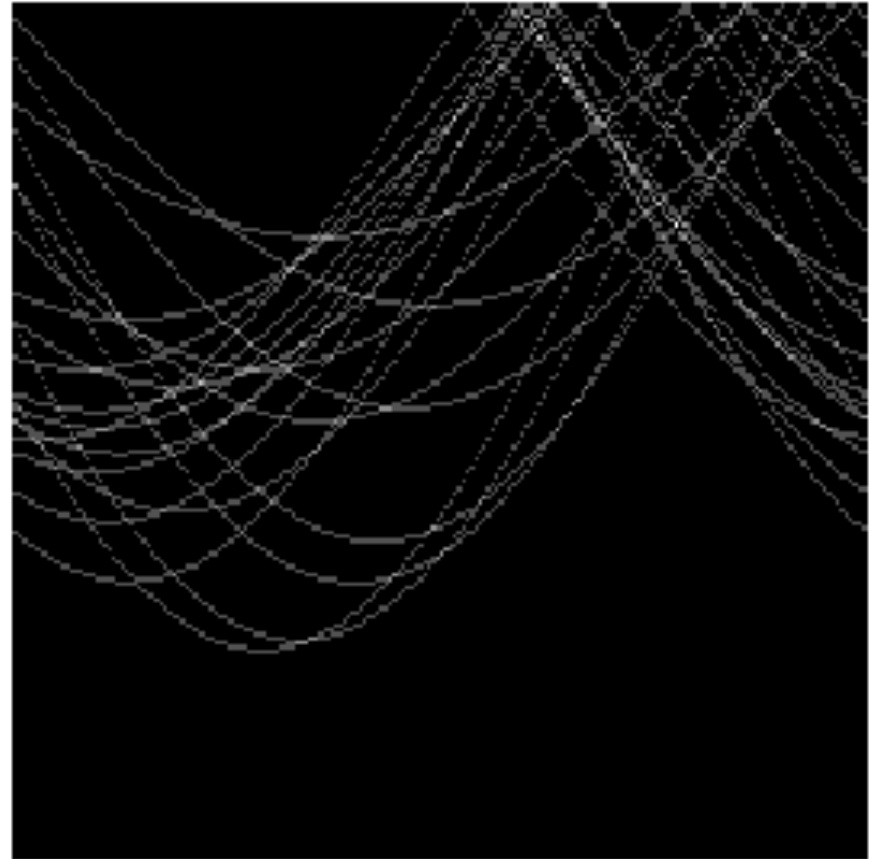


Need to adjust grid size or smooth

Hough transform - experiments



features



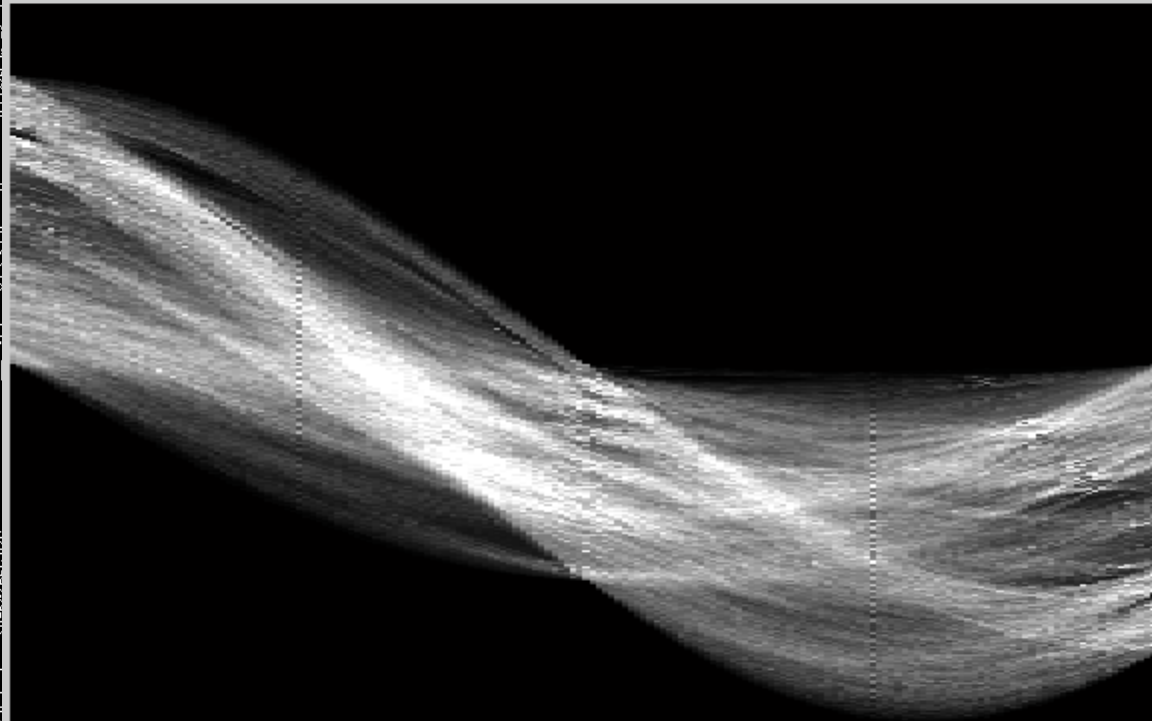
votes

Issue: spurious peaks due to uniform noise

1. Image → Canny

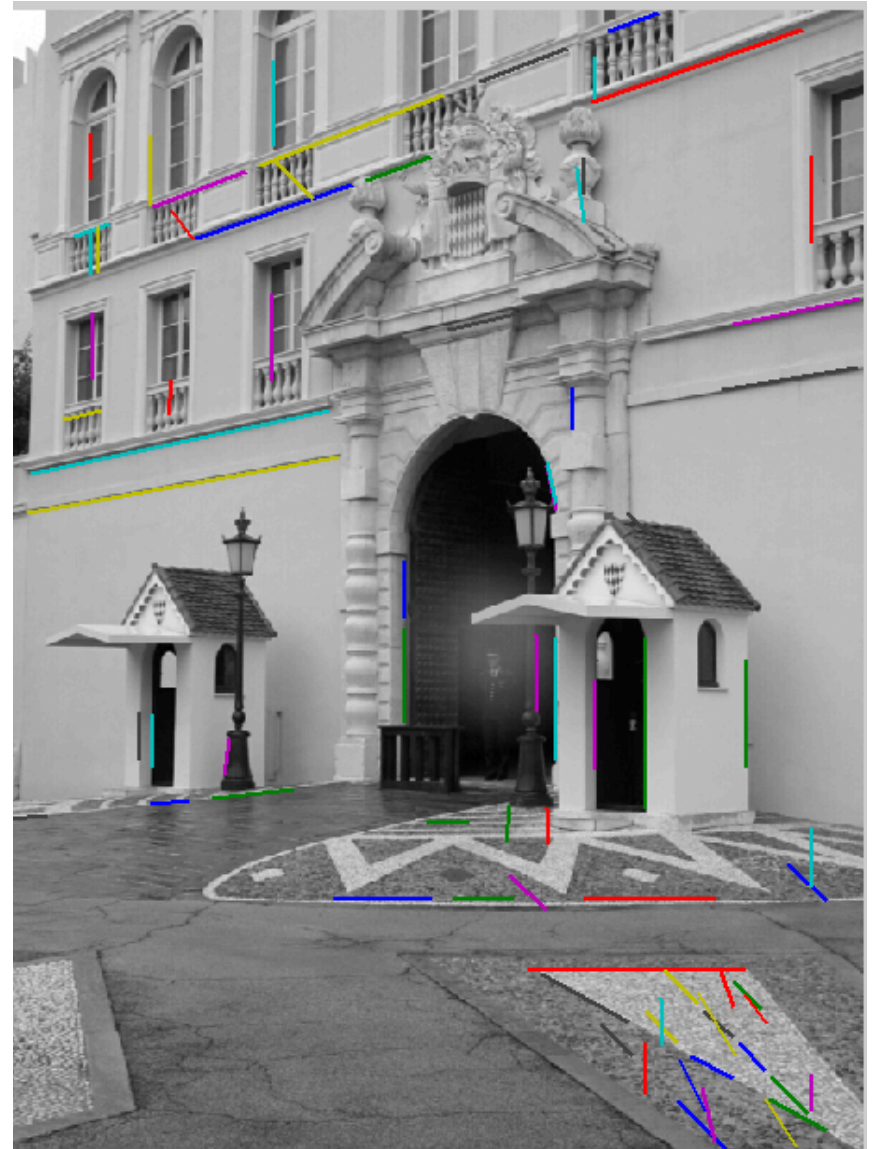
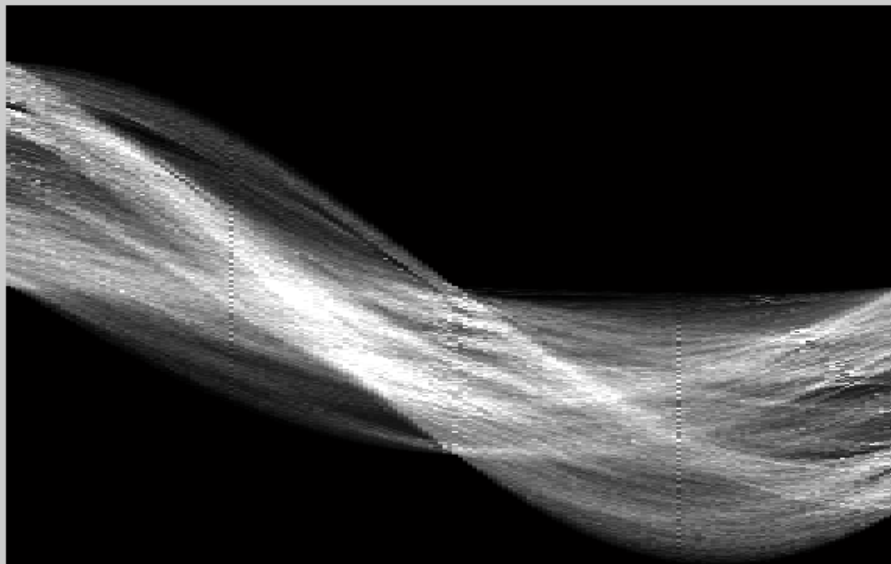


2. Canny \rightarrow Hough votes



3. Hough votes \rightarrow Edges

Find peaks and post-process



Next Time

- Fitting Curves (Generalized Hough)
- Dealing with Noise (RANSAC)

Questions?

Slide Credits

Some slides from Dr. Stanley Birchfield, Dr. Kristen Grauman, Dr. Svetlana Lazebnik, Dr. Jia-Bin Huang, Dr. Silvio Savarese.