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Edges Detection
Lines Detection

Summary

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- Edge detection
  - What is an edge?
    - Are they important?
  - Canny Edge Detector
- Lines
  - Hough Transform
  - Generalized Hough Transform

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Edges Detection

Edge filtering

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- Q: What is an edge? A: A discontinuity in intensity!

Edge detection

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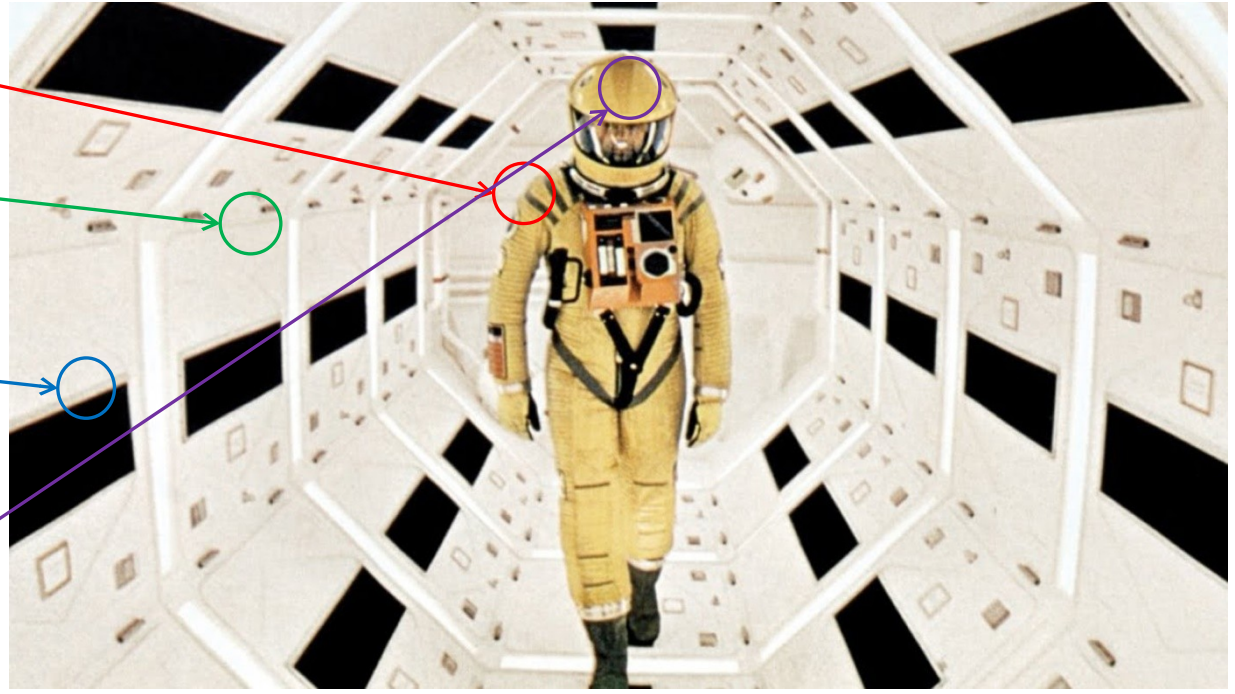
- Q: From where intensity discontinuities (aka edges) come from?

Depth differences

Orientations of surfaces

Properties of surfaces

Different illuminations (i.e. shadows or lights)



Types of edges

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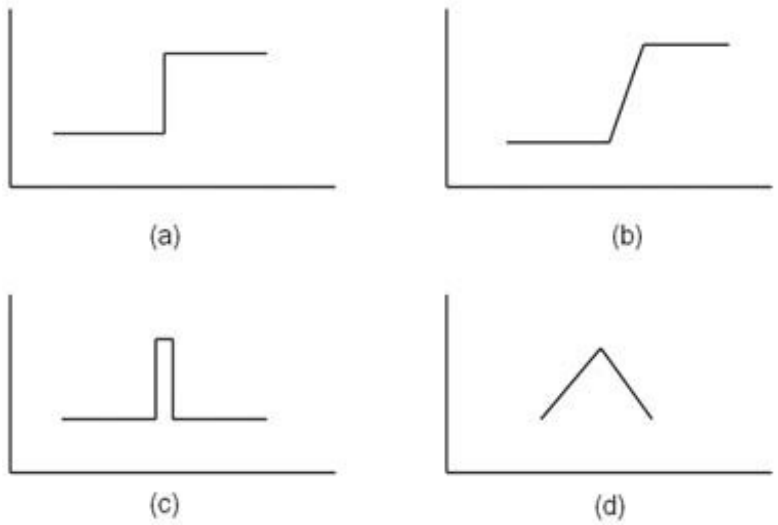
(a) Step edge: abrupt change of intensity

(b) Ramp edge: smooth change

(c) Ridge/line edge: abrupt change followed by a return to starting value

(d) Roof edge: a ridge edge with a smoother change



Edge Importance

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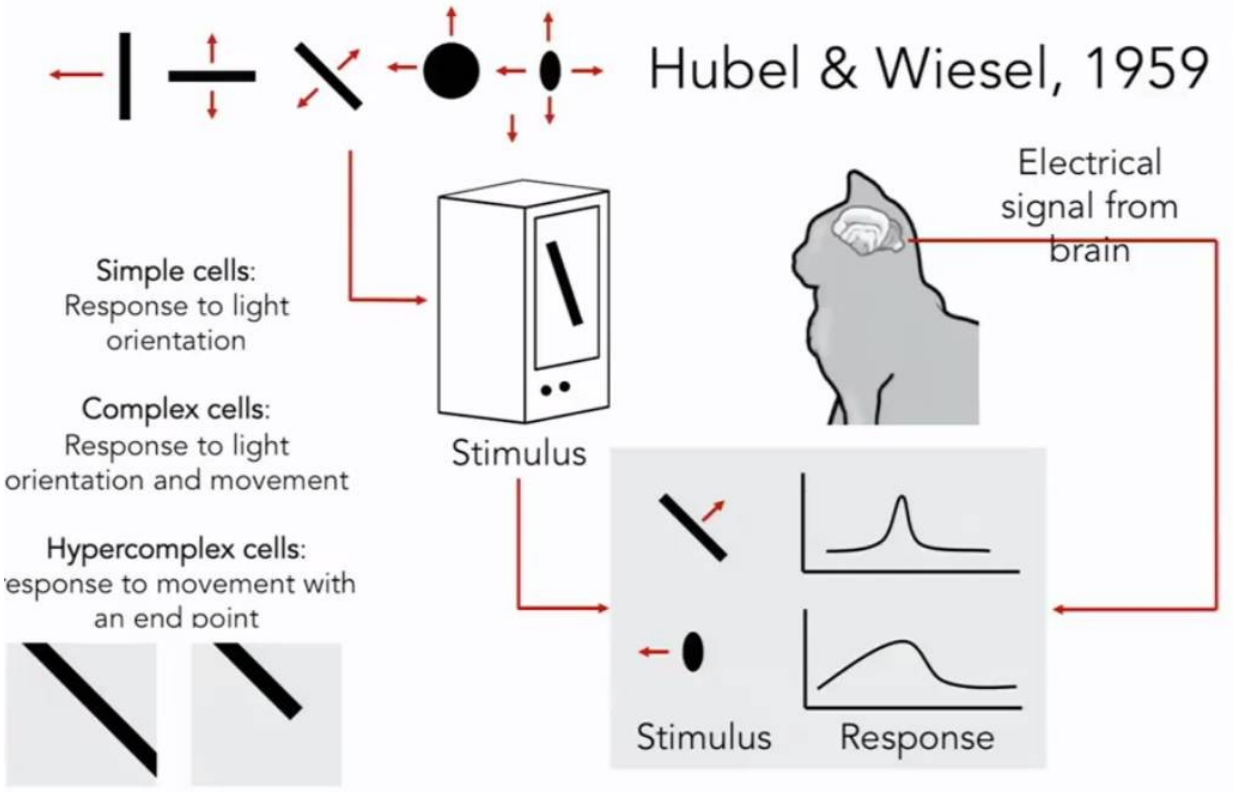
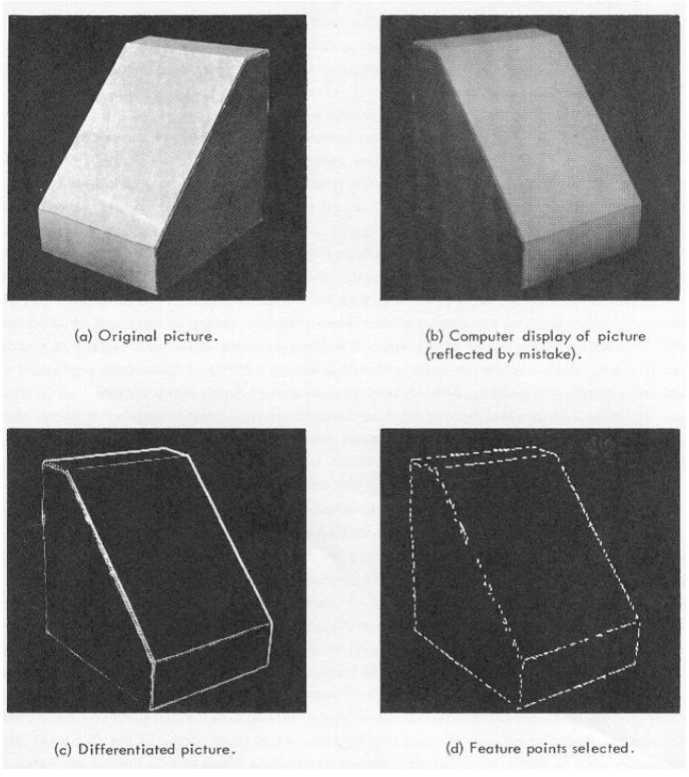
- Why edges are important?



3D from edges

- Why edges are important?



Larry Roberts, 1963

Edge Detection

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- Edges can help:
  - Extract information
  - Detect objects
  - Detect object shapes

Simple Edge Detection

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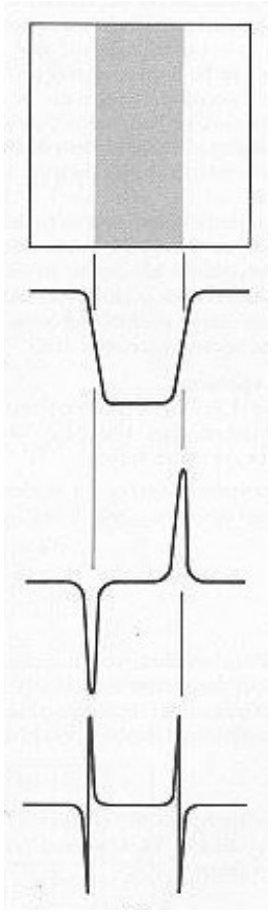
- Already (partially) discussed
- Small recap:
  - Smoothing ⟶ to reduce noise
  - Derivative Horizontal & Vertical filtering ⟶ extract gradient

Gradient



Image

Horizontal Intensity

First derivattive

Second derivattive

Edges are the maximum/minimum in first derivative

Edges corresponds to 0 crossings in second derivative

How we can compute gradient?

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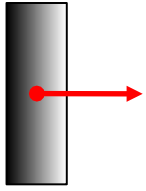
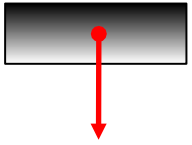
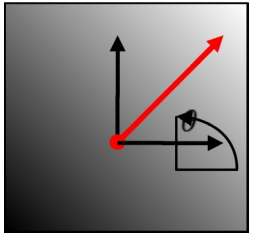
- Gradient of image:



$$\nabla f = \left[\frac{\partial f}{\partial x}, 0\right]$$



$$\nabla f = \left[0, \frac{\partial f}{\partial y}\right]$$



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

- Gradient is a vector:
  - Magnitude/Intensity
  - Direction

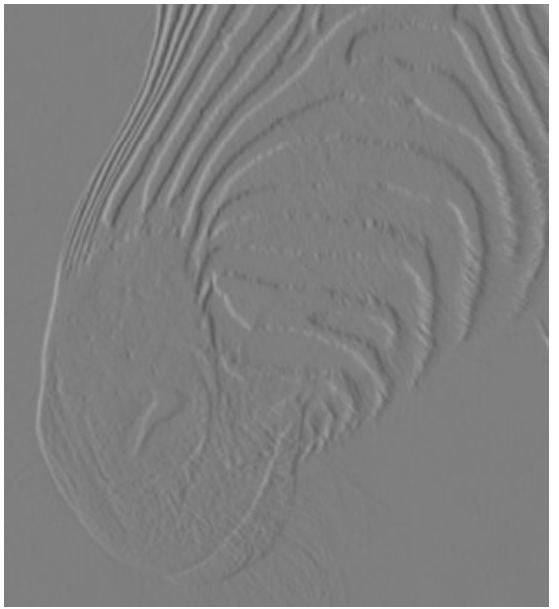
$$\|\nabla f\| = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$$

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

Example

f

$\frac{\partial f}{\partial y}$



$\frac{\partial f}{\partial x}$

Forsyth & Ponce – *Computer Vision A Modern Approach*

Gradient and Noise

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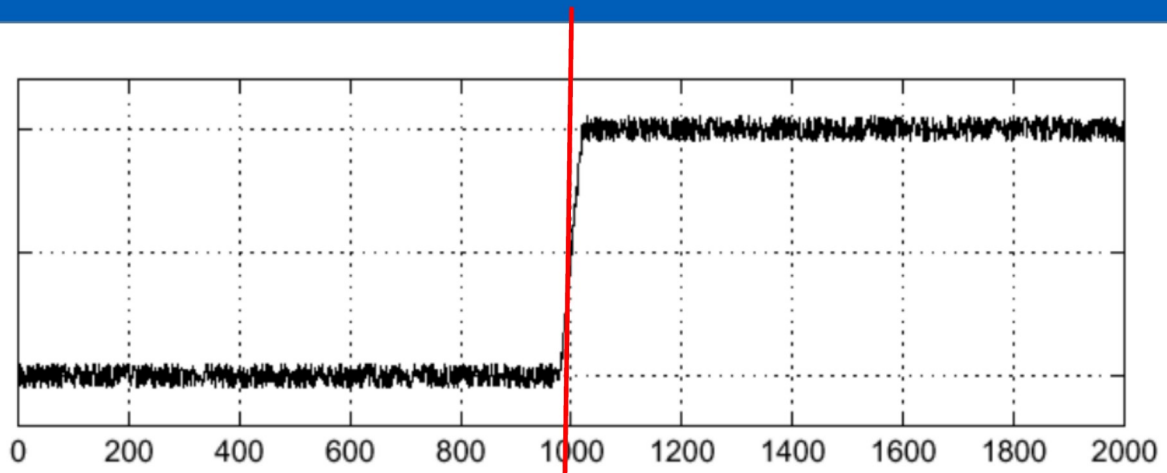
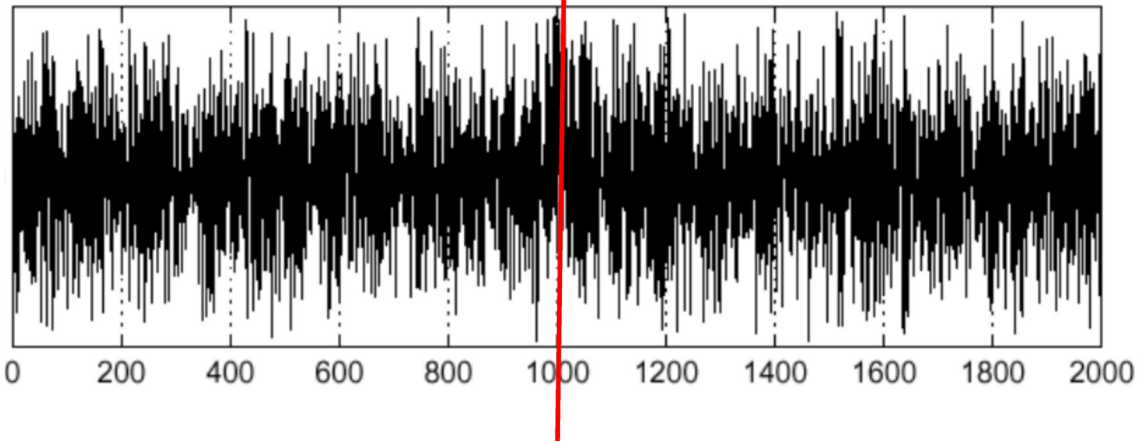
$f(x)$

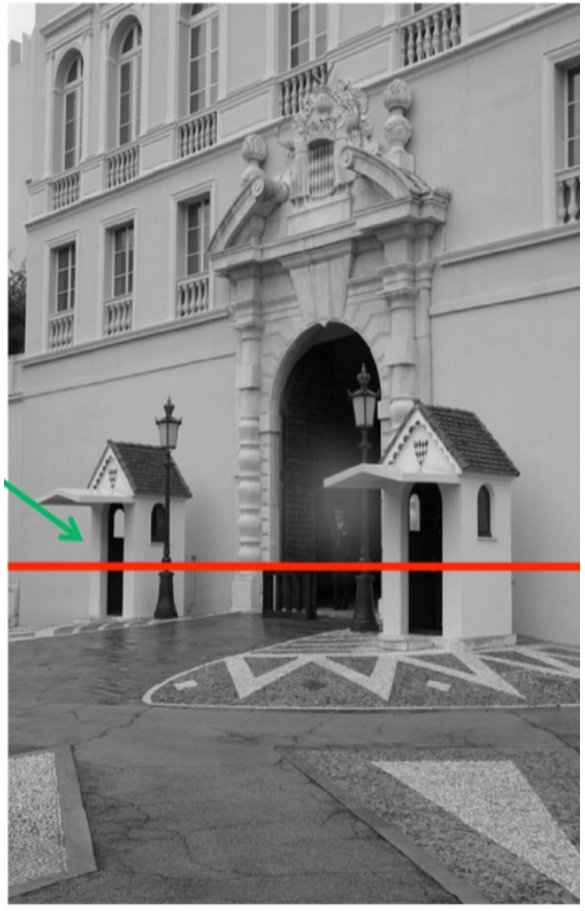


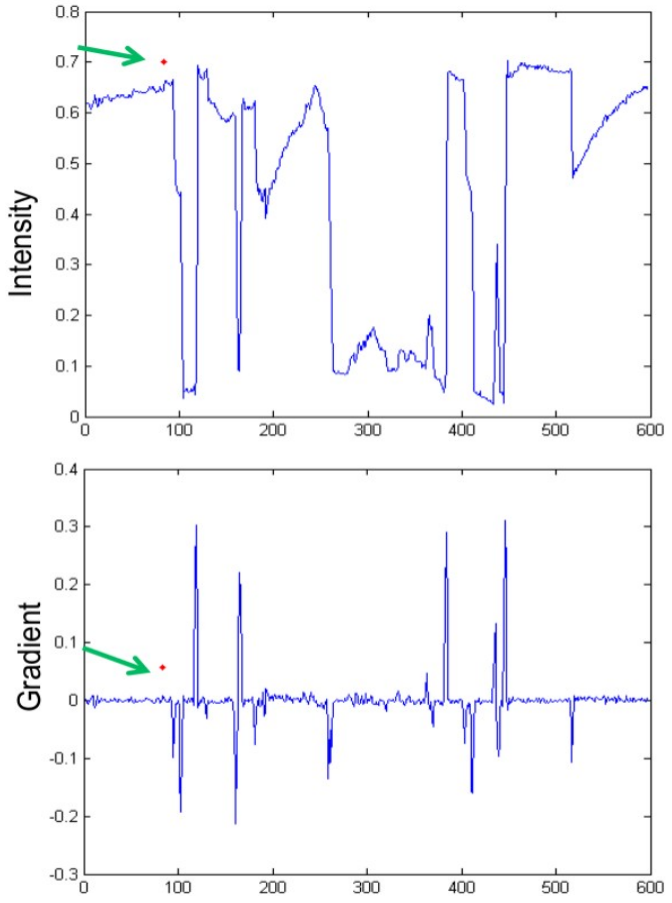
$\frac{d}{dx} f(x)$



From: S. Seitz

Gradient in real images





We have large peaks but also some noise

From: Fei Fei Li

Noise effect

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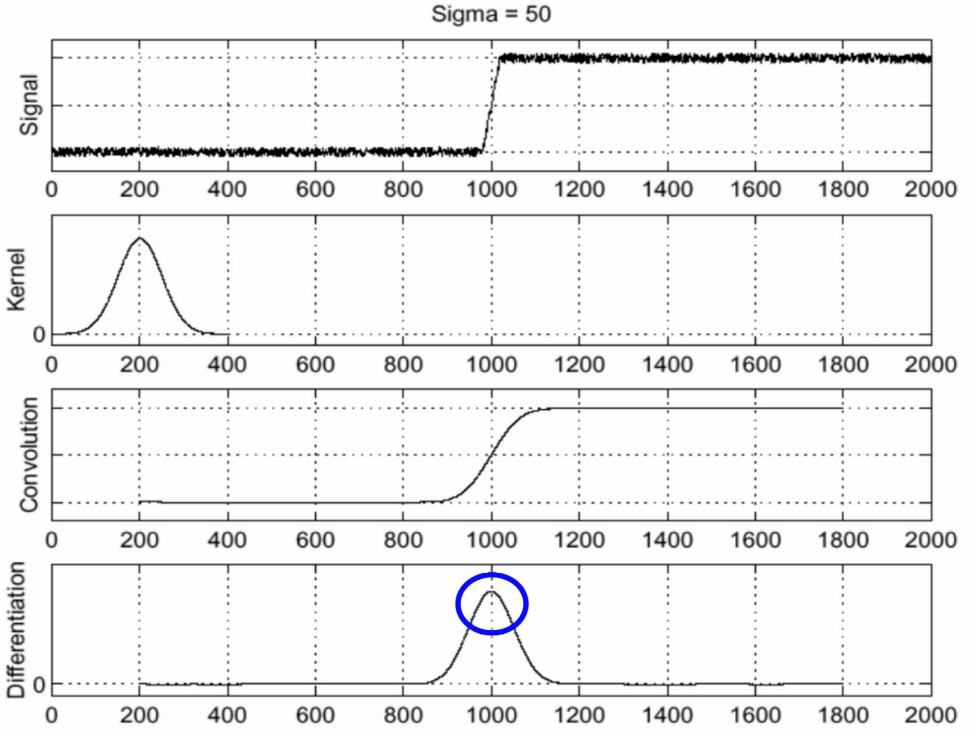
- Derivative filter have a great sensitivity to noise
  - Noise $\longrightarrow$ uniform areas are not so uniform
  - Pixels can be very different wrt neighboors
- Smoothing filtering allows to reduce noise effects

Smoothing & Derivative filtering



f

g

$f * g$

$\frac{d}{dx}(f * g)$

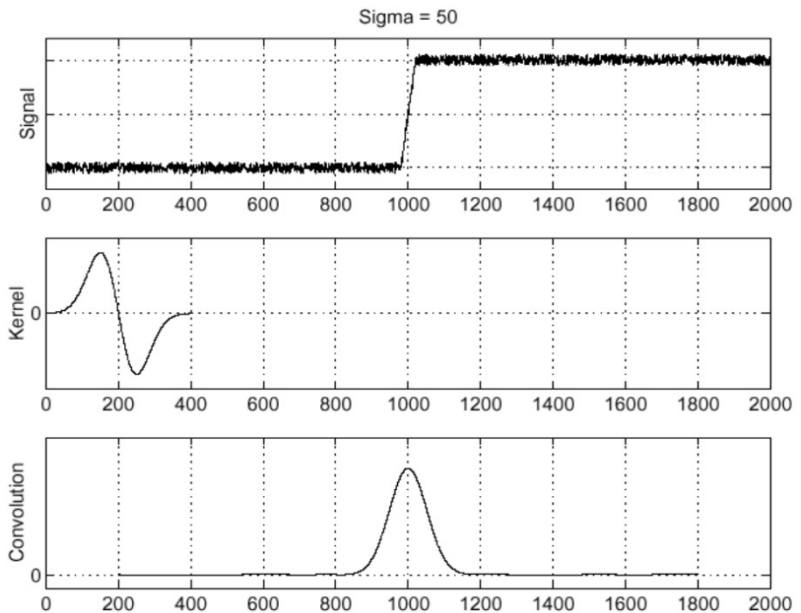
Edges correspond to peaks in derivative of f and g convolution

From: S. Seitz

Convolution properties

- Convolution is an associative operation
- We can optimize

$$\frac{\partial}{\partial x}(f * g) = f * \frac{\partial}{\partial x} g$$



f

$\frac{d}{dx} g$

$f * \frac{d}{dx} g$

From: S. Seitz

Tradeoff

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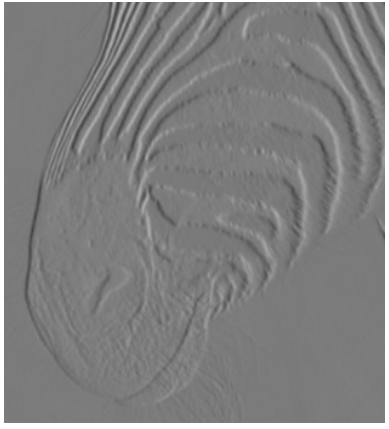
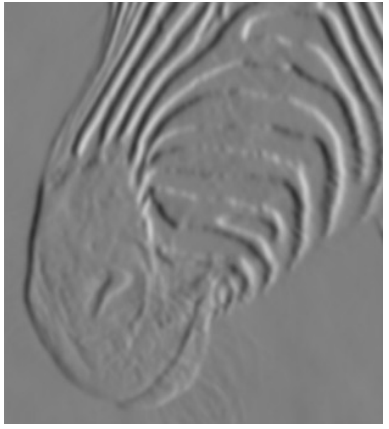
- Between smoothing and localization

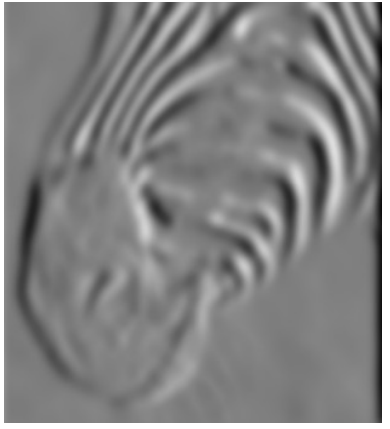
Input image



$\sigma = 1px$



$\sigma = 3px$



$\sigma = 7px$

From: Forsyth & Ponce – *Computer Vision A Modern Approach*

Sobel Edge Detector

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- Composition of a derivative operator and an averaging one
- Anyway a little rough for high frequency variations

-1	-2	-1
0	0	0
1	2	1

$$\begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix} * \begin{bmatrix} 1 & 2 & 1 \end{bmatrix}$$

-1	0	1
-2	0	2
-1	0	1

$$\begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} * \begin{bmatrix} -1 & 0 & 1 \end{bmatrix}$$

Sobel Edge Detector: threshold

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- Sobel operator allows to compute the gradient
  - Not actual edges
- We need a threshold

Sobel Edge Detector: edge thickness

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- Each edge is “fat”

Canny Edge Detector

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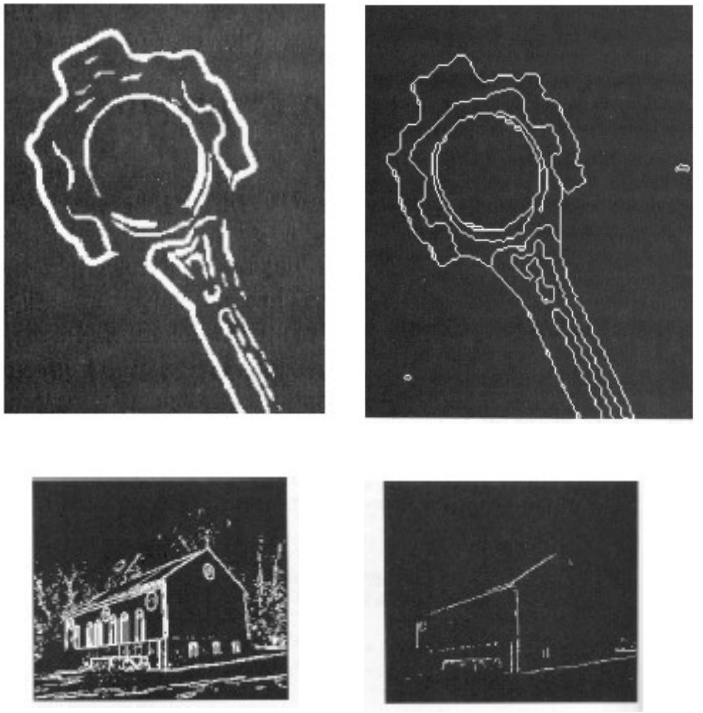
- Sobel is a quick&dirt solution with some issue:
  - Threshold
  - Fat edges
- There is a better approach?
- Yes ⟶ Canny Edge Detector
  - Gradient
  - Thinning
  - Thresholding



Canny Edge Detector

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- Widely used
  - It performs very well!
- Criteria
  - Accuracy: reduce false positives (also negatives)
  - Localization: detected edges should match real edges as much as possible
  - Uniqueness: only one detection for each real edge

J. Canny, *A Computational Approach to Edge Detection, IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol 8, No. 6, Nov 1986

Canny Edge Detection

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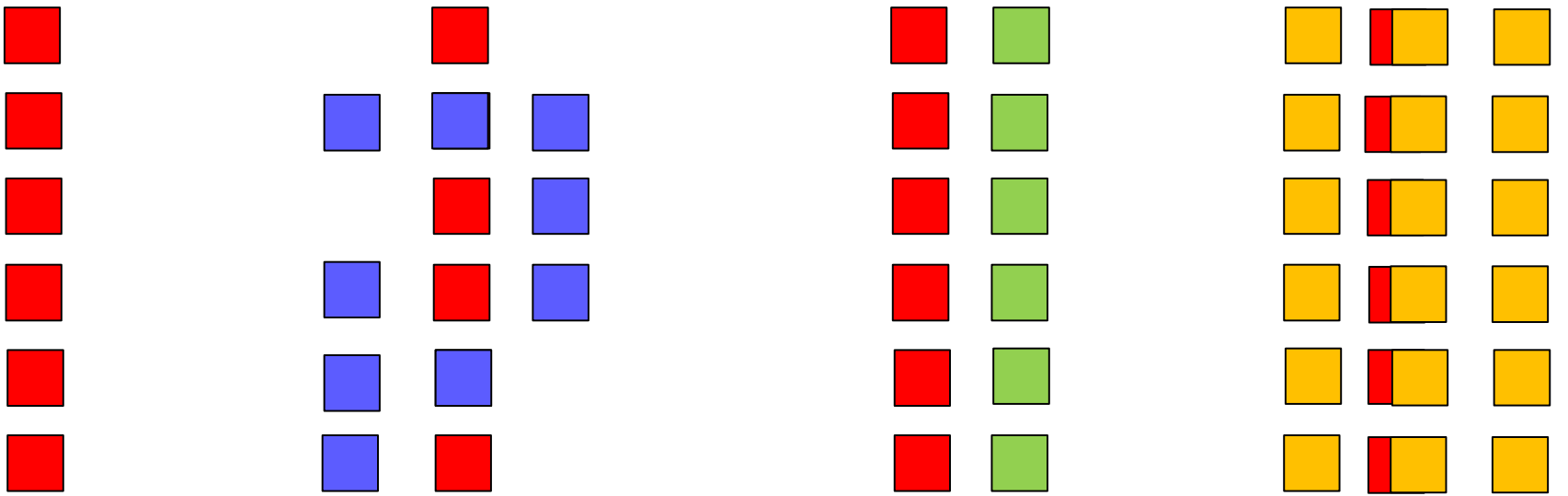
- Examples:



Real edge

Accuracy

Localization

Uniqueness

Canny Edge Detector

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- 3 Main steps
  - Gradient detection: compute horizontal & vertical derivatives
    - Magnitude & Direction
  - Thinning: non local maxima suppression
    - 1 pixel wide gradients
  - Thresholding: hysteresis approach
    - Final result

Input

Gradient Detection

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- Sobel is ok!

Horizontal Gradient G_x

Vertical Gradient G_y

Gradient Detection

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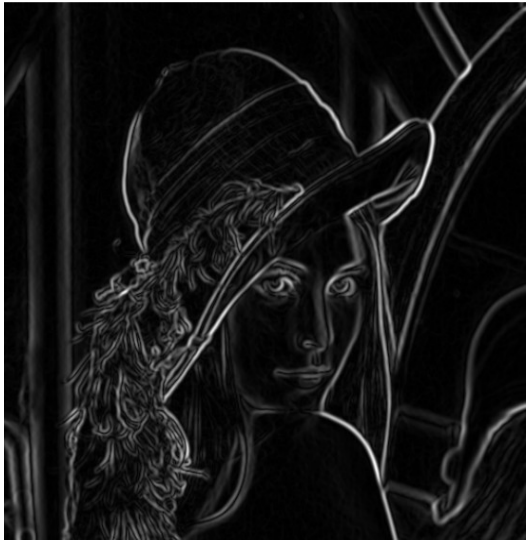
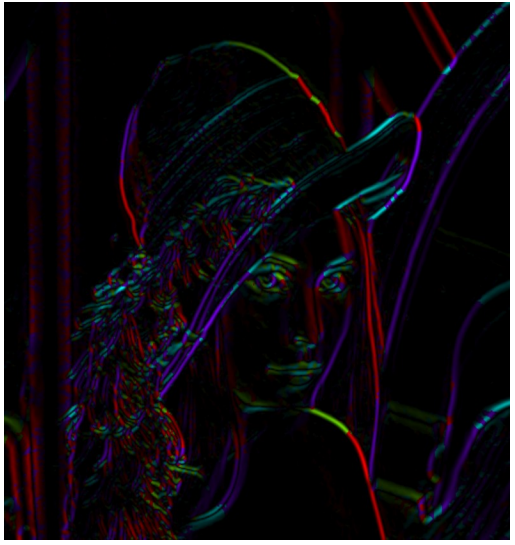
- We have 2 results: gradient magnitude and gradient direction



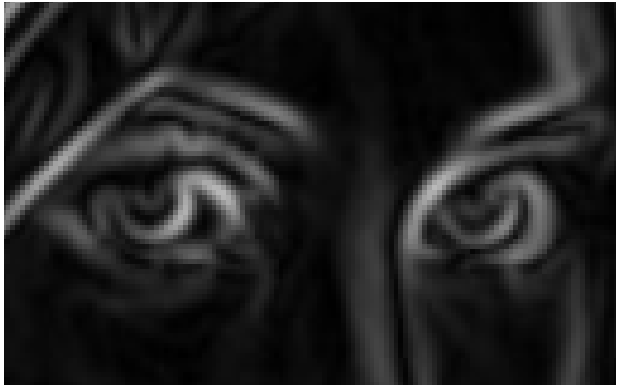
Magnitude

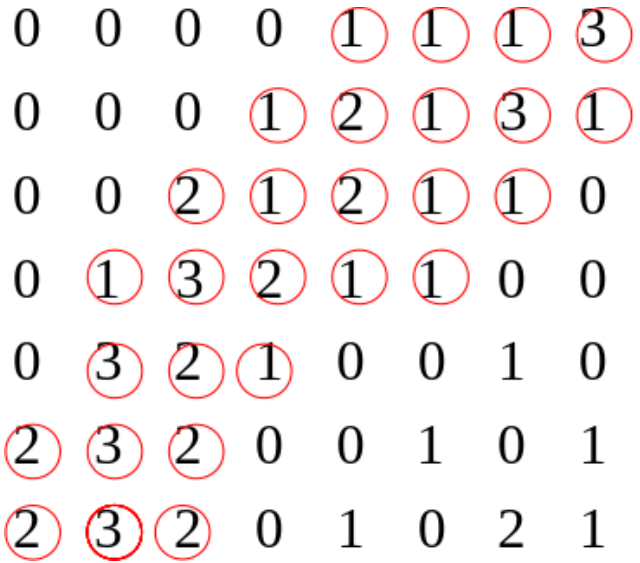


Orientation

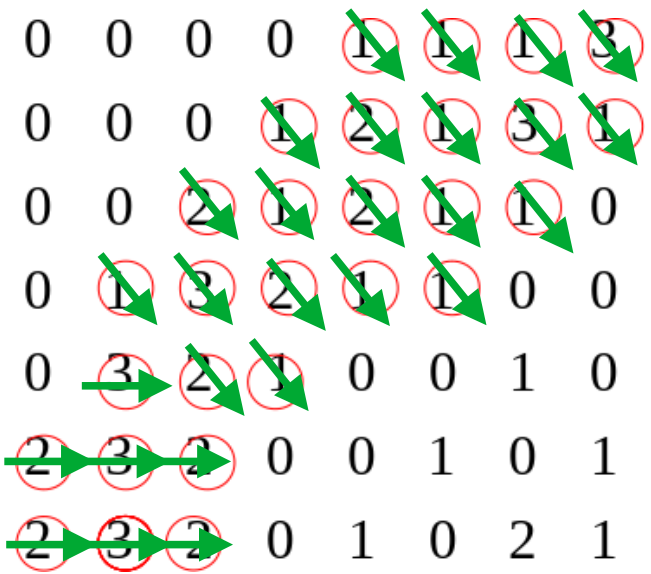
$$M = \sqrt{G_x^2 + G_y^2}$$

$$\Theta = \tan^{-1}\left(\frac{G_y}{G_x}\right) = atan2\left(G_y, G_x\right)$$





- Non Maxima Suppression
  - Only local maxima must survive
  - Orientation and gradient are used to detect local maxima
    - Bilinear interpolation or
    - A 3×3 grid



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Non Maxima Suppression

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- Local Maxima does not mean “strong edges”
- One threshold is not enough
- Two thresholds:
  - Under T_{low} $\longrightarrow$ eliminate edge
  - Over T_{high} $\longrightarrow$ keep edge
  - Between T_{low} and T_{high}?

Hysteresis

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- Edges above T_{high} are iteratively grown using adjacent edges above T_{low}
  - Similar to a labeling technique
- At the end edges < T_{high} are removed

Hysteresis

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Lines Detection

Summary

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- Edges and lines
- Hough transform
- Not only lines
  - Hough transform can be generalized

Beyond edges

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- Edges are not lines… still a low level feature

Lines Detection

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- First approach: determine pixel alignment
  - Expensive!
  - We have to match each pixel to other pixels ⟶ straight lines
    - Check whether other pixels are on those lines
  - For n pixels we have $n(n-1)/2 \sim n^2$ potential straight lines
    - $(n-2)[n(n-1)/2] \sim n^3$ matches
- Real approach: Hough Transform

Hough Transform

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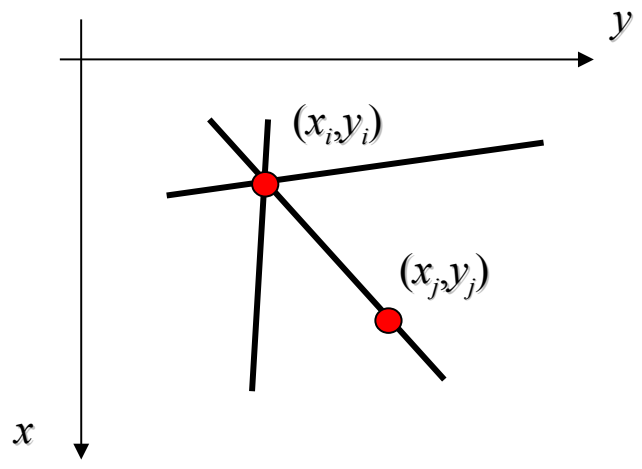
- The family of straight lines that pass through a given point (x_i, y_i) is defined as:

  $y_i = ax_i + b$

- For each parameter set (a, b) we have a given straight line
- Actually x_i and y_i are constant, while a and b are the unknowns



Hough Transform

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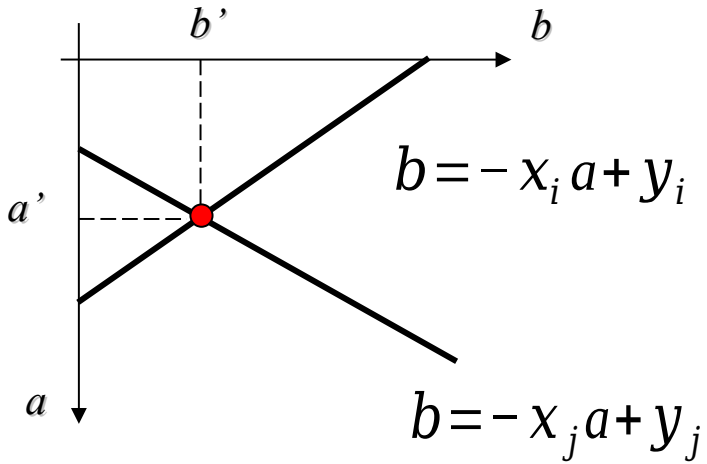
- Therefore, the previous equation can be written as:

  $b = -x_i a + y_i$

- That represents all parameters values for a given point (x_i, y_i)
  - Still a straight line but in parameter space!
- This can be done also for other points, i.e. given point (x_j, y_j)
- The two straight lines intersect in (a', b')



Hough Transform

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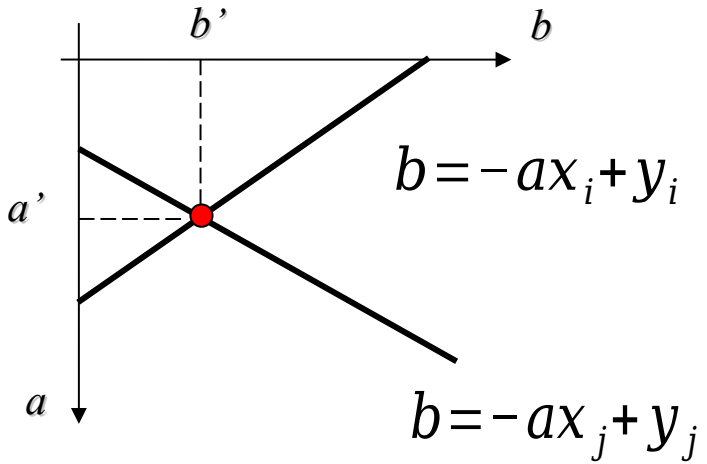
- (a', b') are then the parameters that define the straight line that pass through both (x_i, y_i) and (x_j, y_j)
- More generally, all points that lie on the same line in the x,y space generate straight lines that intersect in a specific point in the a,b space
- This is the underlying rationale of the Hough Transform



Hough Transform

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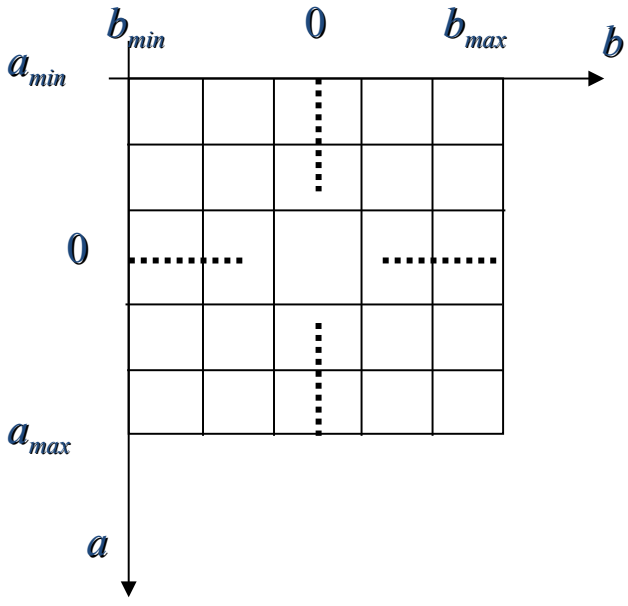
- Main steps:
  - Define a discrete accumulator matrix for the a,b space
  - For each (x_k, y_k) compute all possible b values using
    - All a values in the a_{min} - a_{max} range
    - $b = -x_k a + y_k$
  - Increase the corresponding a,b cells in the accumulator matrix



Hough Transform

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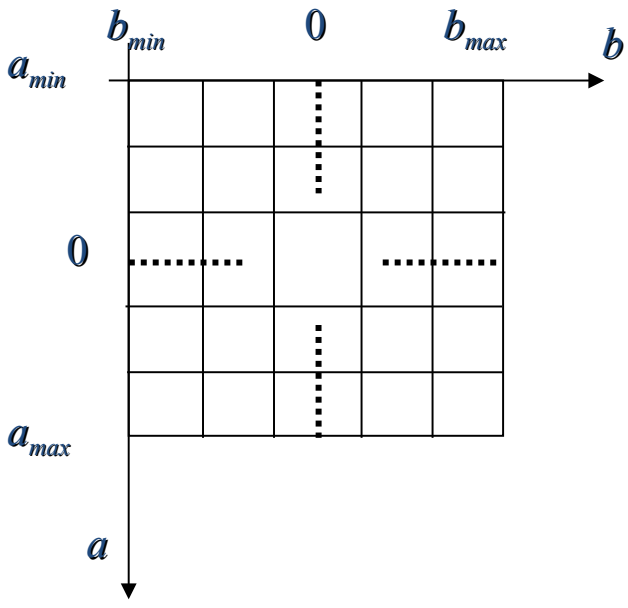
- At the end of the process each accumulation cell gives us information on how much pixels lie on the same straight line
- i.e. if a cell (a_i, b_i) contains the value M this means that in the image we have M points that lie on the $y=a_ix+b_i$ line
- A threshold is generally used to extract biggest values
  - Namely detected straight lines



Hough Transform

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- If the a axis is subdivided in k intervals for each (x, y) point we get k values for b
- For n points we need to compute $n \times k$ values
  - O(n) better than $O(n^3)$
- Open issues:
  - Which value for k?
  - What range for a?
  - Vertical lines?

Hough Transform

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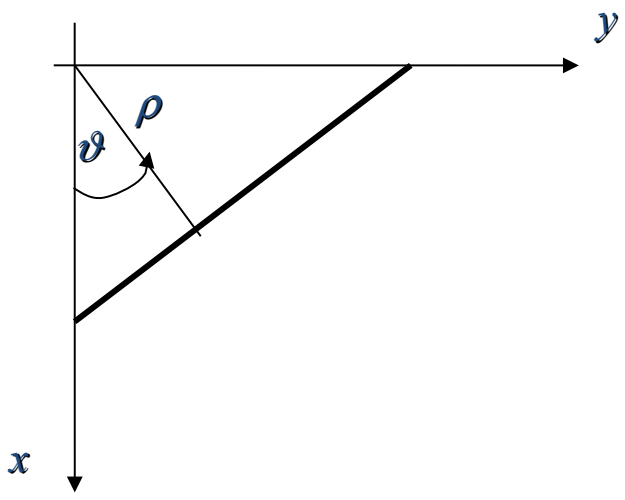
- To solve some issues Euclidean space is used instead of Cartesian one

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

- Both parameters have a limited range
  - θ is an angle
  - ρ is limited by image diagonal
- Similar procedure as before
- In the parameters space we have curves



Hough Transform

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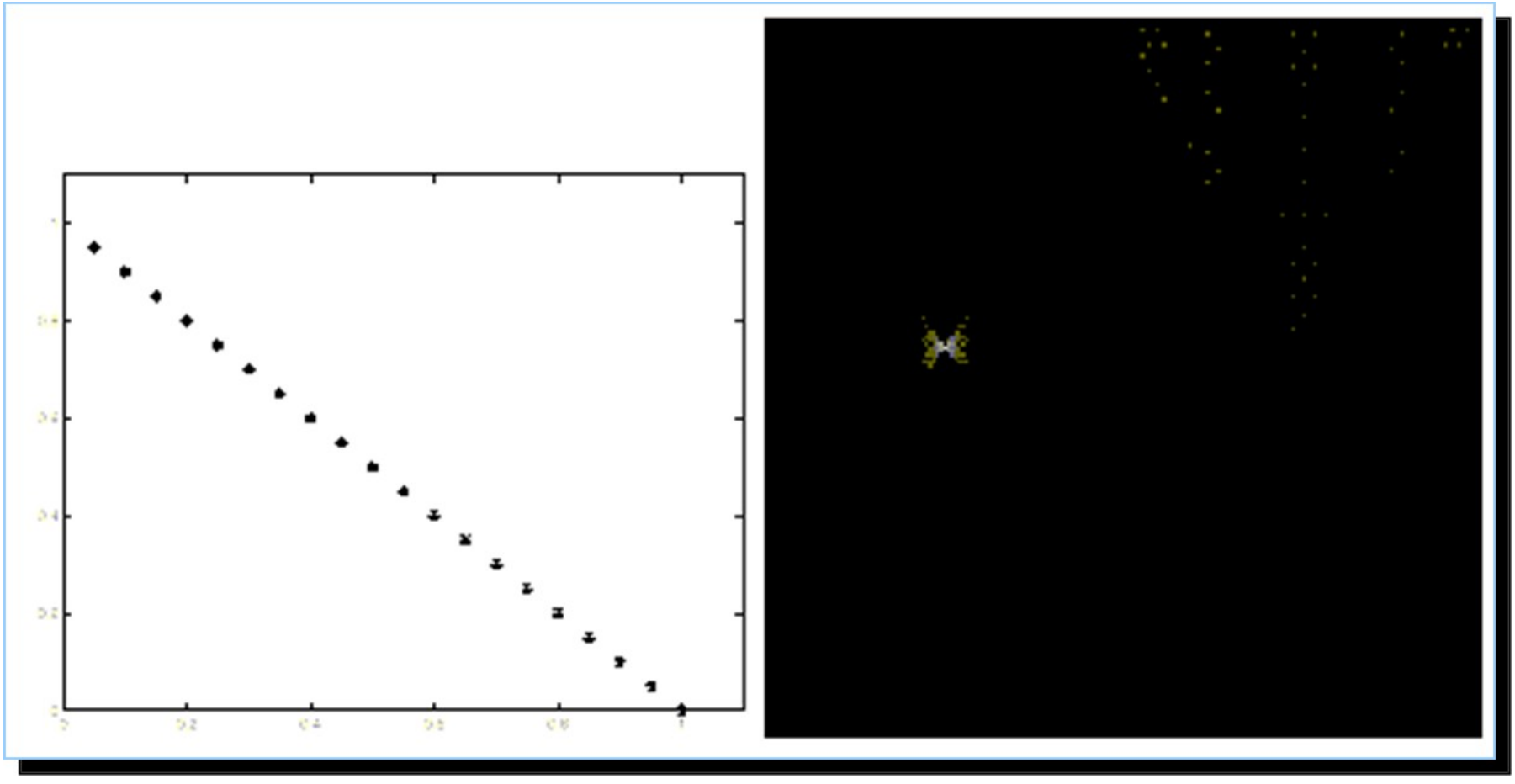

Hough Transform

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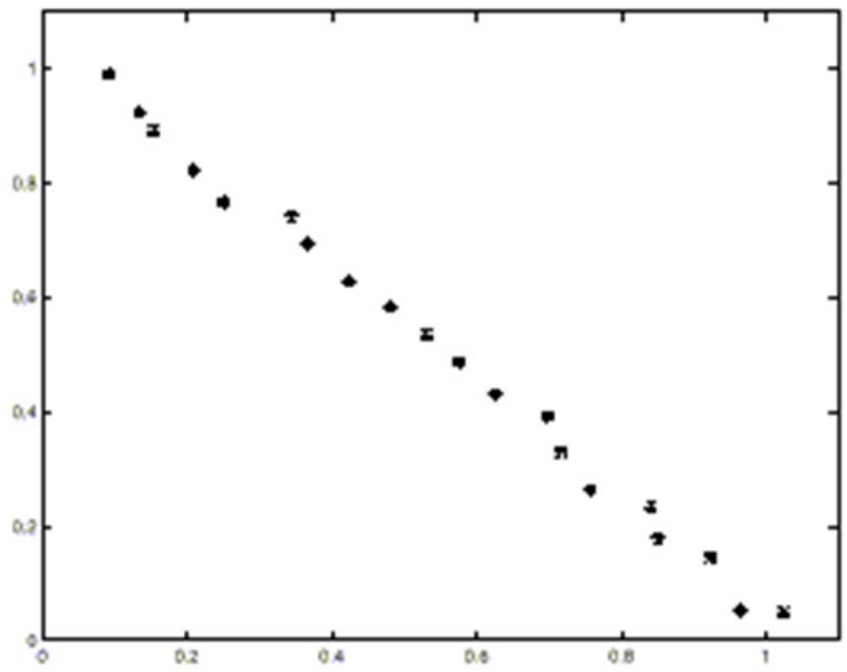

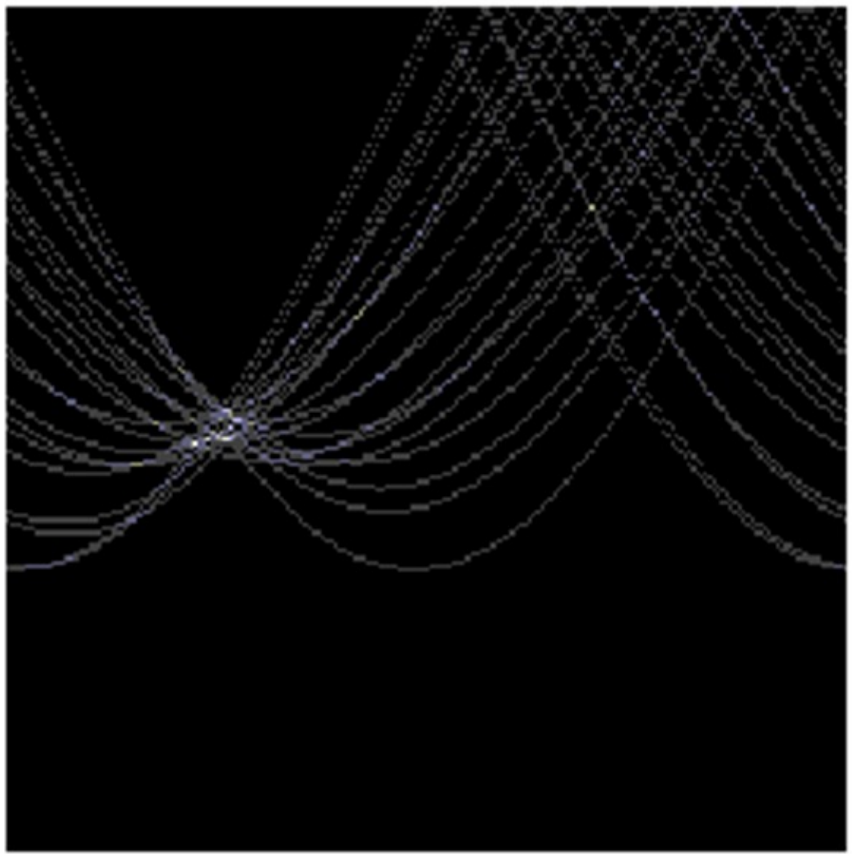

Hough Transform

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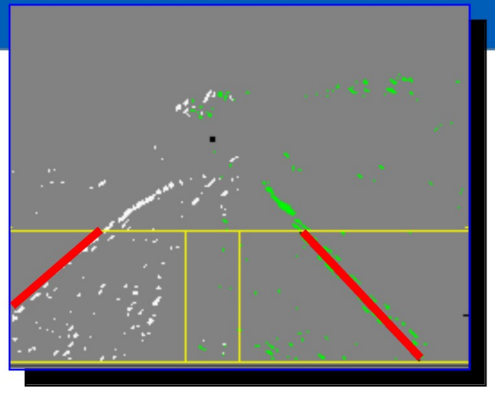

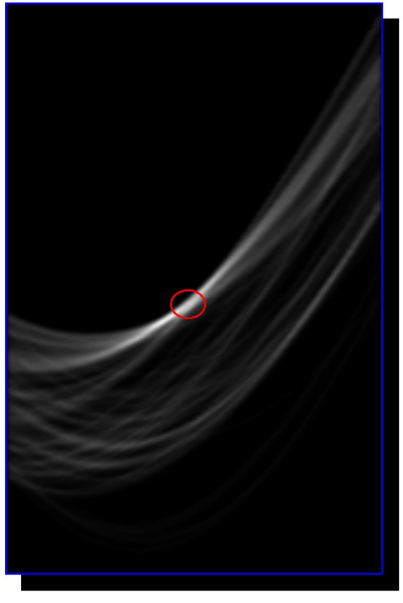

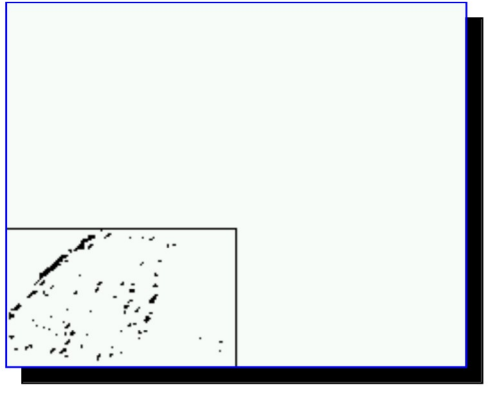

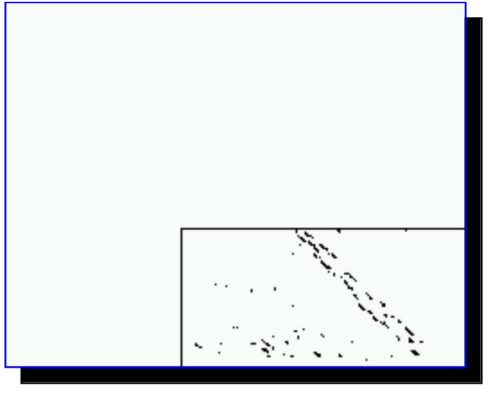

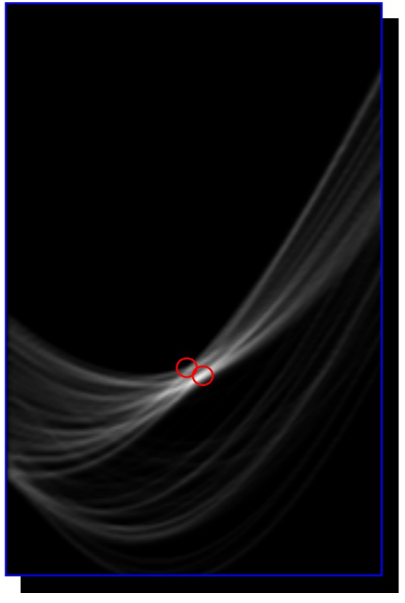

Generalized Hough Transform

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- Described approach is for straight lines
- Anyway it can be applied to any analytical curve
- The only differences are the number and ranges of parameters
  - i.e. for a circle $(x-c_x)^2+(y-c_y)^2=r^2$
  - We need to use a 3D accumulator
  - Similar approach ($O(n^2)$)