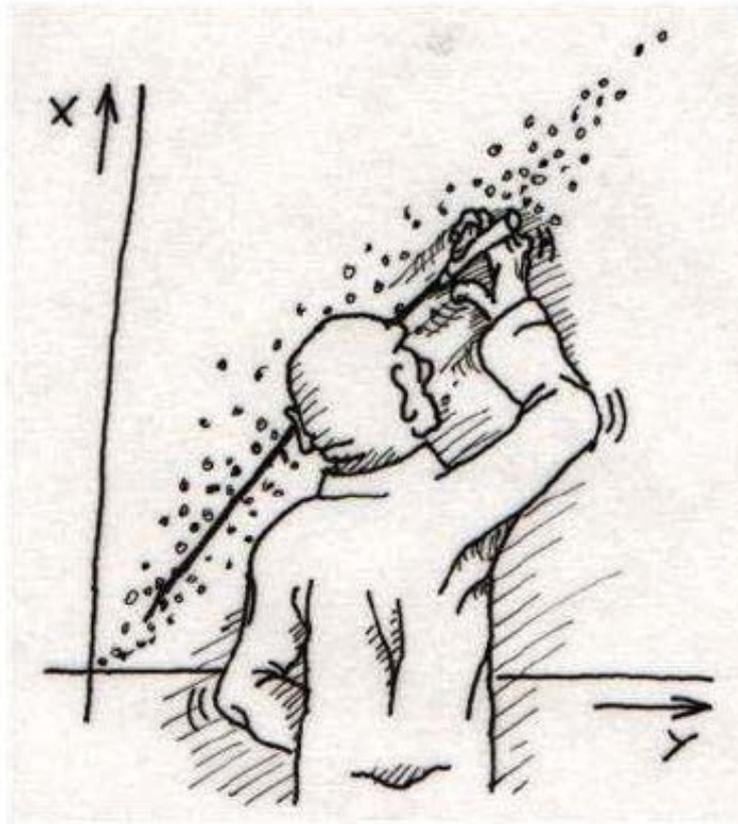


Model Fitting: The Hough transform I

Guido Gerig, CS6640 Image Processing, Utah



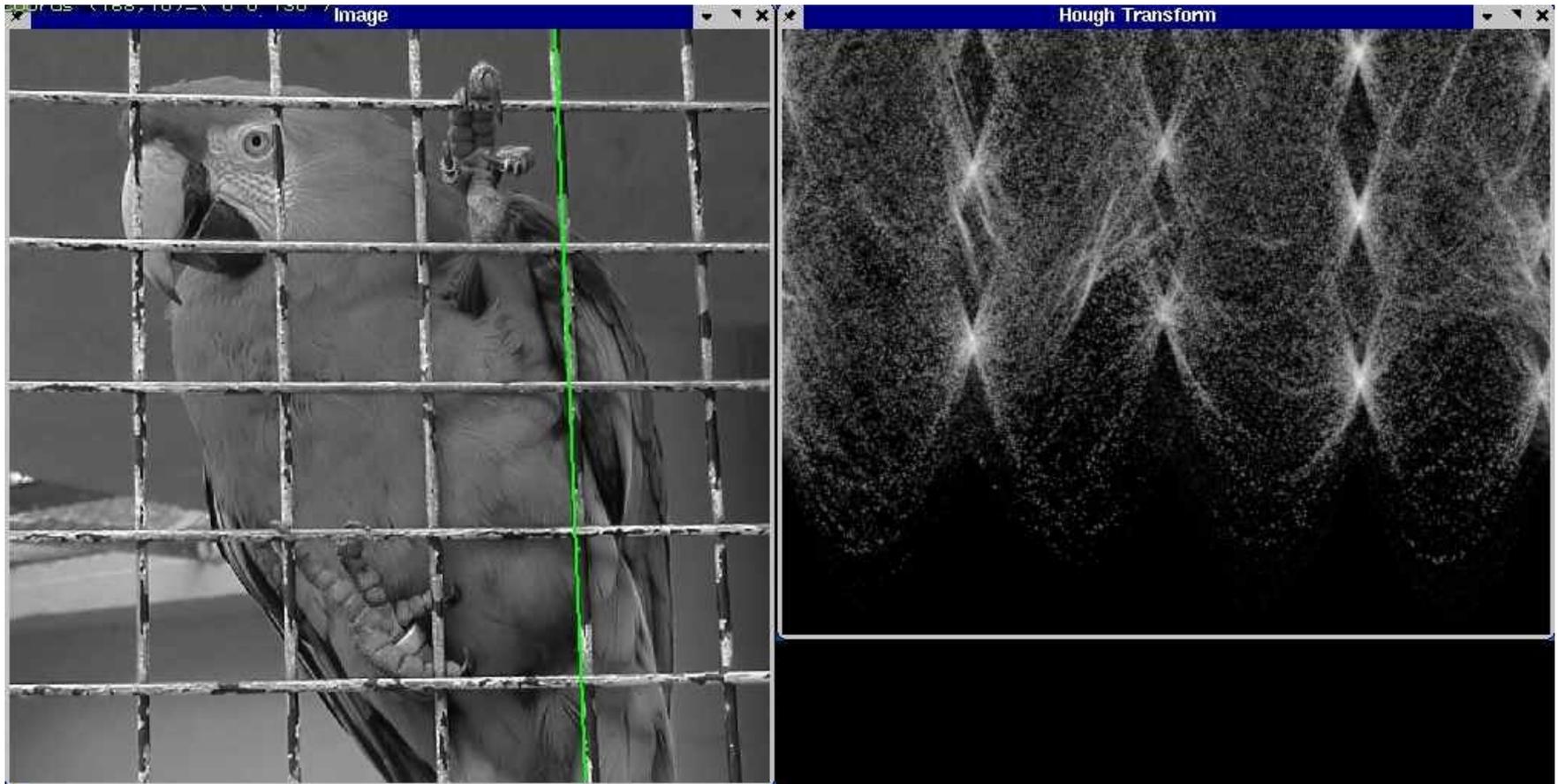
Materials:

**DIP book: 10.2,
pages 733-738**

Handouts G. Gerig

Credit to most slides: Svetlana Lazebnik, University of Illinois at Urbana-Champaign ([slides](#))

Fitting: The Hough transform



http://web.engr.illinois.edu/~slazebni/spring14/lec11_hough.pptx

Voting schemes

- Let each feature vote for all the models that are compatible with it
- Hopefully the noise features will not vote consistently for any single model
- Missing data doesn't matter as long as there are enough features remaining to agree on a good model

Hough transform

- An early type of voting scheme
- General outline:
 - Discretize *parameter space* into bins
 - For each feature point in the image, put a vote in every bin in the parameter space that could have generated this point
 - Find bins that have the most votes

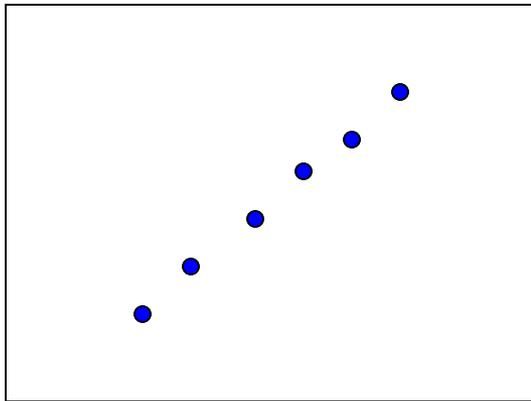
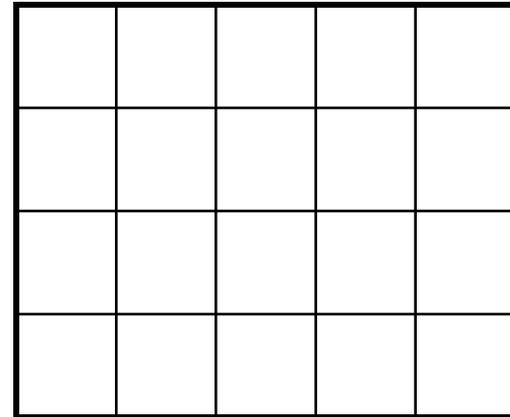
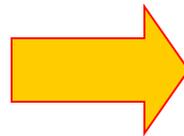


Image space

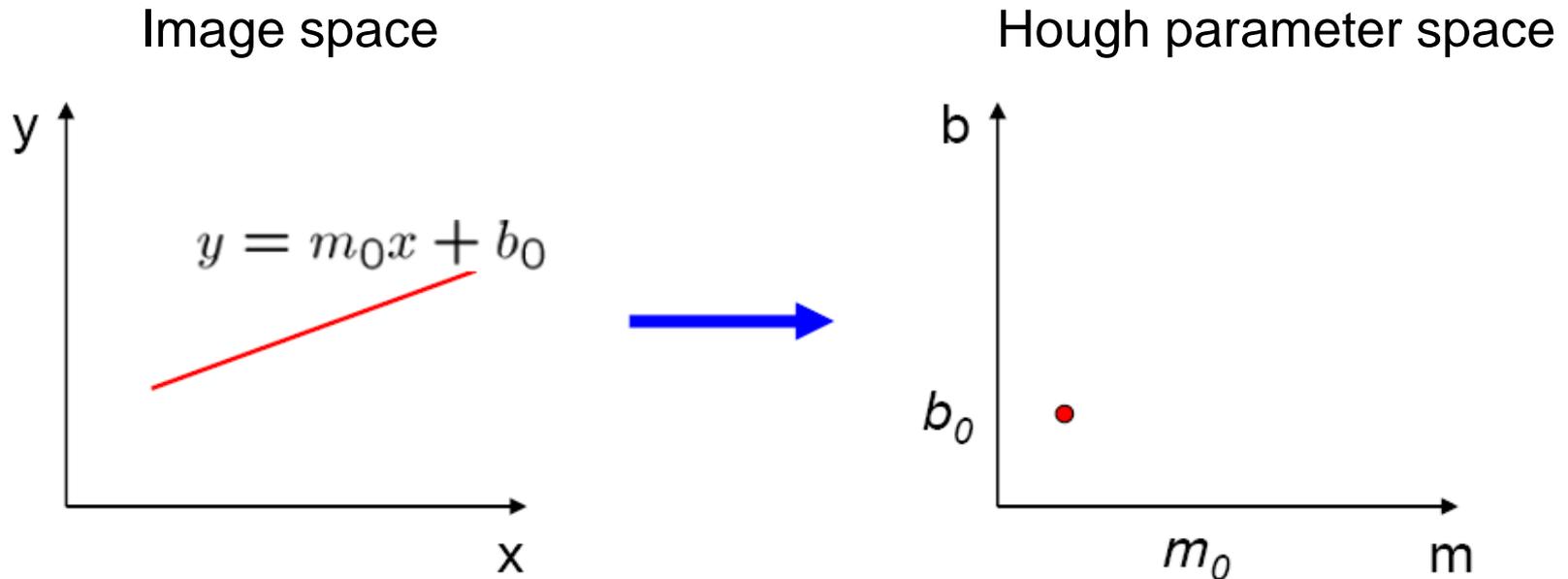


Hough parameter space

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

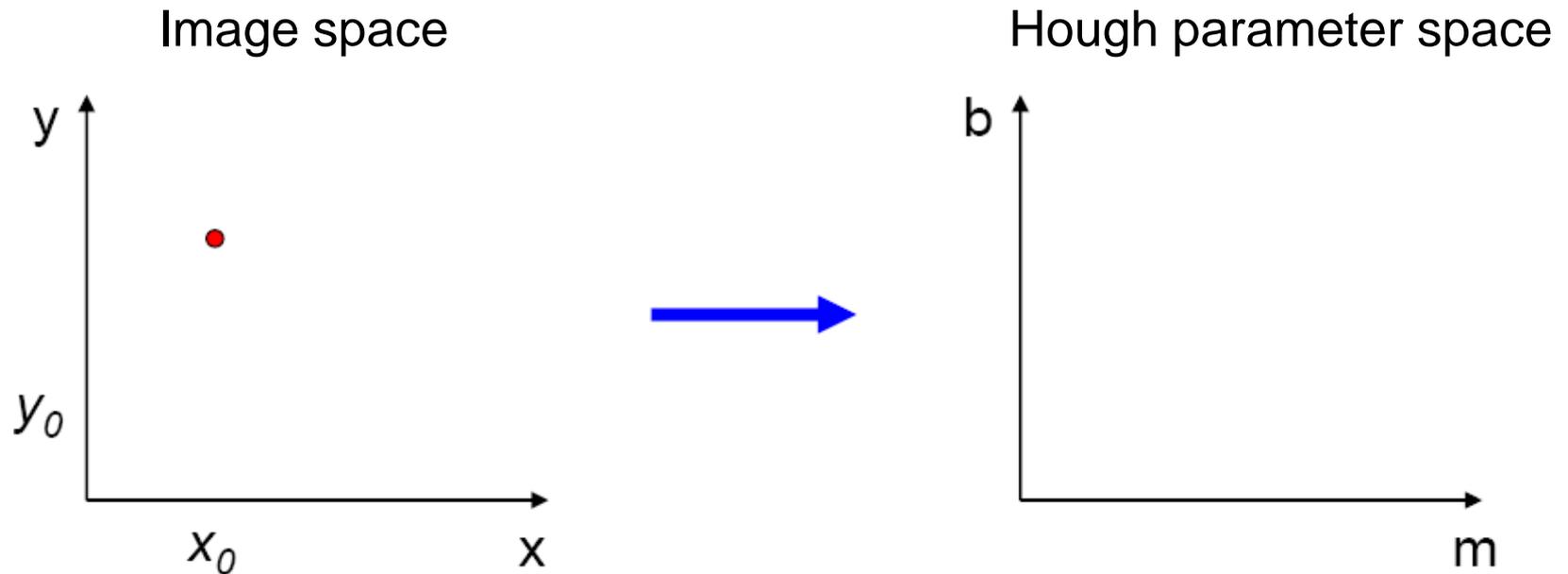
Parameter space representation

- A line in the image corresponds to a point in Hough space



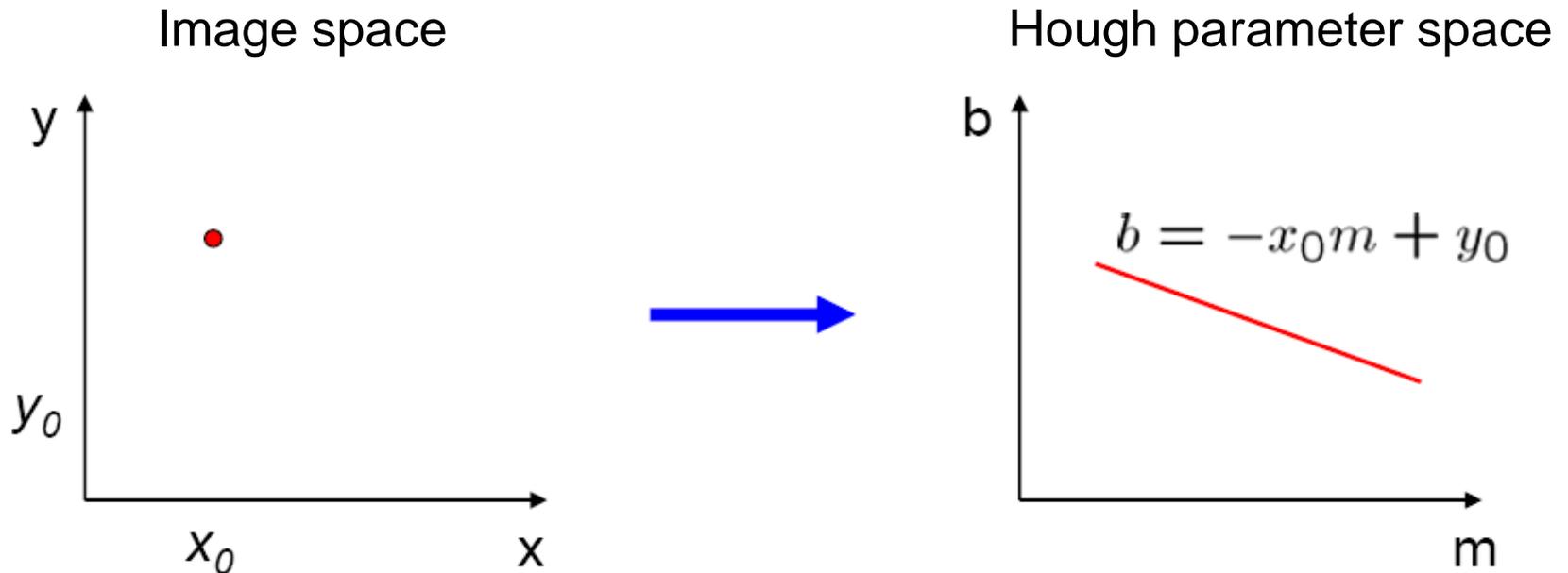
Parameter space representation

- What does a point (x_0, y_0) in the image space map to in the Hough space?



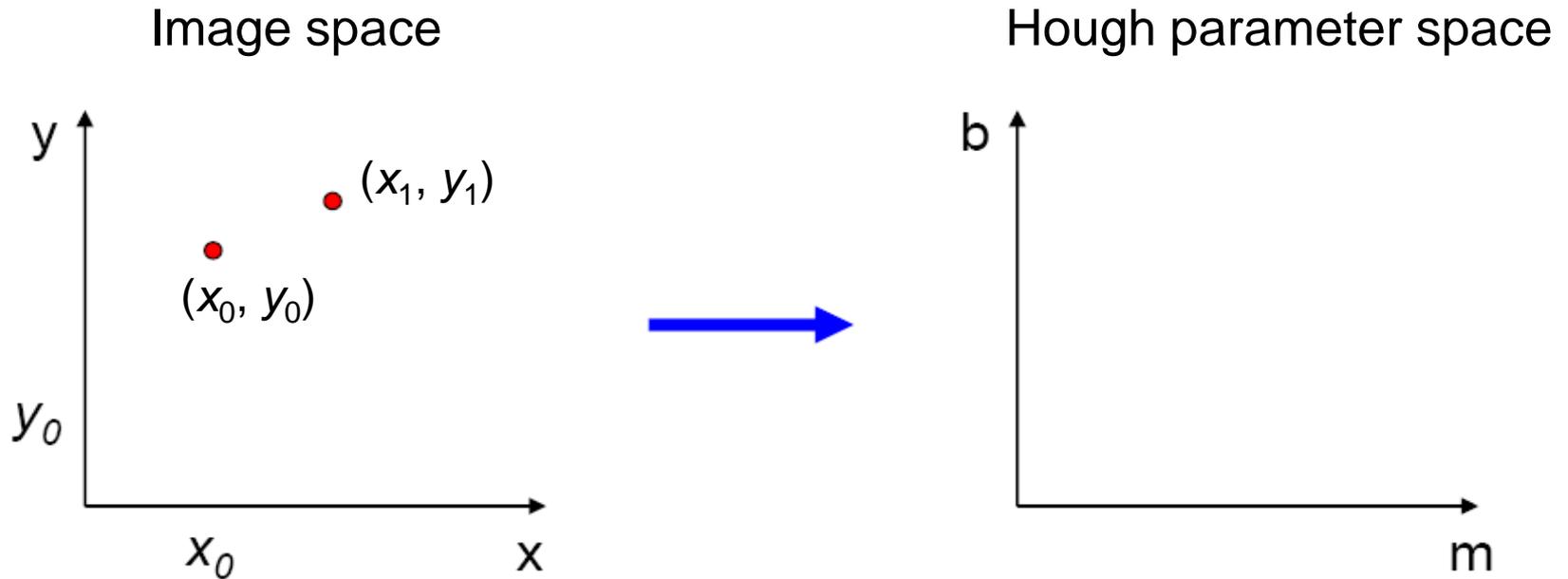
Parameter space representation

- What does a point (x_0, y_0) in the image space map to in the Hough space?
 - Answer: the solutions of $b = -x_0m + y_0$
 - This is a line in Hough space



Parameter space representation

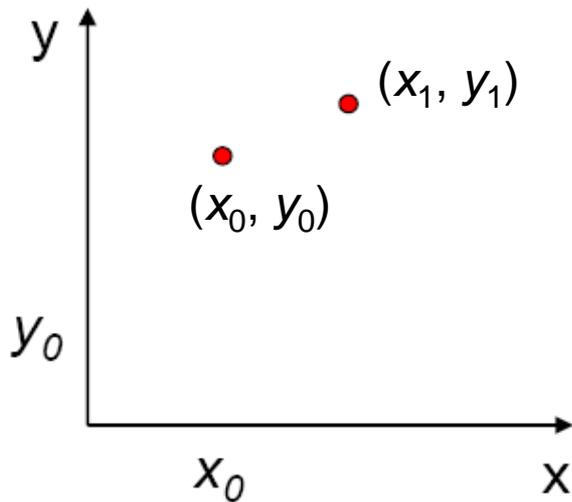
- Where is the line that contains both (x_0, y_0) and (x_1, y_1) ?



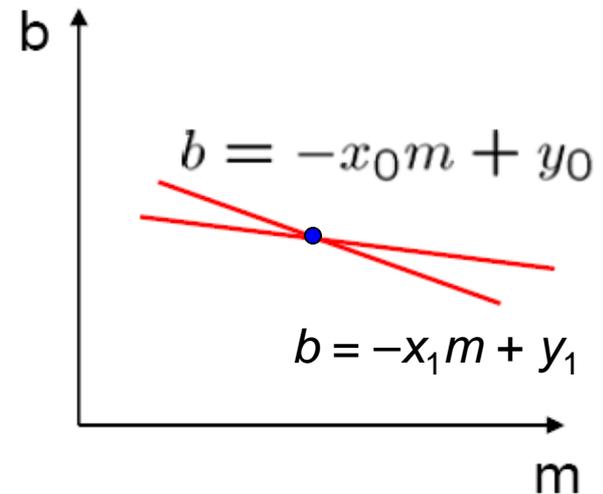
Parameter space representation

- Where is the line that contains both (x_0, y_0) and (x_1, y_1) ?
 - It is the intersection of the lines $b = -x_0m + y_0$ and $b = -x_1m + y_1$

Image space



Hough parameter space

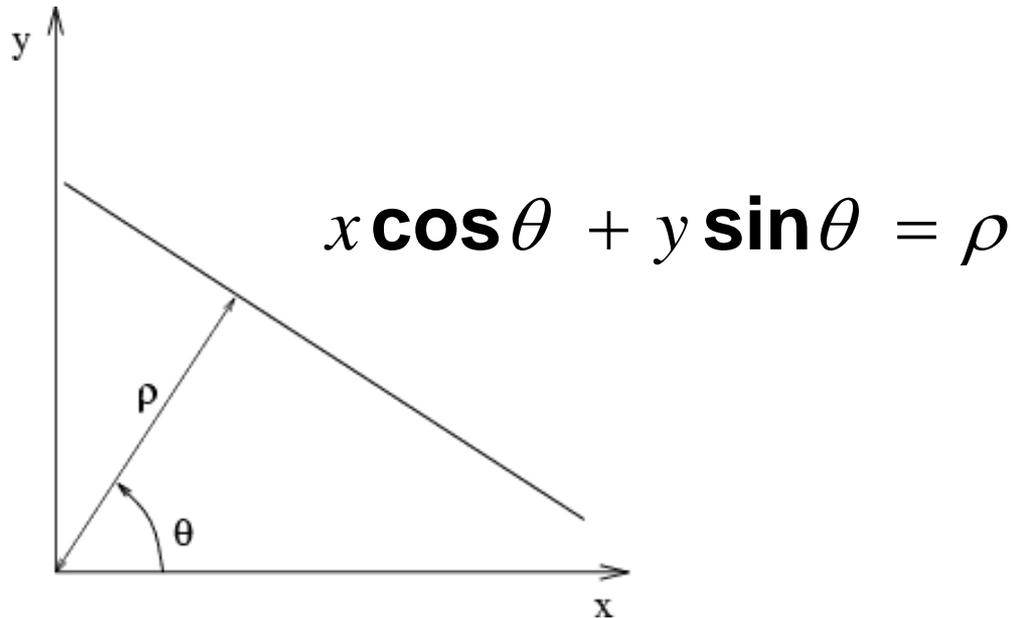


Parameter space representation

- Problems with the (m,b) space:
 - Unbounded parameter domains
 - Vertical lines require infinite m

Parameter space representation

- Problems with the (m,b) space:
 - Unbounded parameter domains
 - Vertical lines require infinite m
- Alternative: *polar representation*



Each point (x,y) will add a sinusoid in the (θ,ρ) parameter space

Properties of polar representation

See handwritten notes G. Gerig

Web-based demonstrations:

- Duality of image space and parameter space: Interactive demo: <http://users.cs.cf.ac.uk/Paul.Rosin/CM3102/LABS/dual2/hough.html>
- Similar to above: <http://www.dis.uniroma1.it/~iocchi/slides/icra2001/java/hough.html>
- Select among images, then show results: http://users.ecs.soton.ac.uk/msn/book/new_demo/hough/
- Load own images, then run: <http://peaks.informatik.uni-erlangen.de/peaks/cv/Hough.html>

Algorithm outline

- Initialize accumulator H to all zeros
- For each feature point (x,y) in the image

For $\theta = 0$ to 180

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

$$H(\theta, \rho) = H(\theta, \rho) + 1$$

end

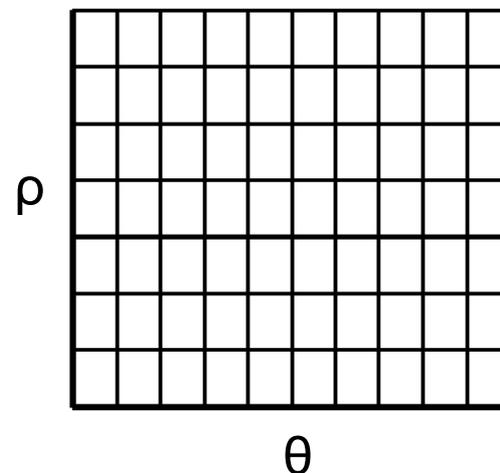
end

- Find the value(s) of (θ, ρ) where $H(\theta, \rho)$ is a local maximum

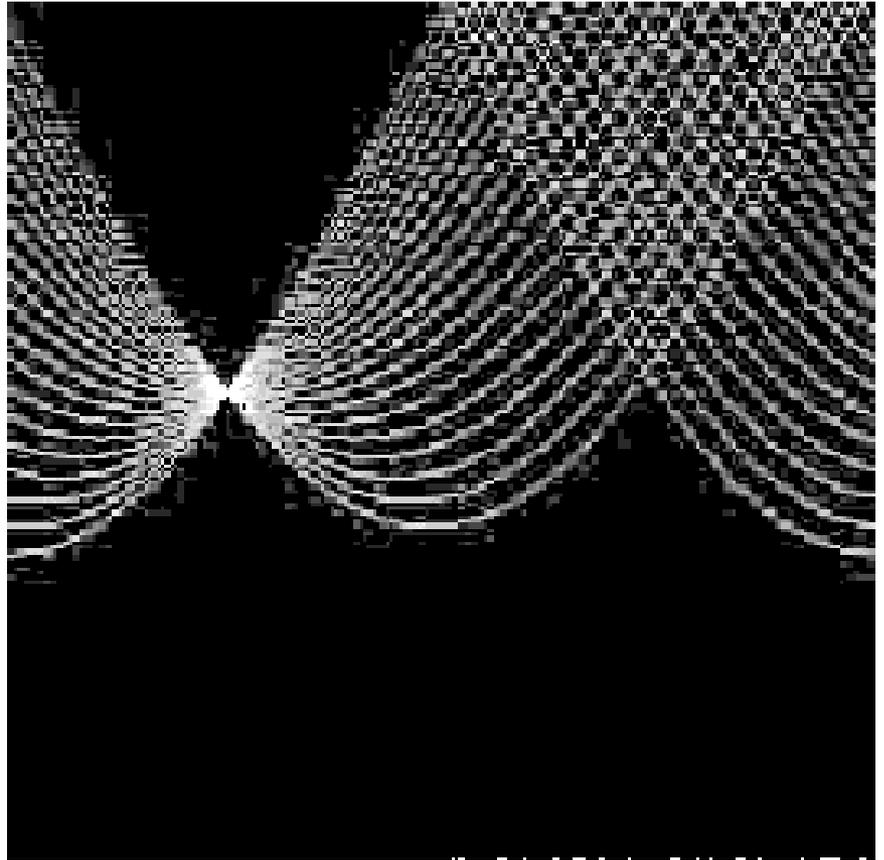
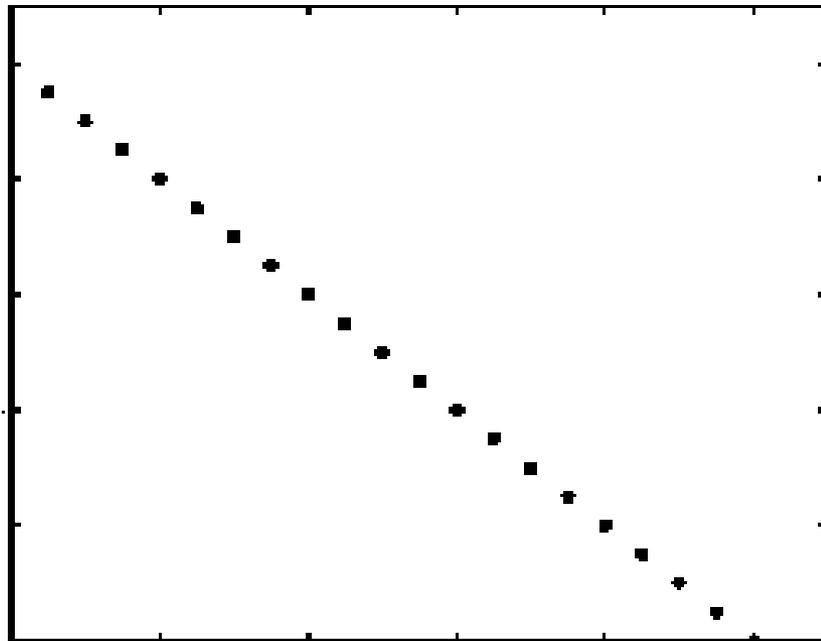
- The detected line in the image is given by

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

H: accumulator array (votes)

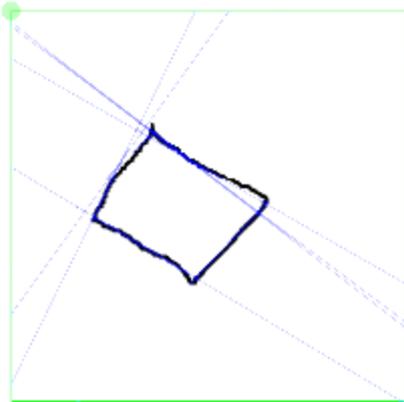


Basic illustration

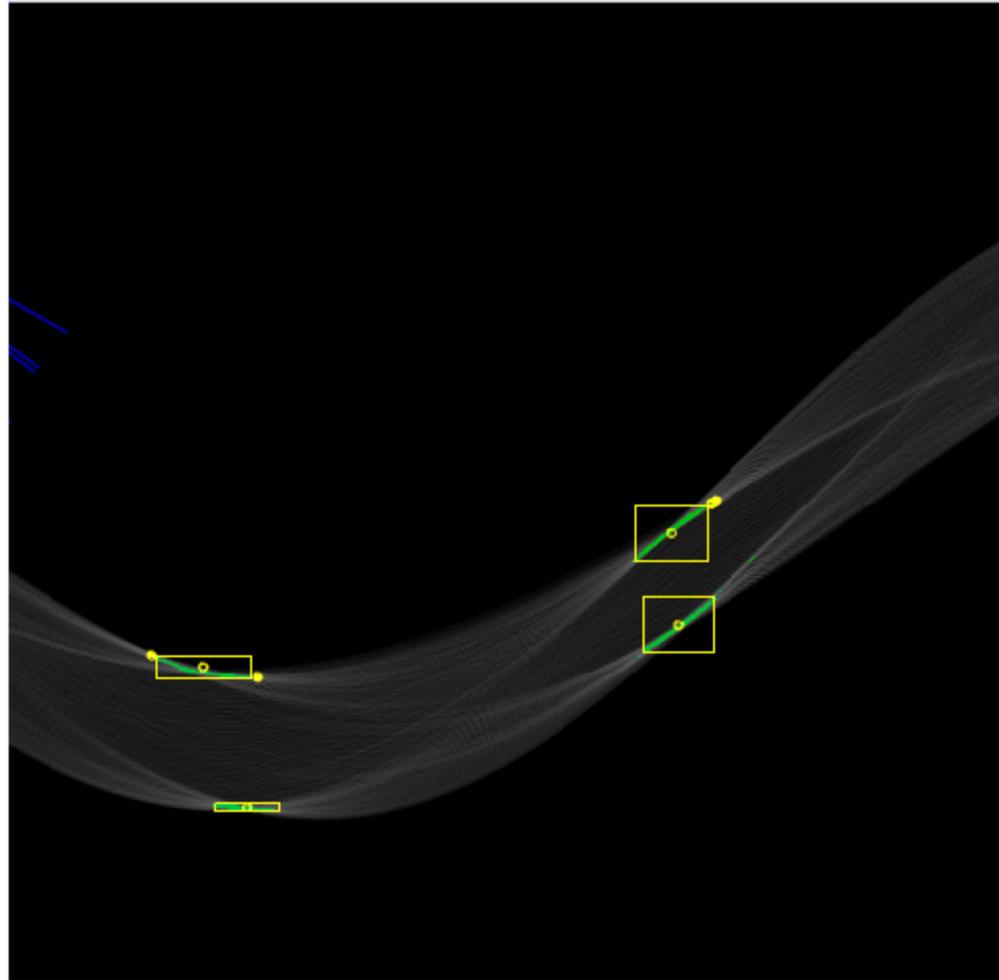


Detection of Clusters

Draw Run



```
0
0
500
Thres: 30
0 2 (x=355, y=254, w=2, h=1)
1 6 (x=352, y=255, w=3, h=2)
2 1036 (x=315, y=257, w=37, h=28)
3 1008 (x=319, y=304, w=36, h=28)
4 2 (x=71, y=333, w=2, h=1)
5 528 (x=74, y=334, w=48, h=11)
6 3 (x=124, y=344, w=3, h=1)
7 128 (x=104, y=409, w=32, h=4)
Blobs: 8
```

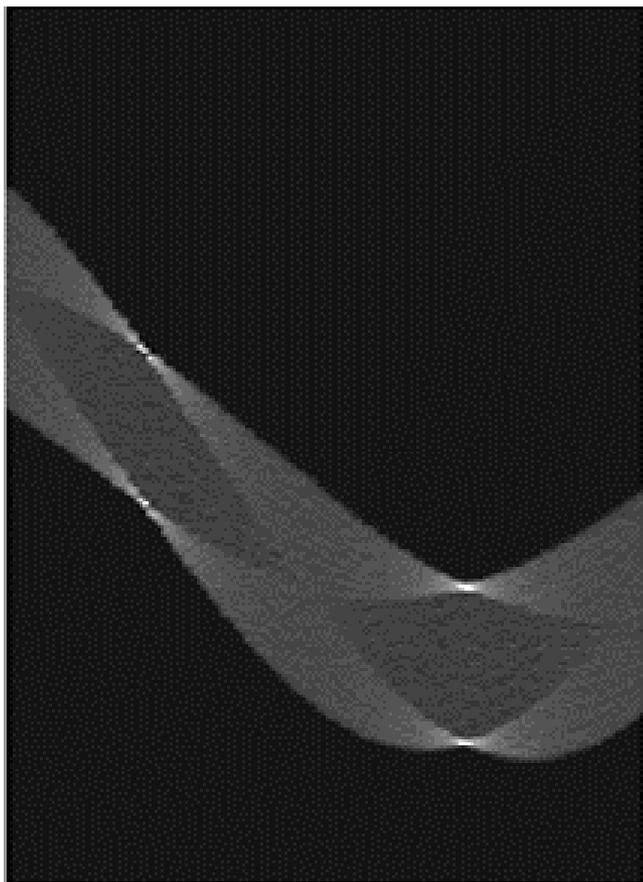


Hough transform demo:

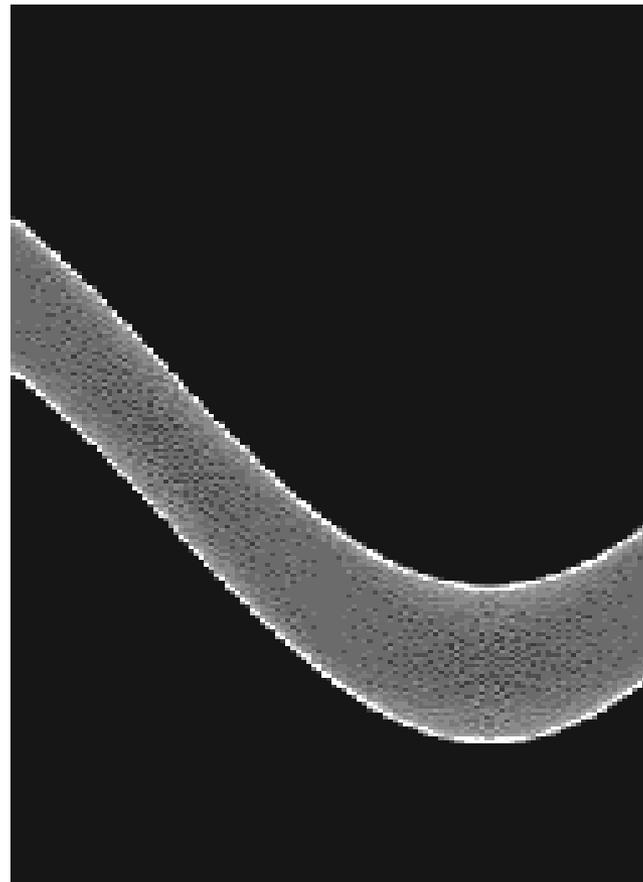
<http://liquify.eu/swf/HoughTransform.swf>

Other shapes

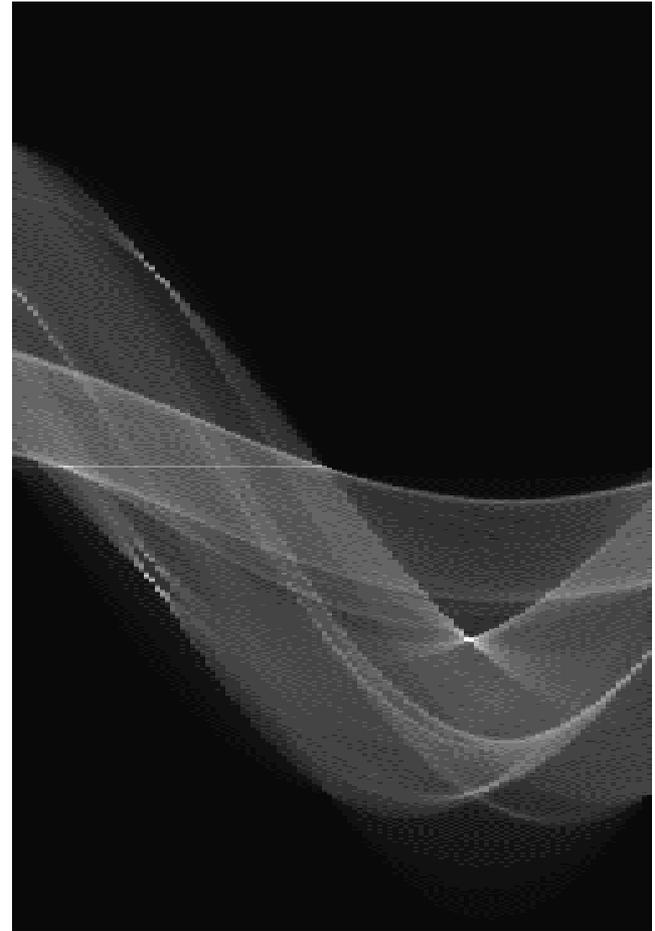
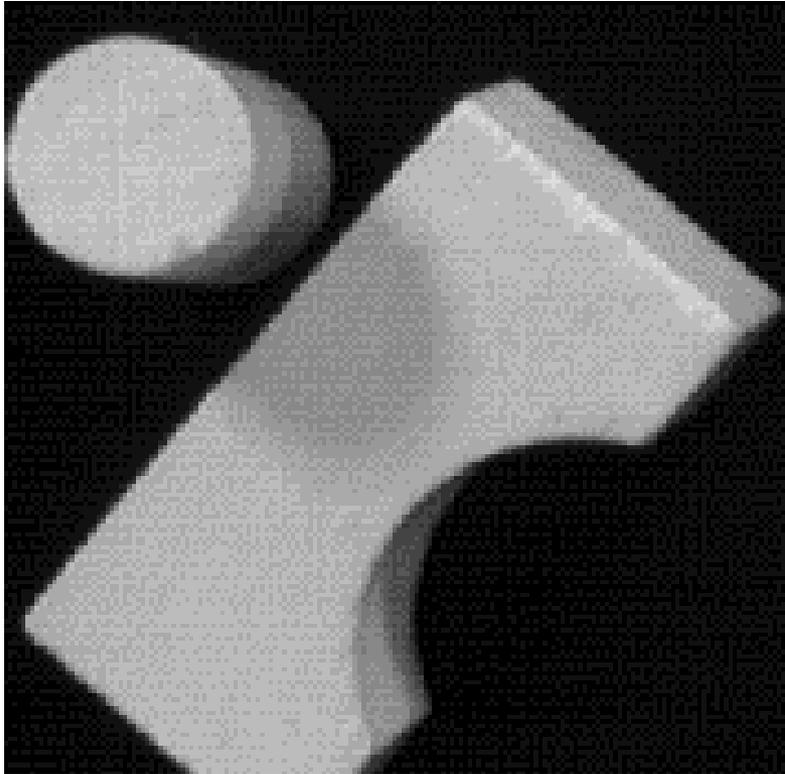
Square



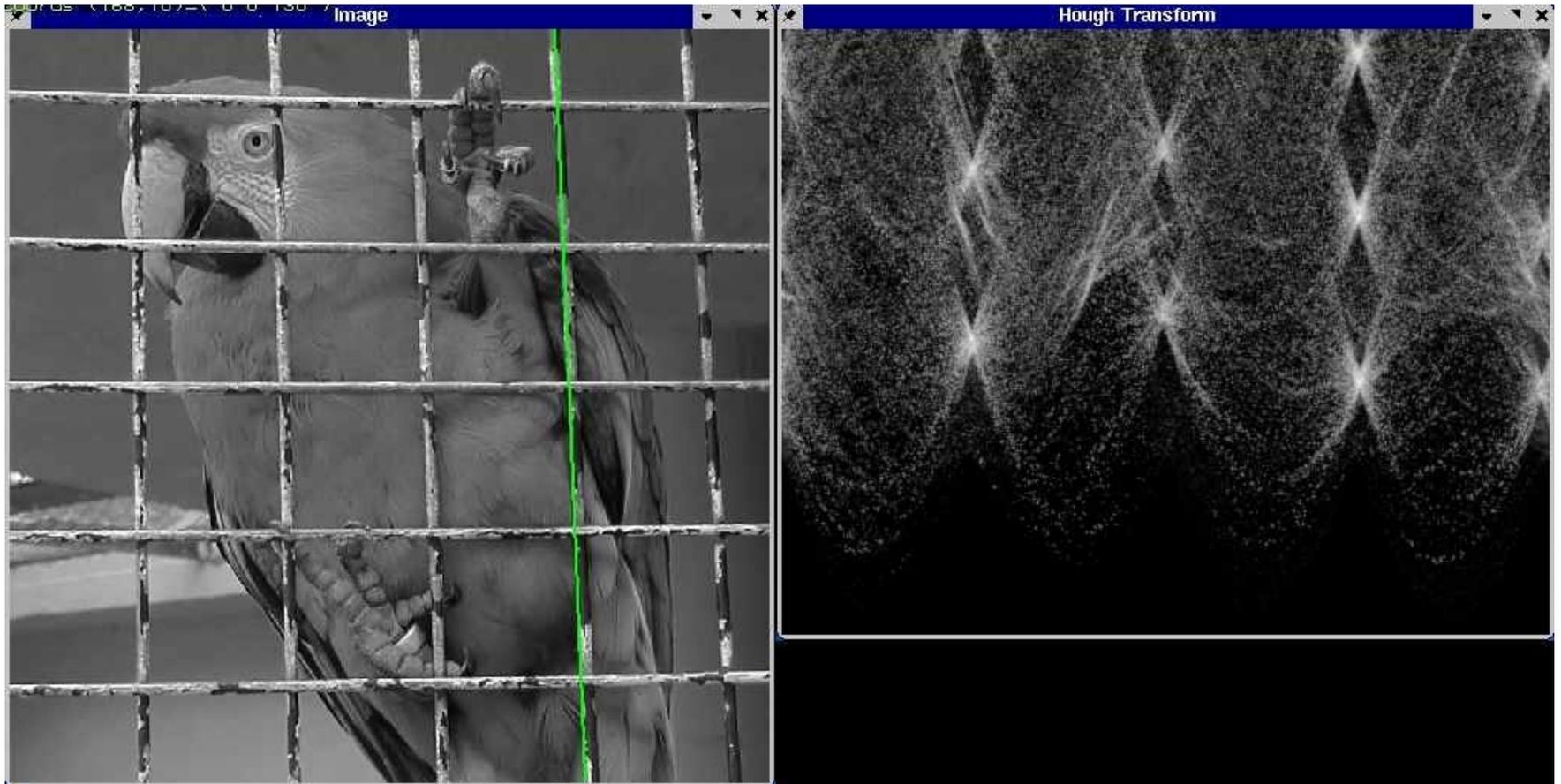
Circle



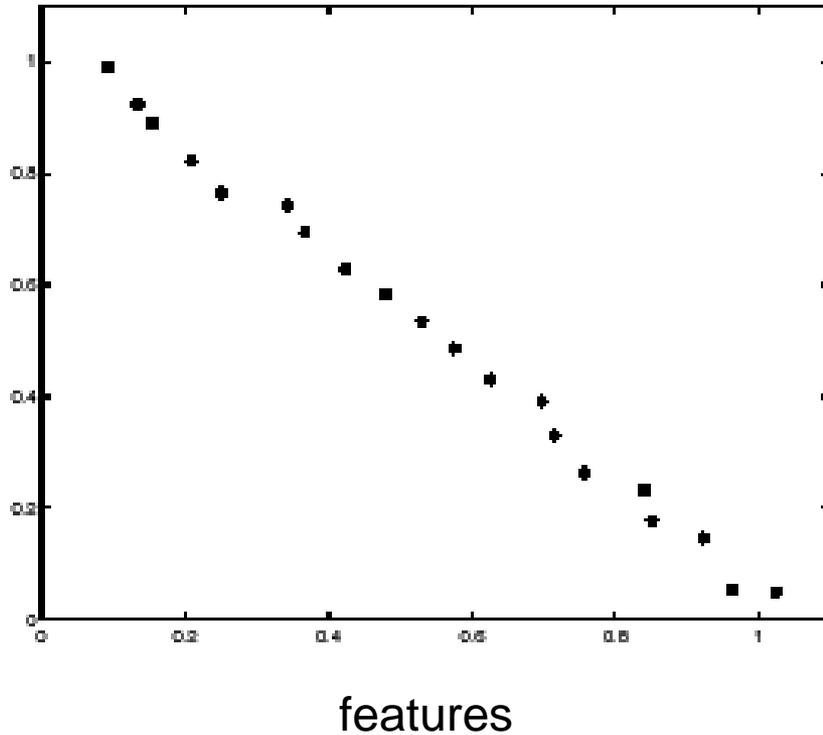
Several lines



A more complicated image



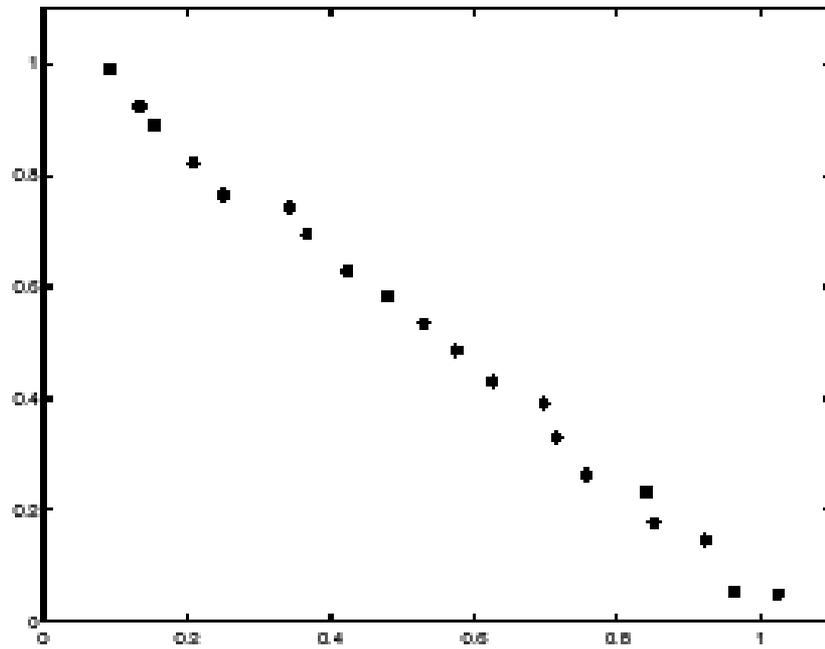
Effect of noise



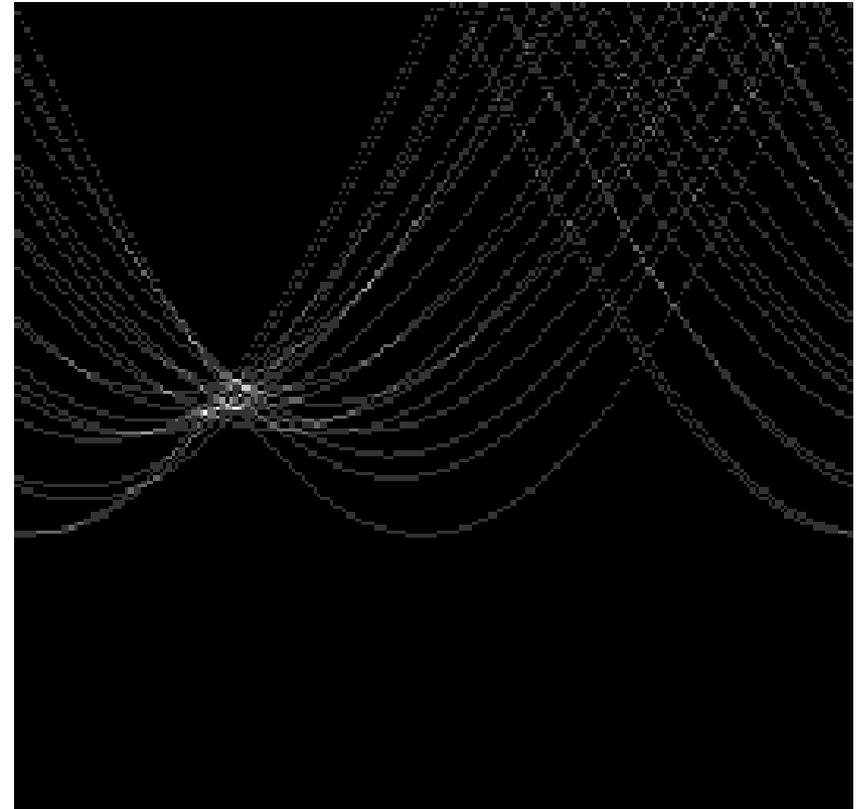
Show with demo:

<http://liquify.eu/swf/HoughTransform.swf>

Effect of noise



features

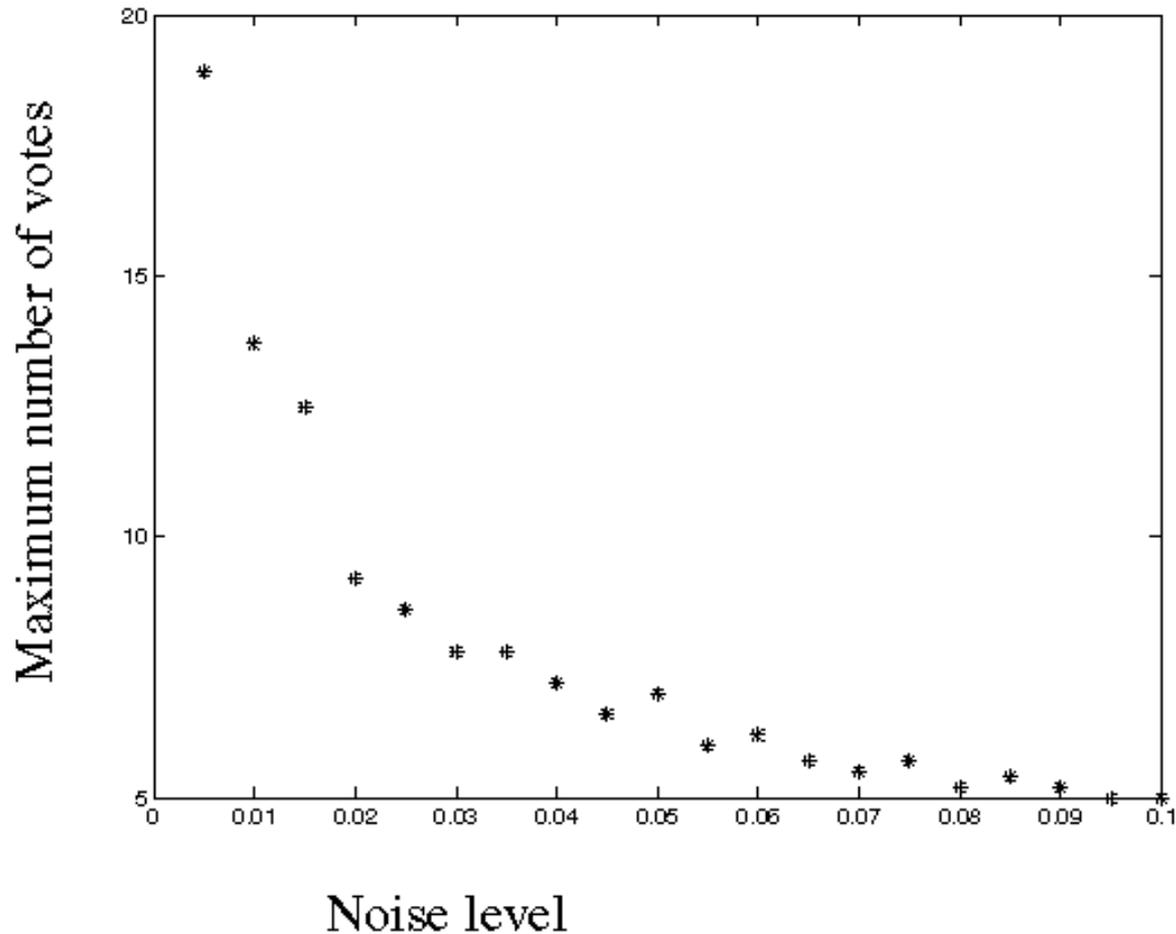


votes

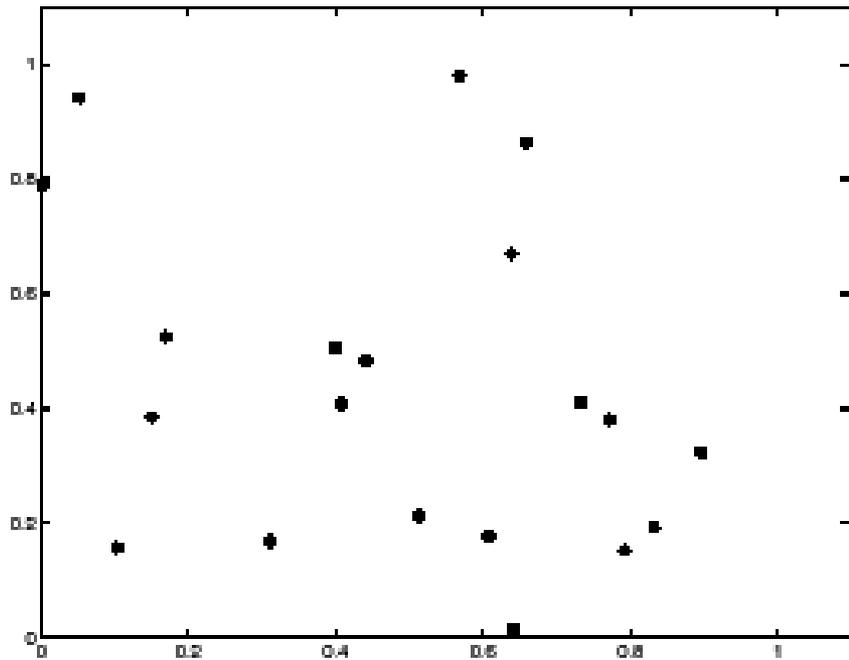
Peak gets fuzzy and hard to locate

Effect of noise

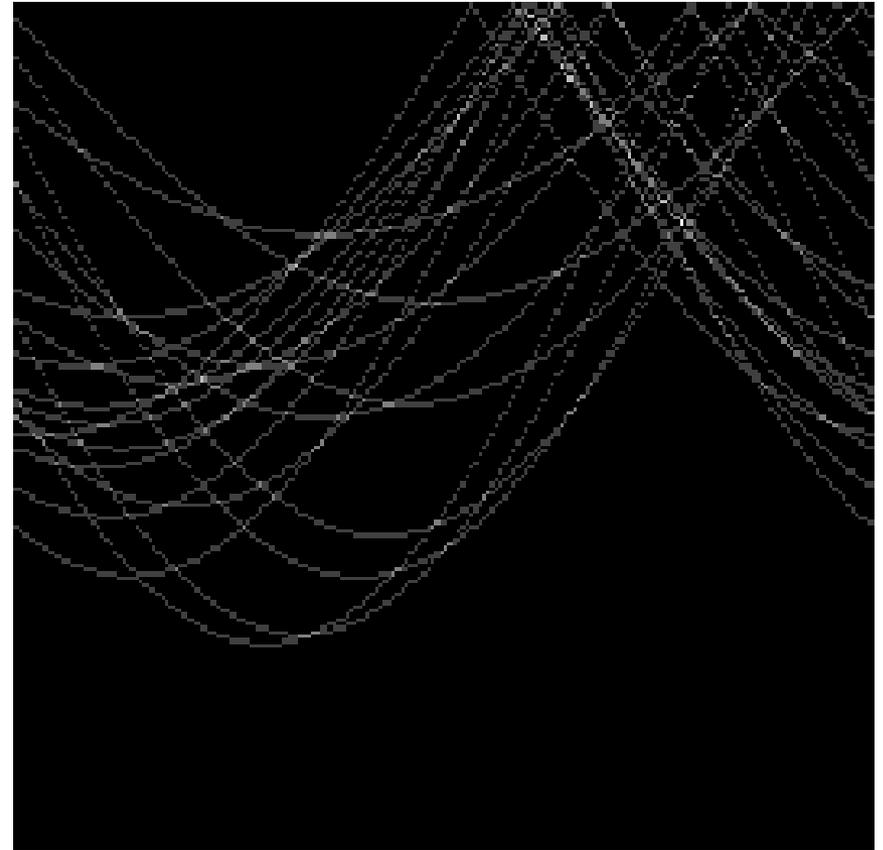
- Number of votes for a line of 20 points with increasing noise:



Random points



features

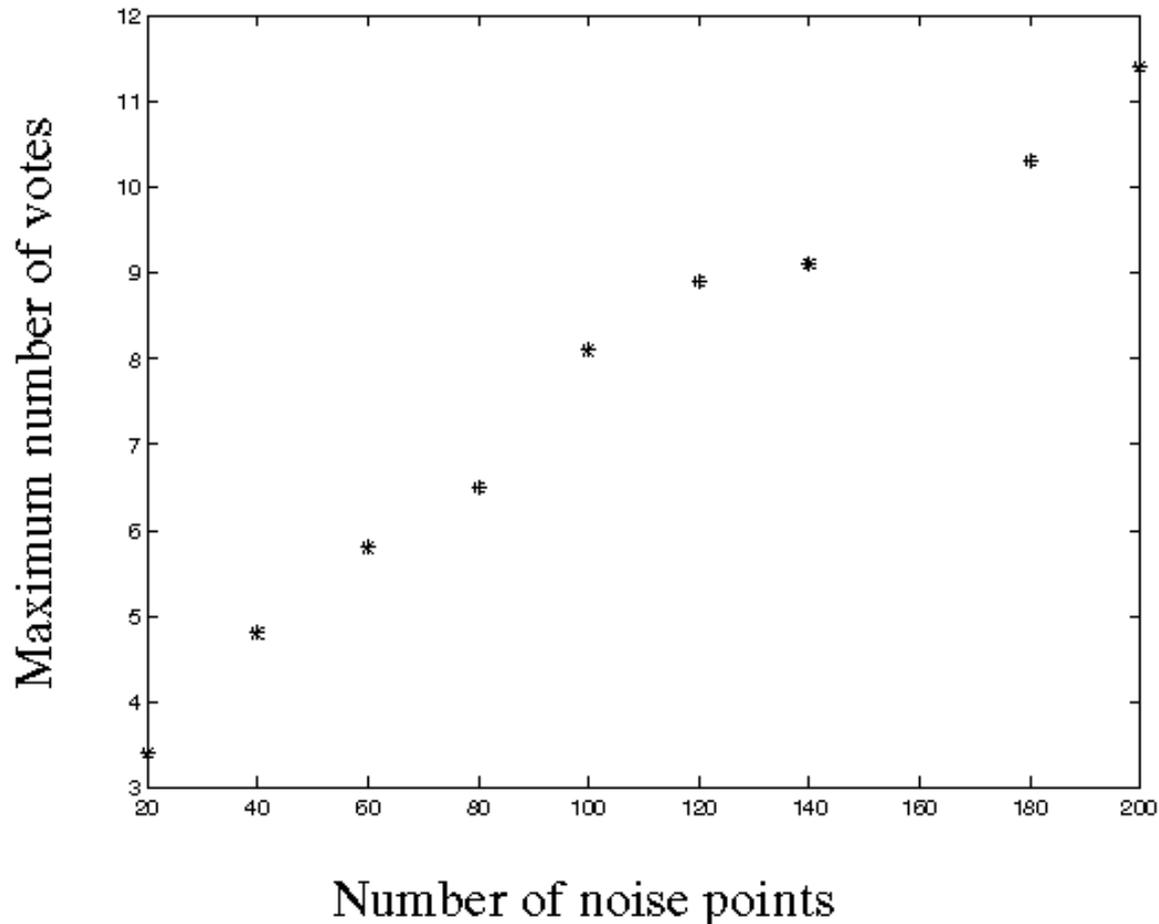


votes

Uniform noise can lead to spurious peaks in the array

Random points

- As the level of uniform noise increases, the maximum number of votes increases too:

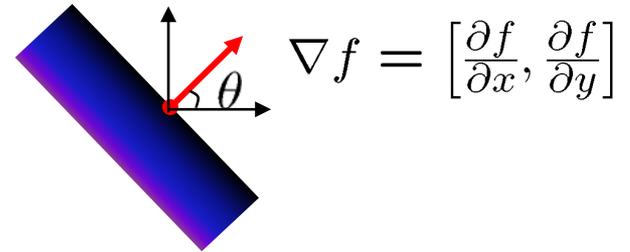


Dealing with noise

- Choose a good grid / discretization
 - **Too coarse:** large votes obtained when too many different lines correspond to a single bucket
 - **Too fine:** miss lines because some points that are not exactly collinear cast votes for different buckets
 - Show discretization with following demo:
<http://www.dis.uniroma1.it/~iocchi/slides/icra2001/java/hough.html>
- Increment neighboring bins (smoothing in accumulator array)
- Try to get rid of irrelevant features
 - E.g., take only edge points with significant gradient magnitude

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!
- Modified Hough transform:



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

For each edge point (x,y)

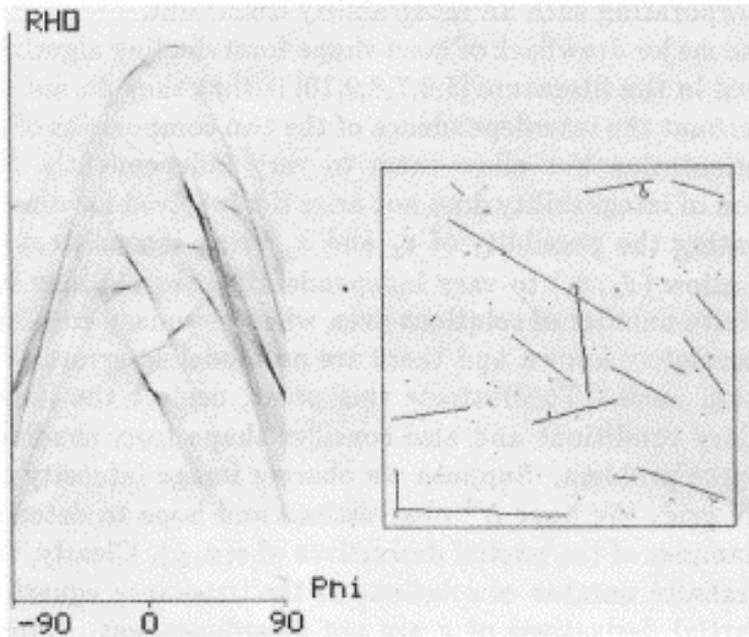
θ = gradient orientation at (x,y)

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

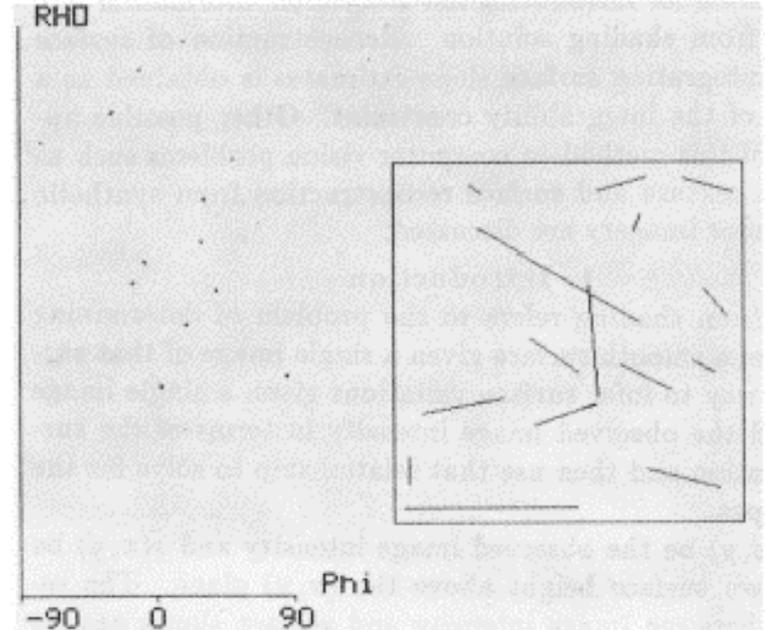
$H(\theta, \rho) = H(\theta, \rho) + 1$

end

Comparison with/without edge orientation



Full parameter space



Using edge orientation

Challenge: Presence of noise creates scattering around expected strong peaks.

Solution: Accumulate subregions rather than points.

Hough transform for circles

- How many dimensions will the parameter space have?
- Given an unoriented edge point, what are all possible bins that it can vote for?
- What about an *oriented* edge point?