

Nonlinear Filters

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Book: Gonzalez & Woods

Nonlinear Filters

Non Linear Filters are such that the relation

$$H[\lambda f(t) + \mu g(t)] = \lambda H[f](t) + \mu H[g](t)$$

does not hold, at least for some value of λ, μ, f, g or point t .

Examples of nonlinear filter are

- Median Filter (Weighted Median)
- Ordered Statistics based Filters
- Threshold, Shrinkage

There are many others, such as data adaptive filtering procedures (e.g LPA-ICI)

Blockwise Median

Block-wise median: replaces each pixel with the median of its neighborhood. It is still a local spatial transformation!

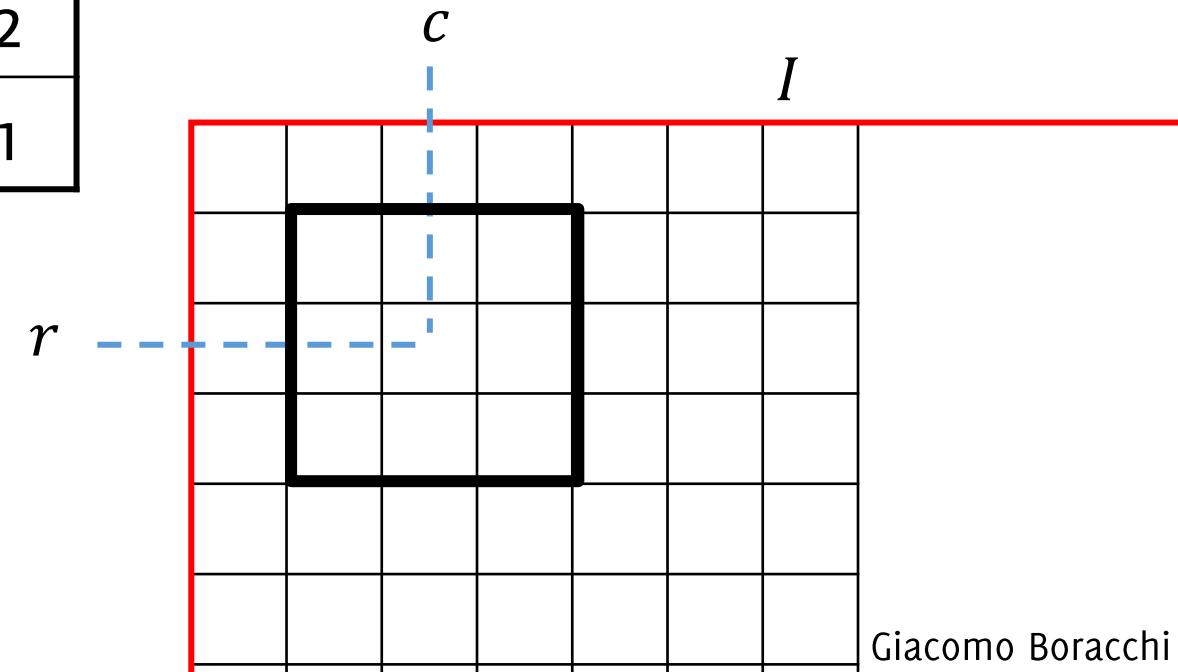
This is edge-preserving and robust to outliers!

	2	

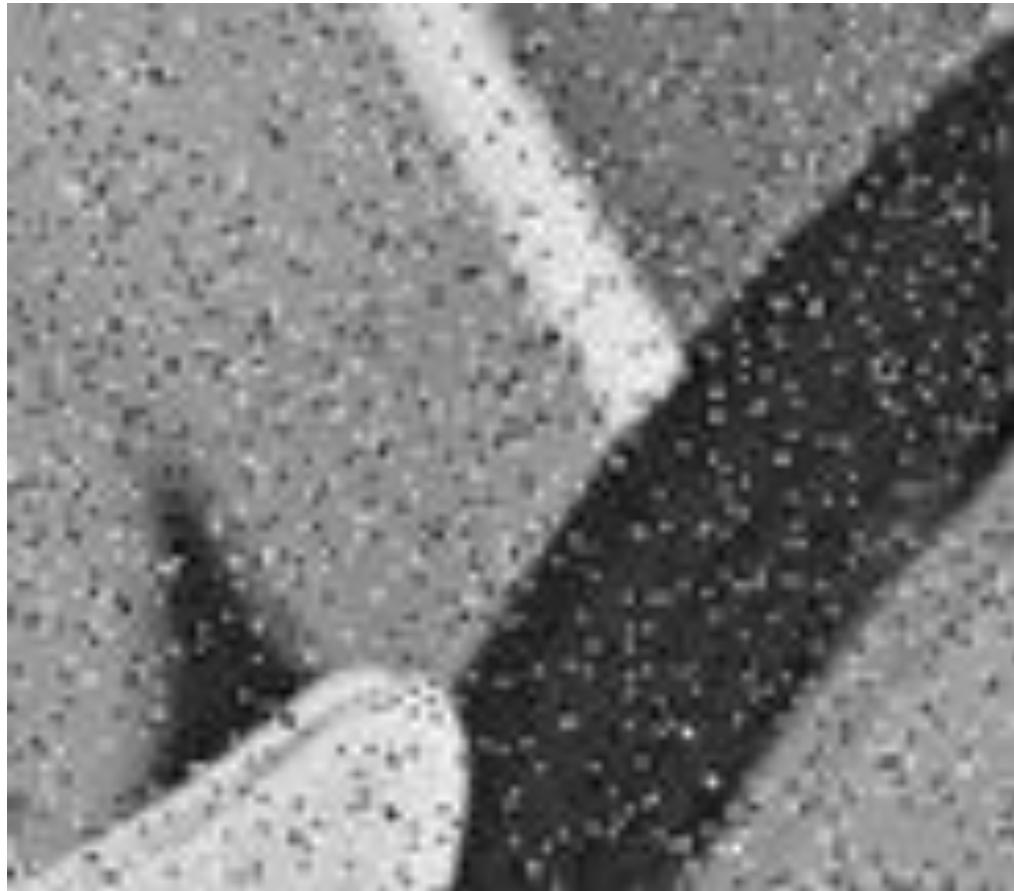
med

1	3	0
2	10	2
4	1	1

$$m = \text{median}(1,3,0,2,10,2,4,1,1) = 2$$



Salt-and-pepper noise



Salt and Pepper (Impulsive) noise

Denoising using local smoothing 3x3



Denoising using median filter 3x3



Salt and Pepper (Impulsive) noise

Morphological Operations

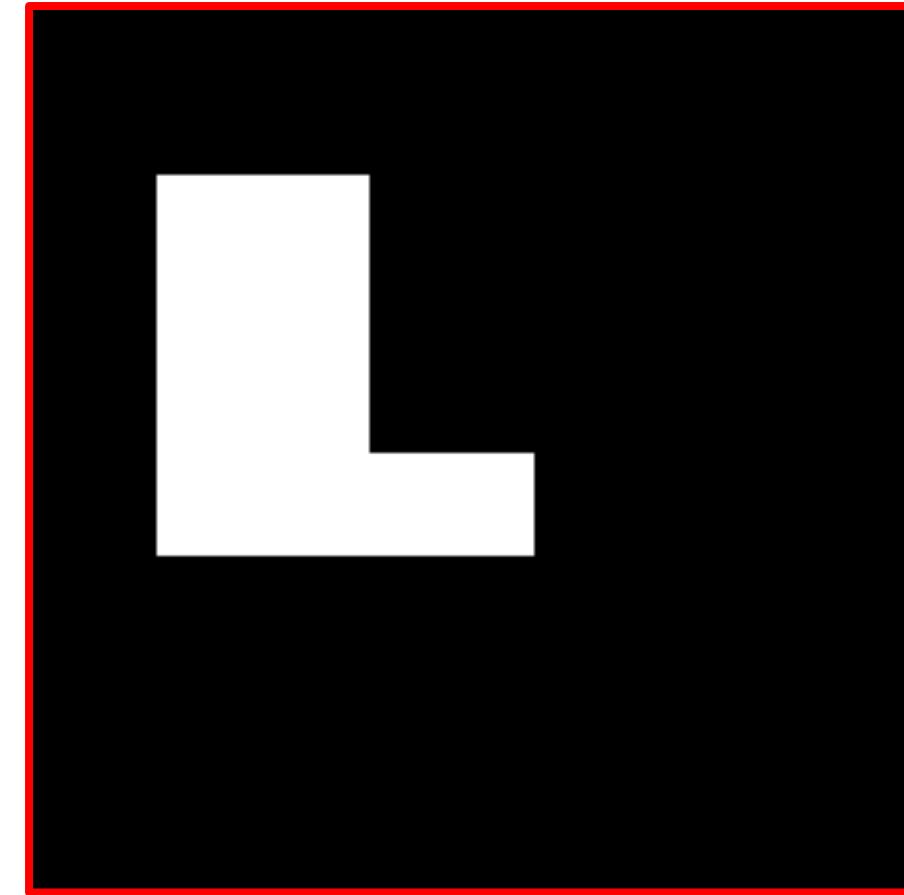
Ordered Statistics and Blob Labeling

Binary images

A binary image is defined as $I \in \{0,1\}^{R \times C}$

Each pixel can be either true (1) / false (0)

Typically binary images are the result of pre-processing operations including thresholding



An overview on morphological operations

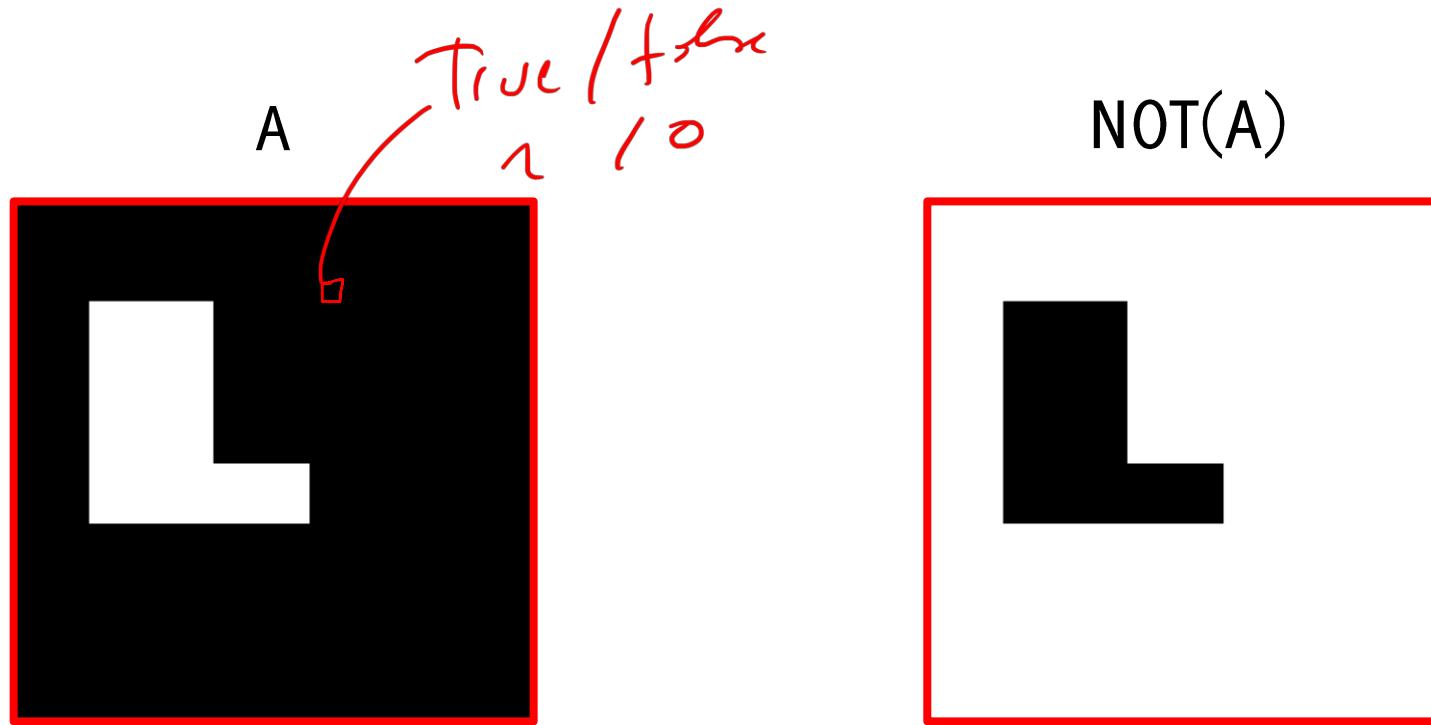
Erosion, Dilation

Open, Closure

We assume the image being processed is binary, as these operators are typically meant for refining “mask” images.

Boolean operations on binary images

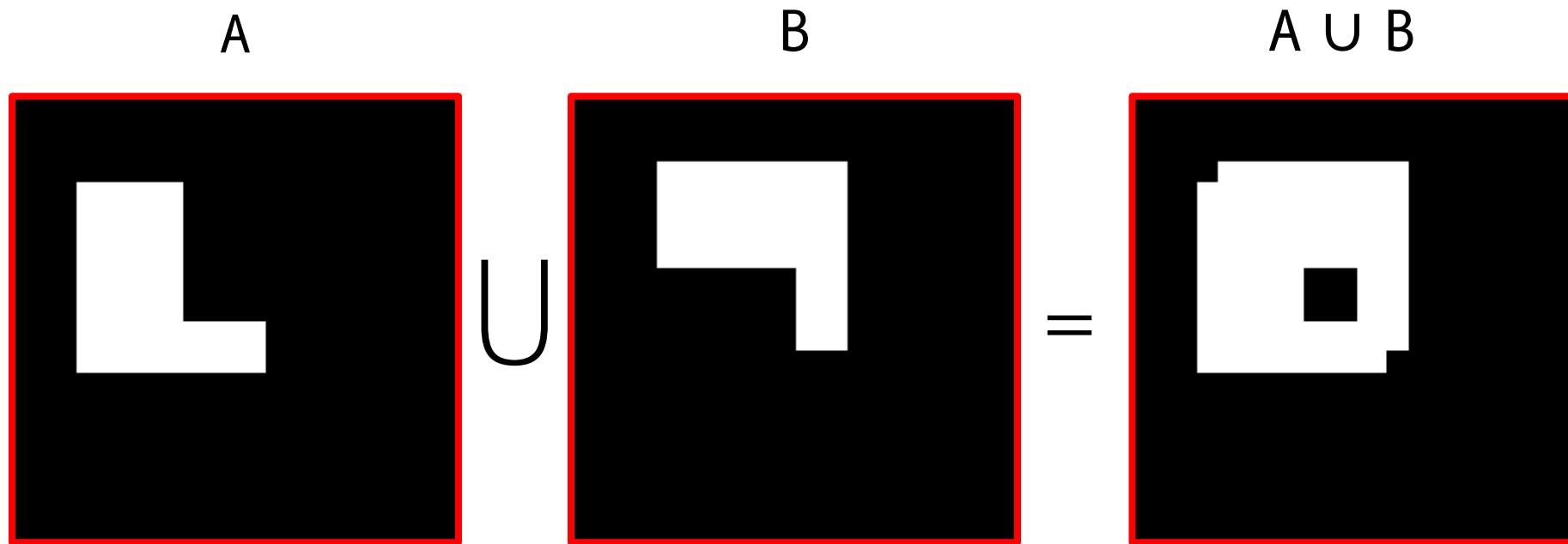
$$\hat{I} \in \{0, 1\}^{R \times C}$$



$$\text{NOT}_A = A == 0$$

UNION of binary images

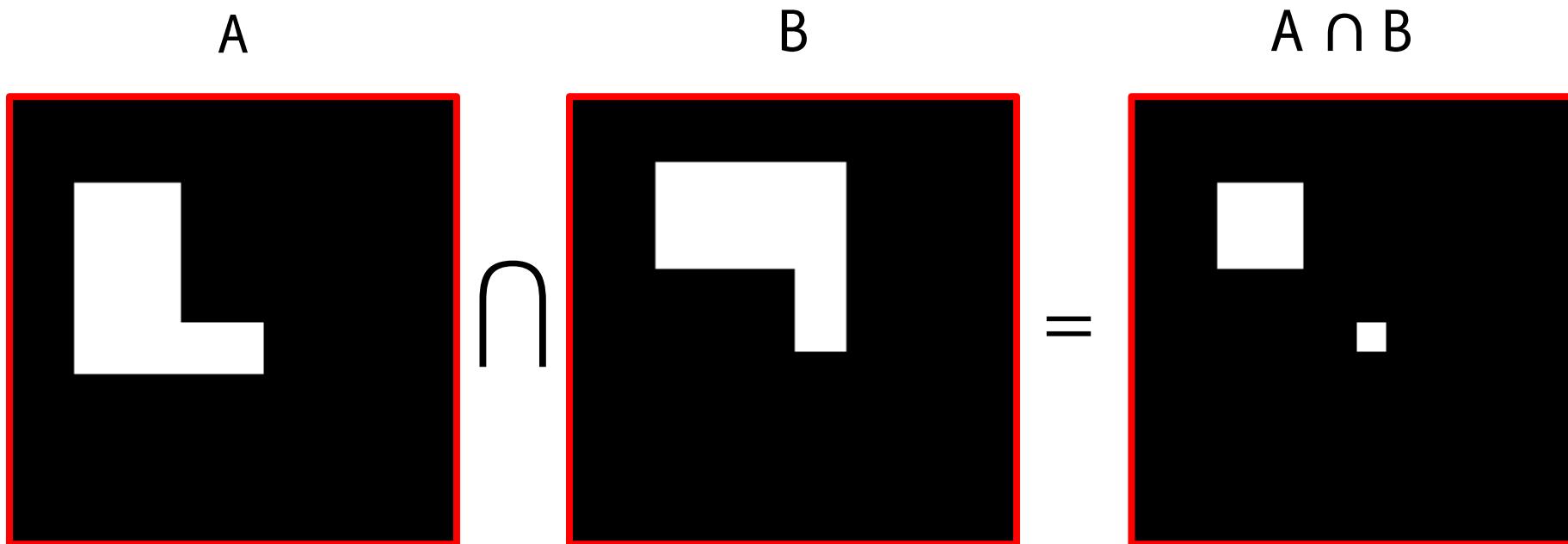
Equivalent to the OR operation



$$A \cup B = A + B > 0$$

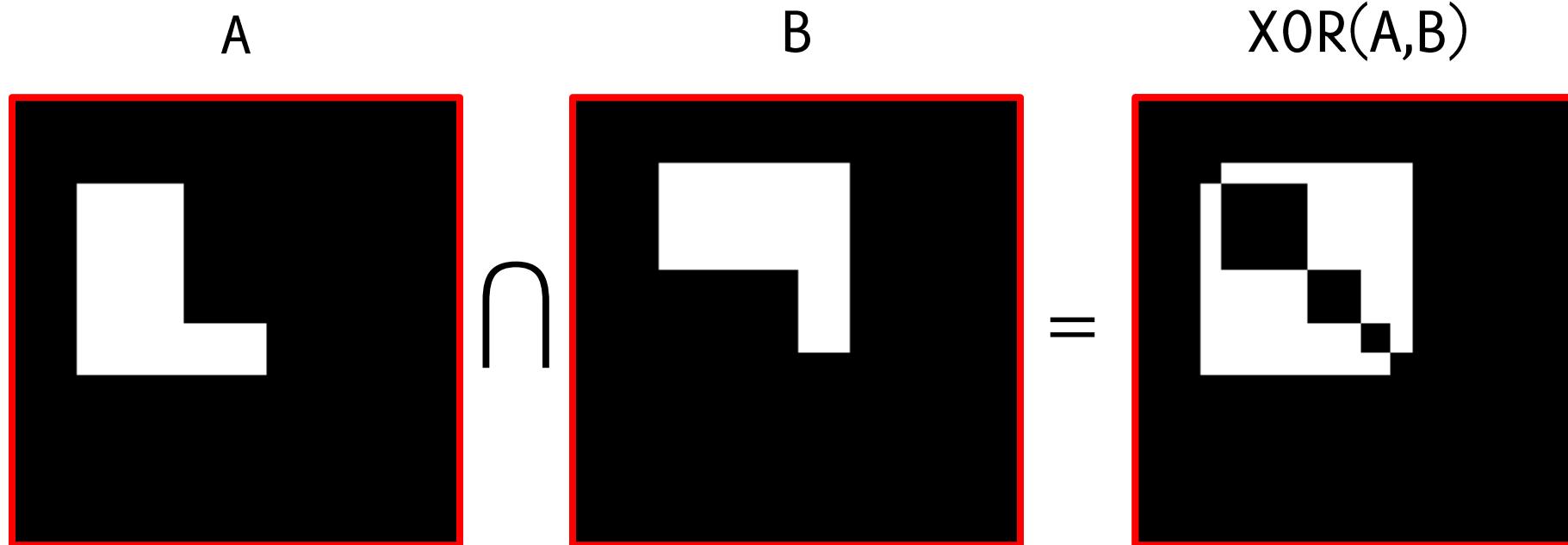
INTERSECTION of binary images

Equivalent to the AND operation



$$A \cap B = A + B > 1$$

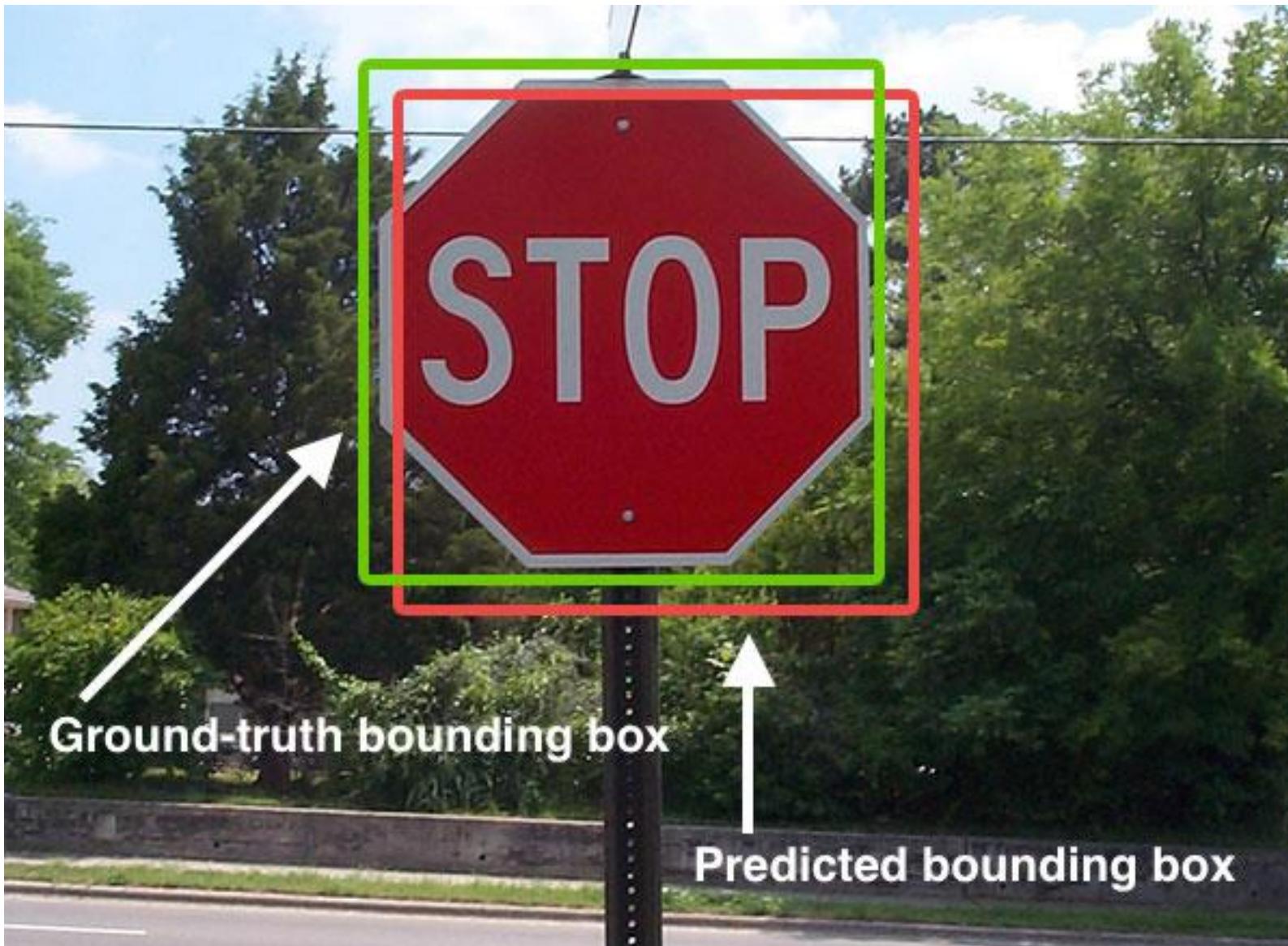
On binary images it is possible to define XOR



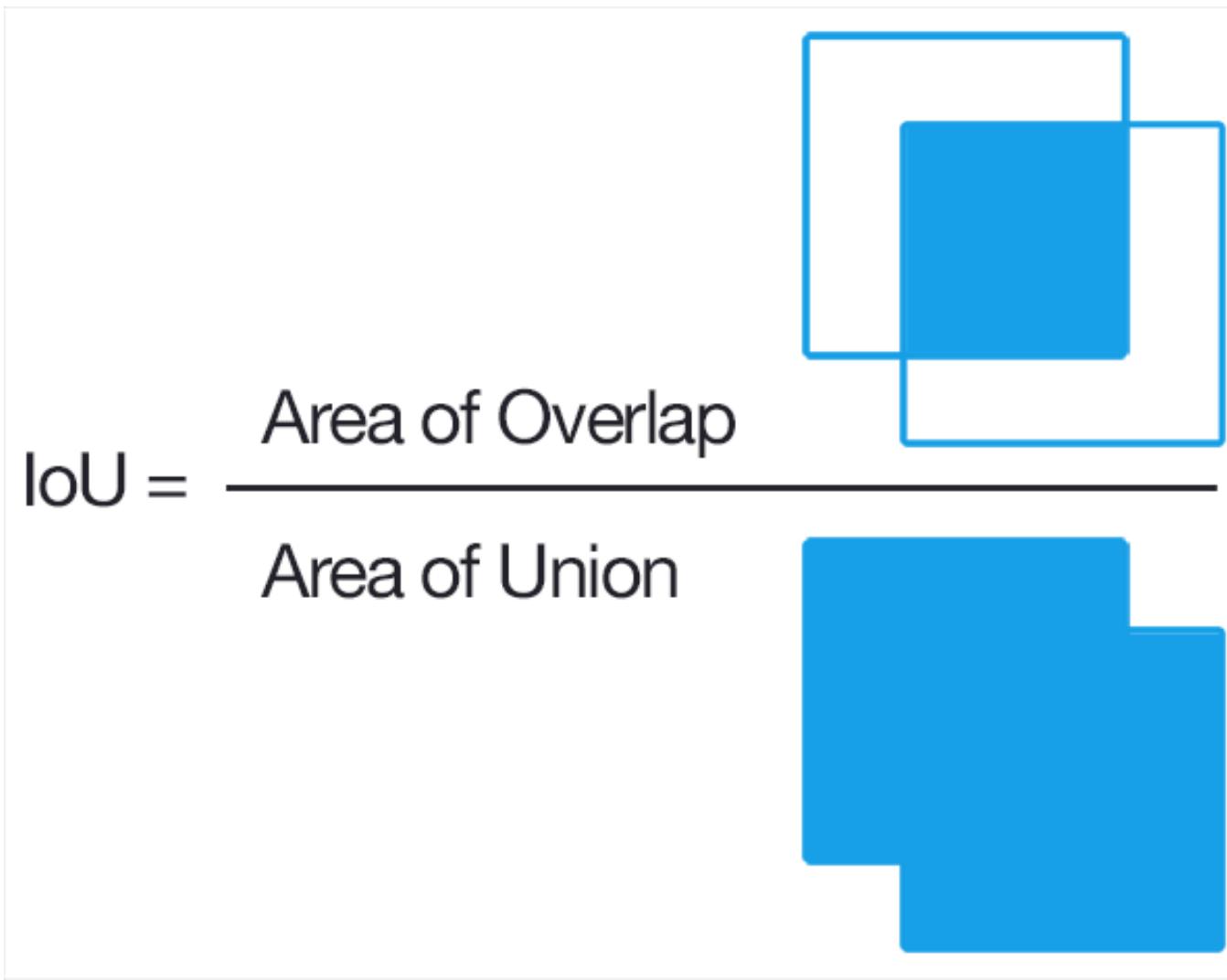
$$\text{XOR}(A, B) = A \cup B - A \cap B$$

What do we use this for?

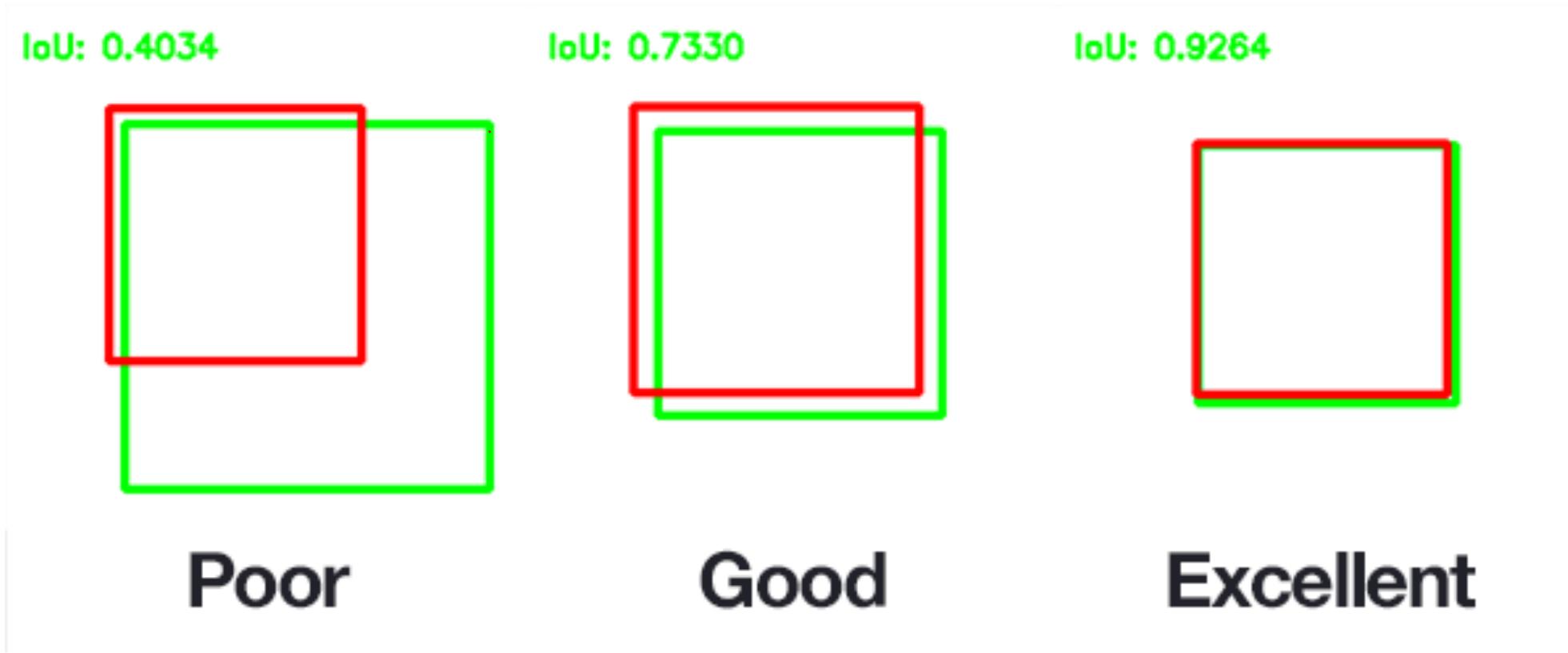
Intersection over the Union (IoU, Jaccard Index)



Intersection over the Union (IoU, Jaccard Index)



Intersection over the Union (IoU, Jaccard Index)



Jaccard Index (IoU)

It is a statistical measure of similarity between two sets, being in case of images the coordinates of the pixels set to true

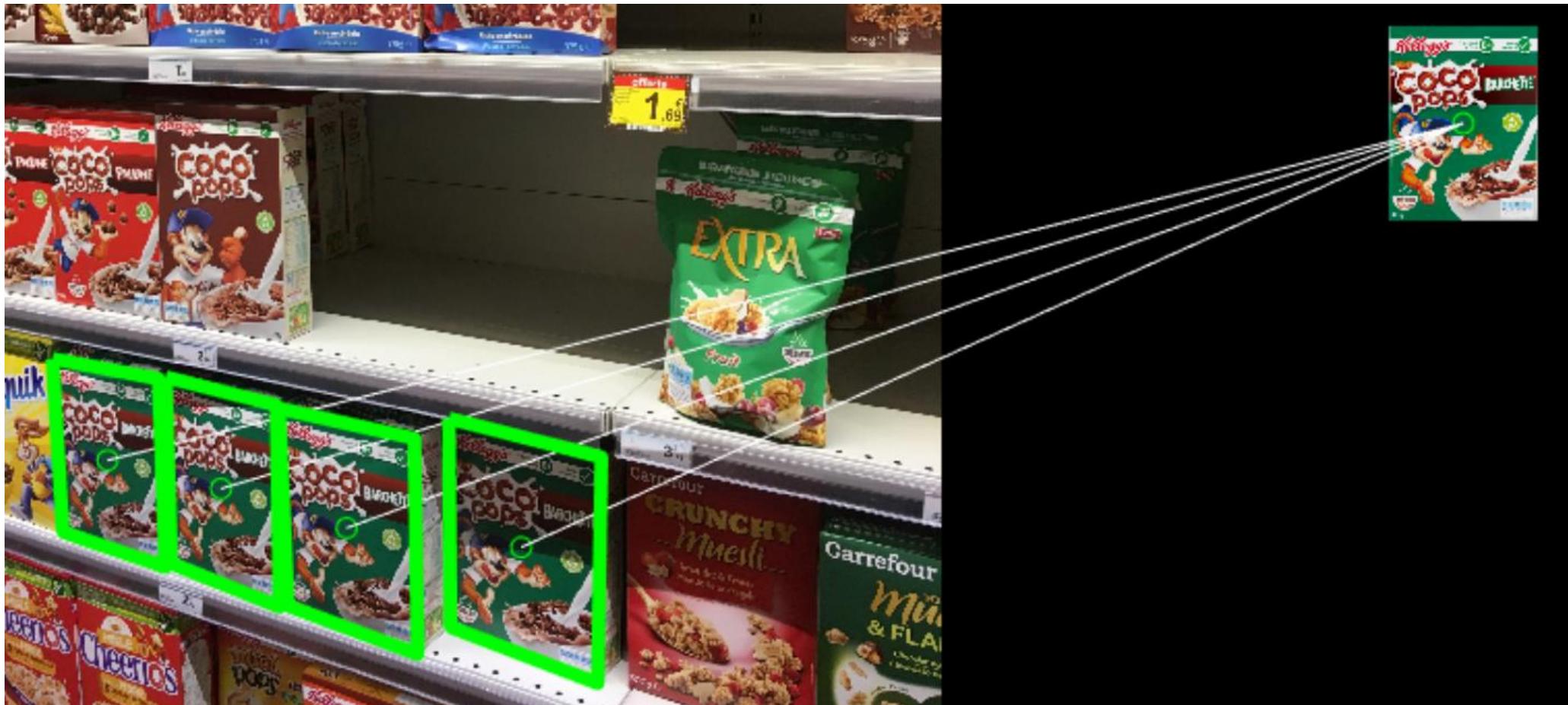
$$J(A, B) = \frac{|A \cap B|}{|A \cup B|}$$

It ranges between $[0,1]$ being $J(A, B) = 0$ when A and B are disjoint, and $J(A, B) = 1$, when the two sets coincides.

It is a standard reference measure for detection performance

Jaccard Index (IoU)

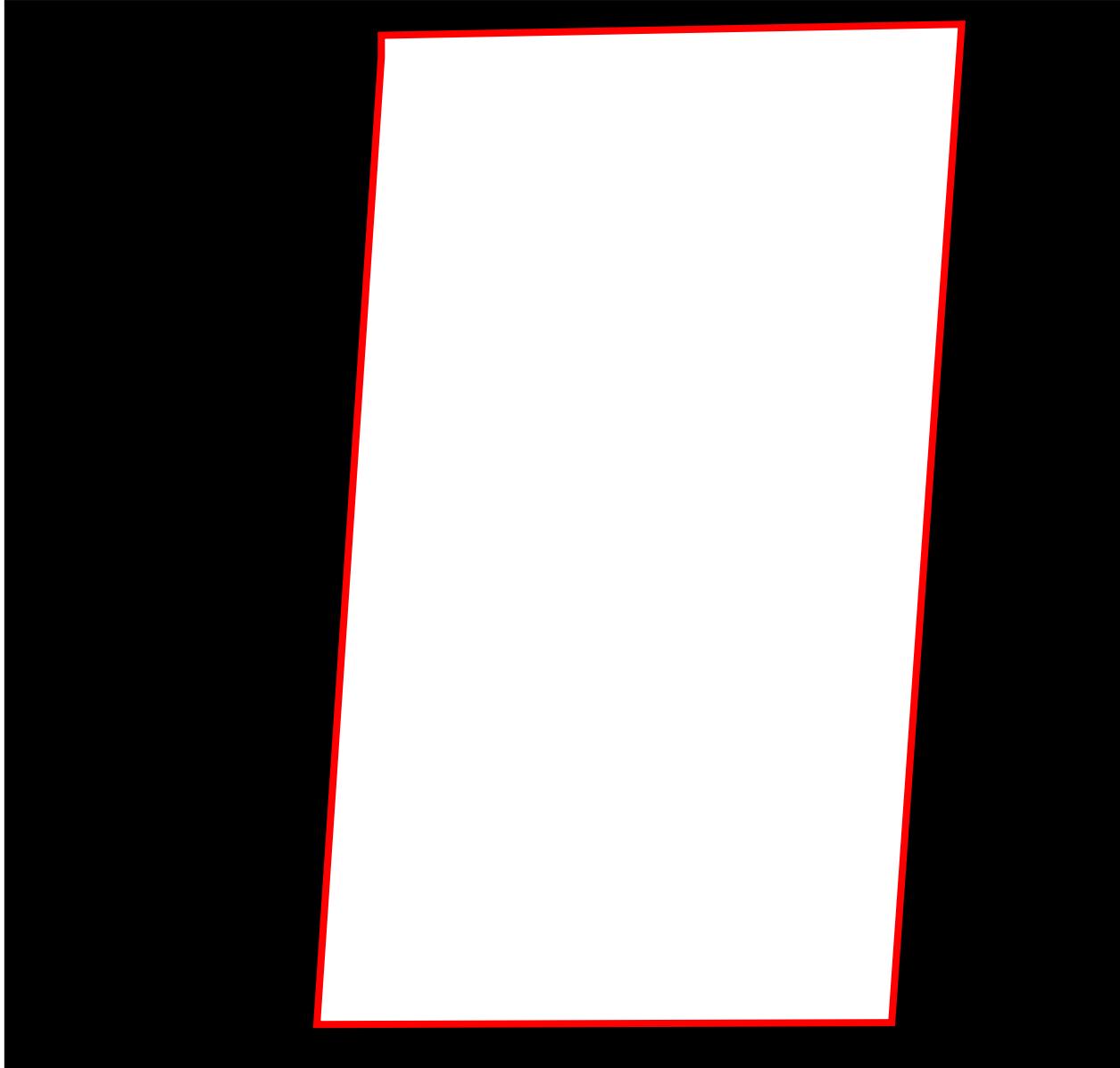
It is not necessarily defined for bounding boxes (even though most of deep learning networks for detections provide bb as outputs)



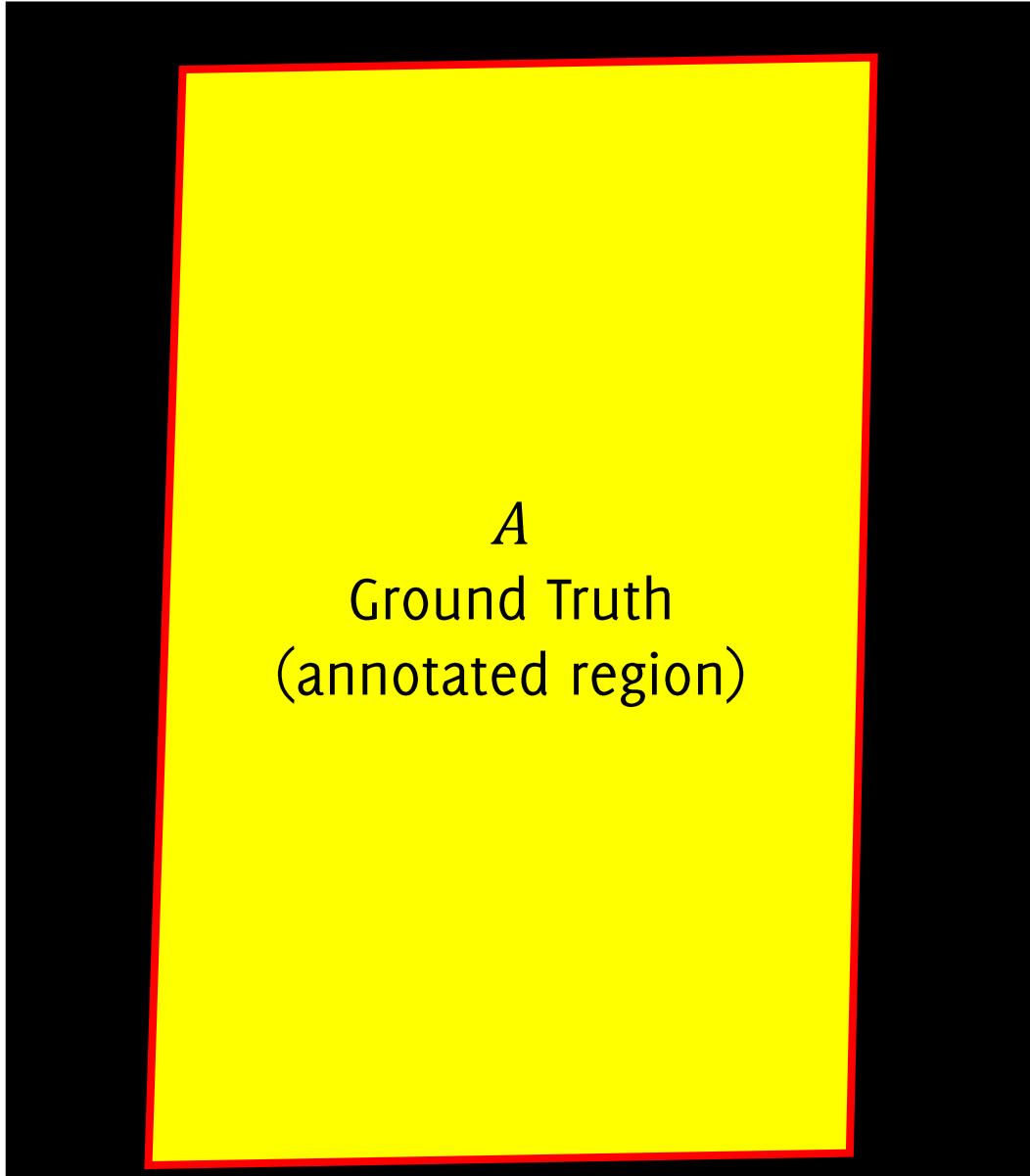
Jaccard Index (IoU)



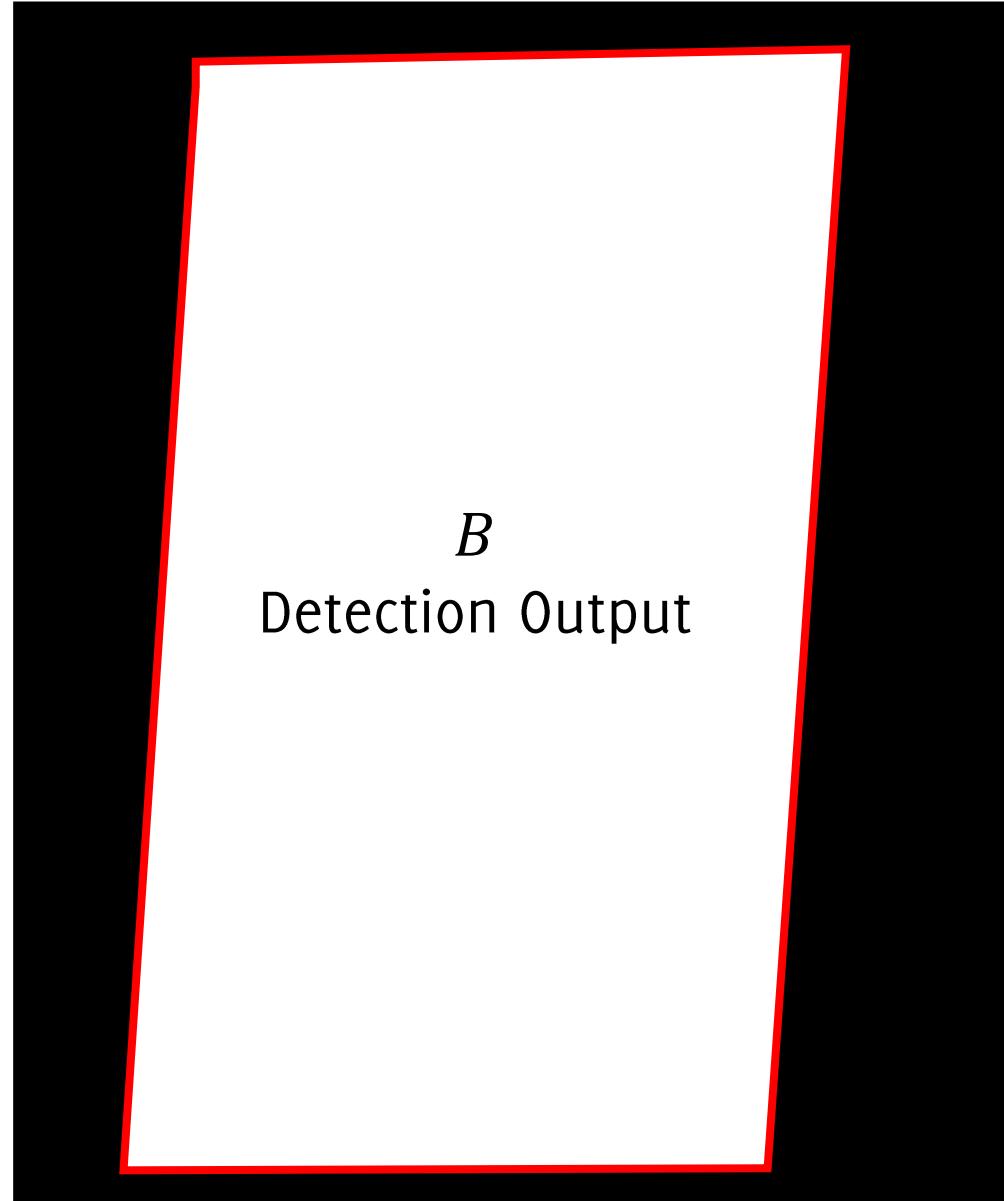
Jaccard Index (IoU)



Jaccard Index (IoU)



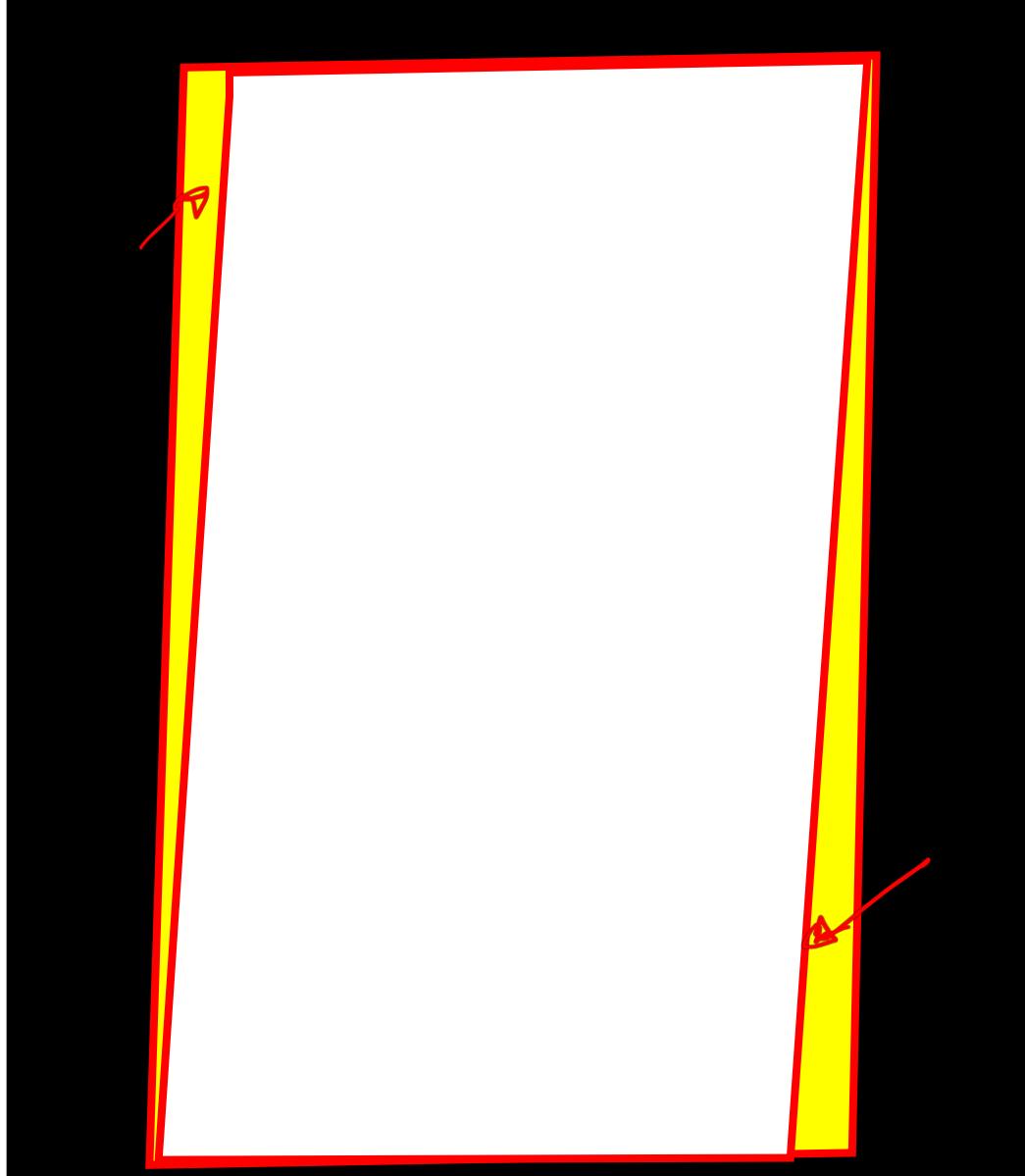
A
Ground Truth
(annotated region)



B
Detection Output

Jaccard Index (IoU)

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|}$$



Filters on binary images

It is possible to define filtering operations between binary images

Consider also binary filters, i.e. spatial filters having binary weights.

In the context of object detection, these can be used to refine the detection boundaries

Erosion

General definition:

Nonlinear Filtering procedure that replaces each pixel value with the minimum on a given neighbor

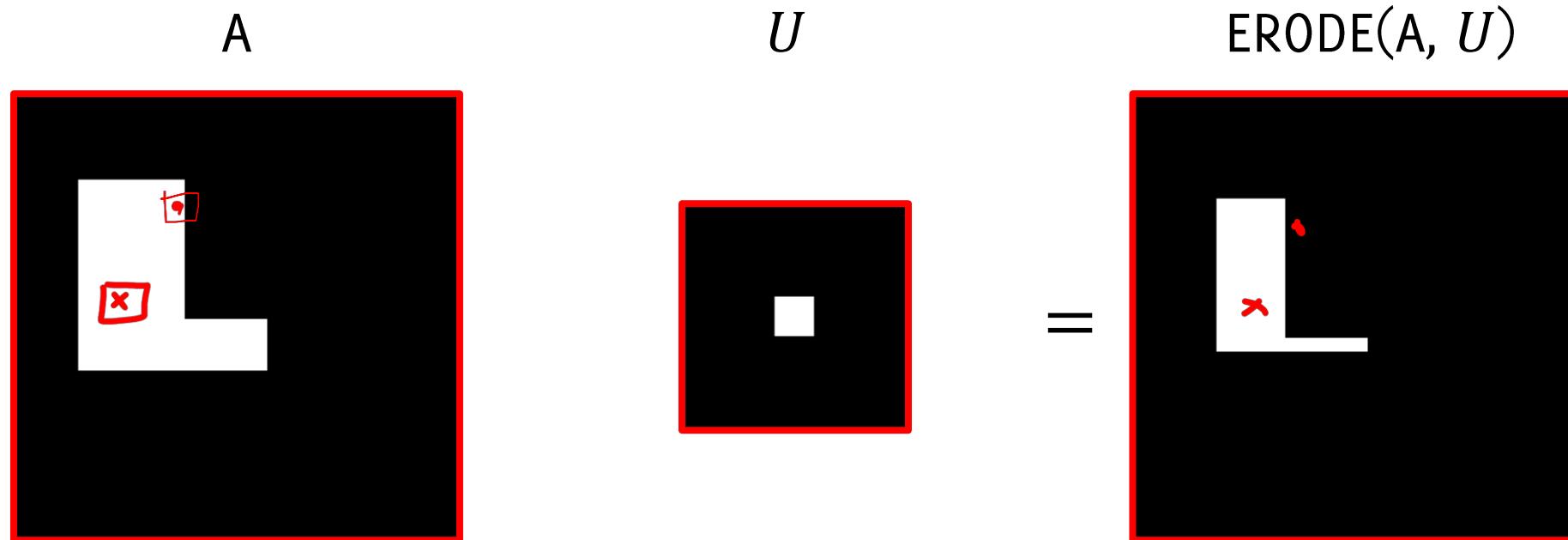
As a consequence on binary images, it is equivalent to the following rule:

$E(x)=1$ iff the image in the neighbor is constantly 1

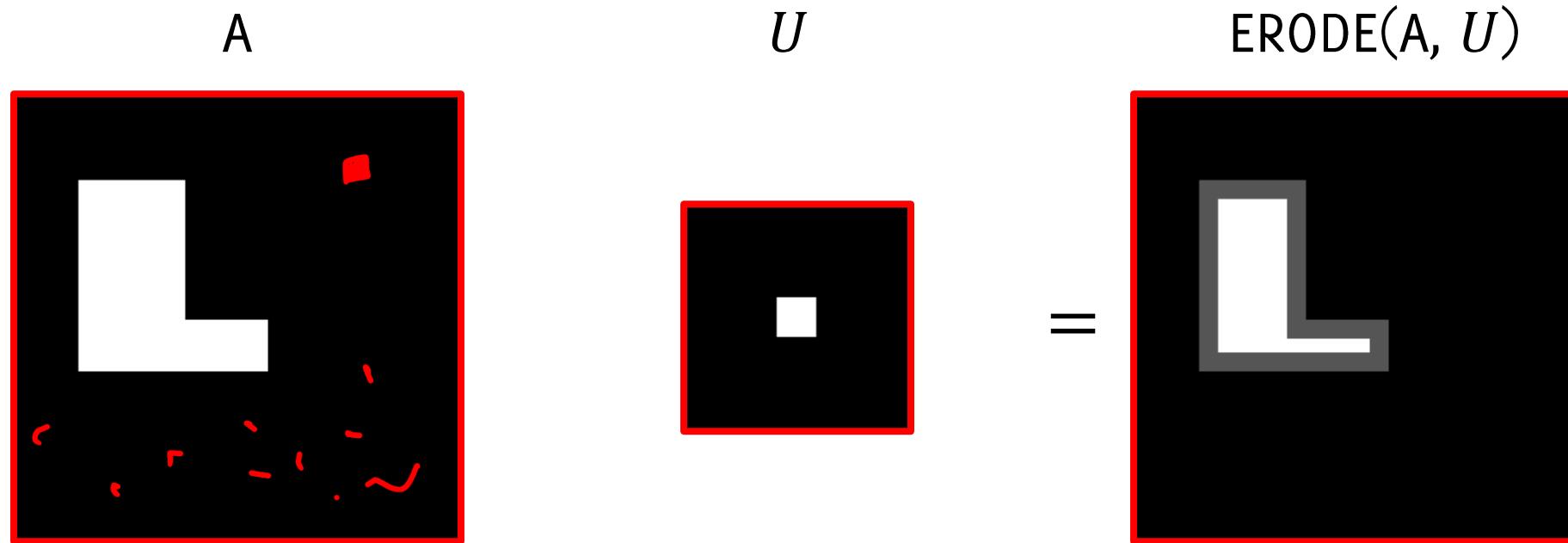
This operation reduces thus the boundaries of binary images

It can be interpreted as an AND operation of the image and the neighbour overlapped at each pixel

Erosion



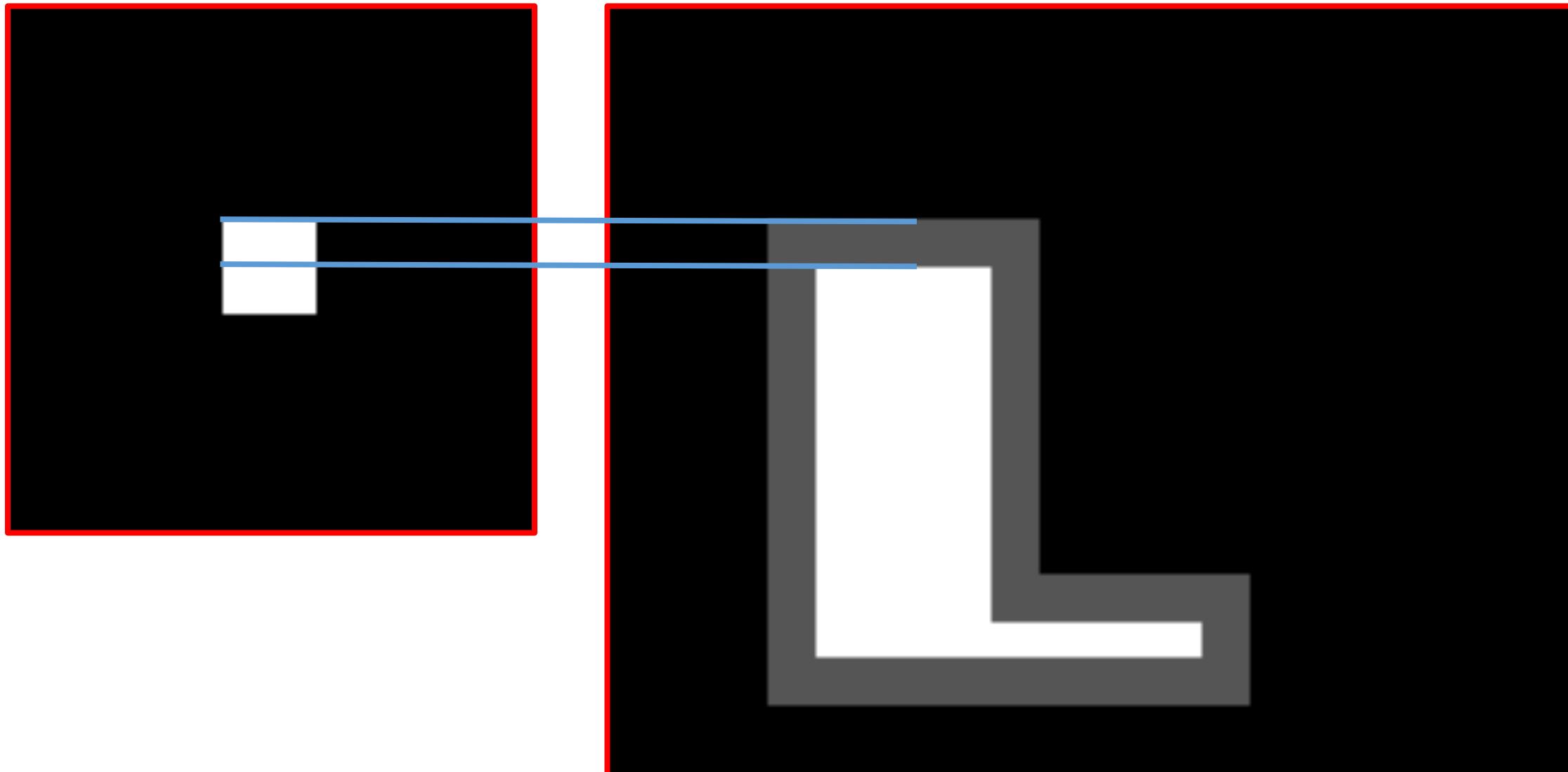
Erosion



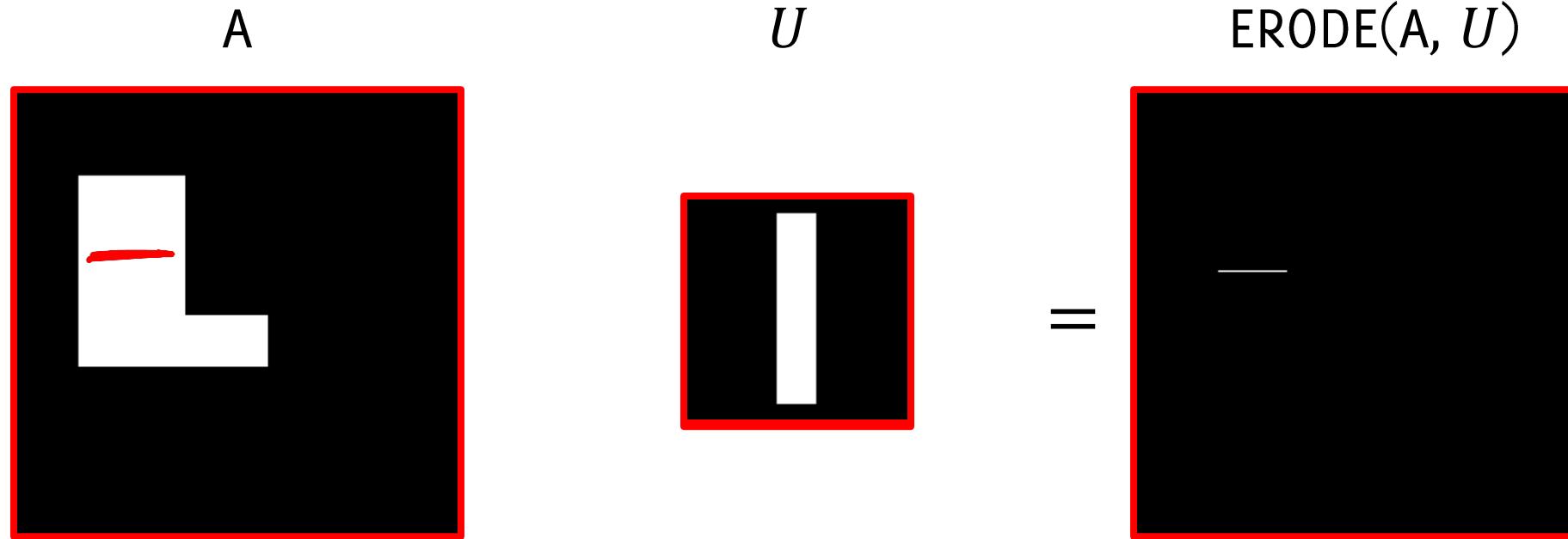
The gray area corresponds
to the input

Erosion

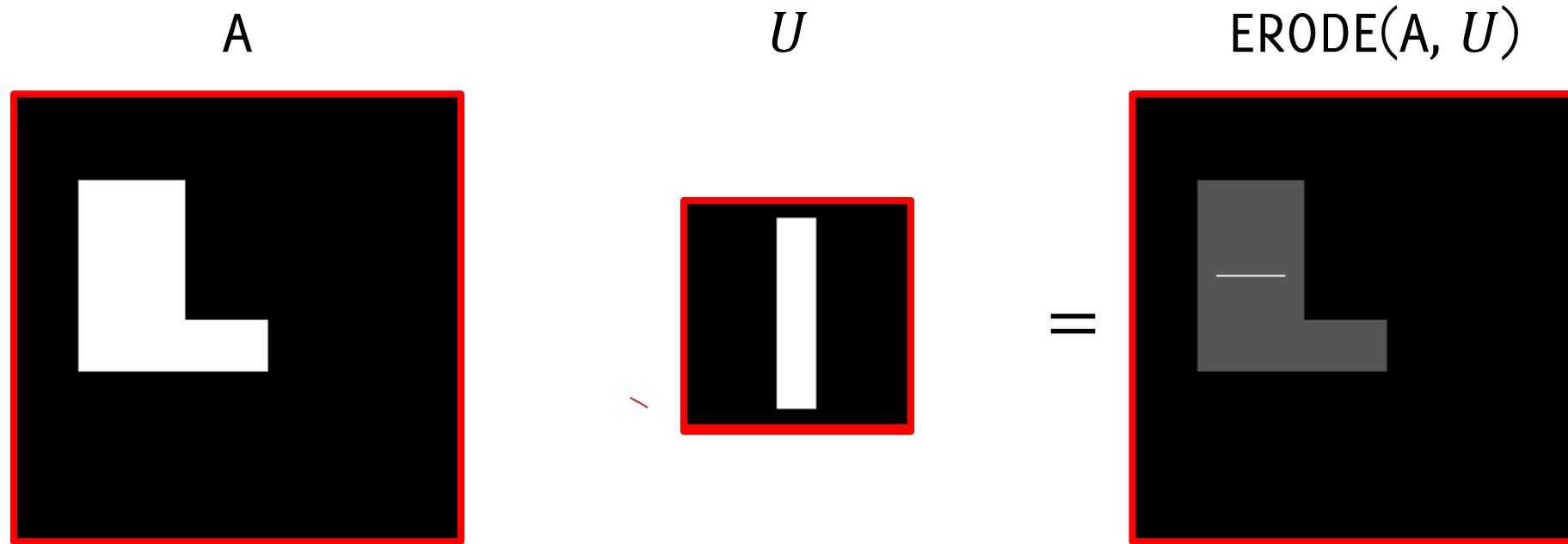
Erosion removes half size of the structuring element used as filter



Erosion



Erosion



Dilation

General definition:

Nonlinear Filtering procedure that replaces to each pixel value the maximum on a given neighbor

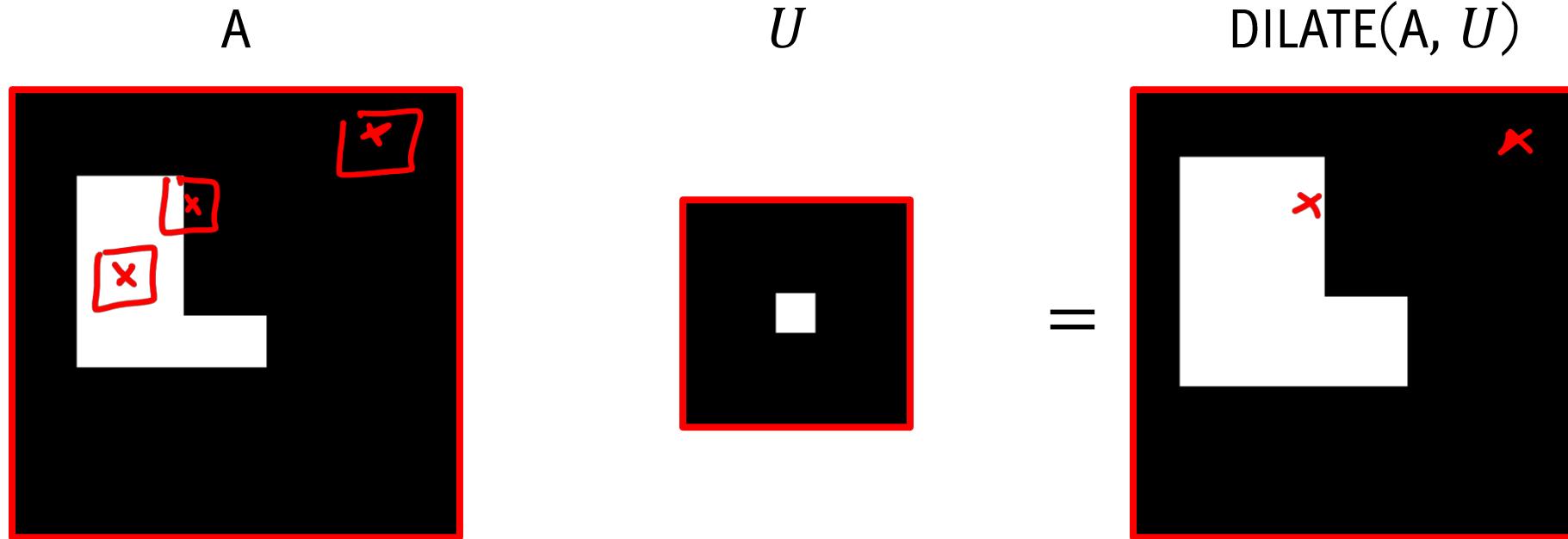
As a consequence on binary images, it is equivalent to the following rule:

$$E(x)=1 \text{ iff at least a pixel in the neighbor is } 1$$

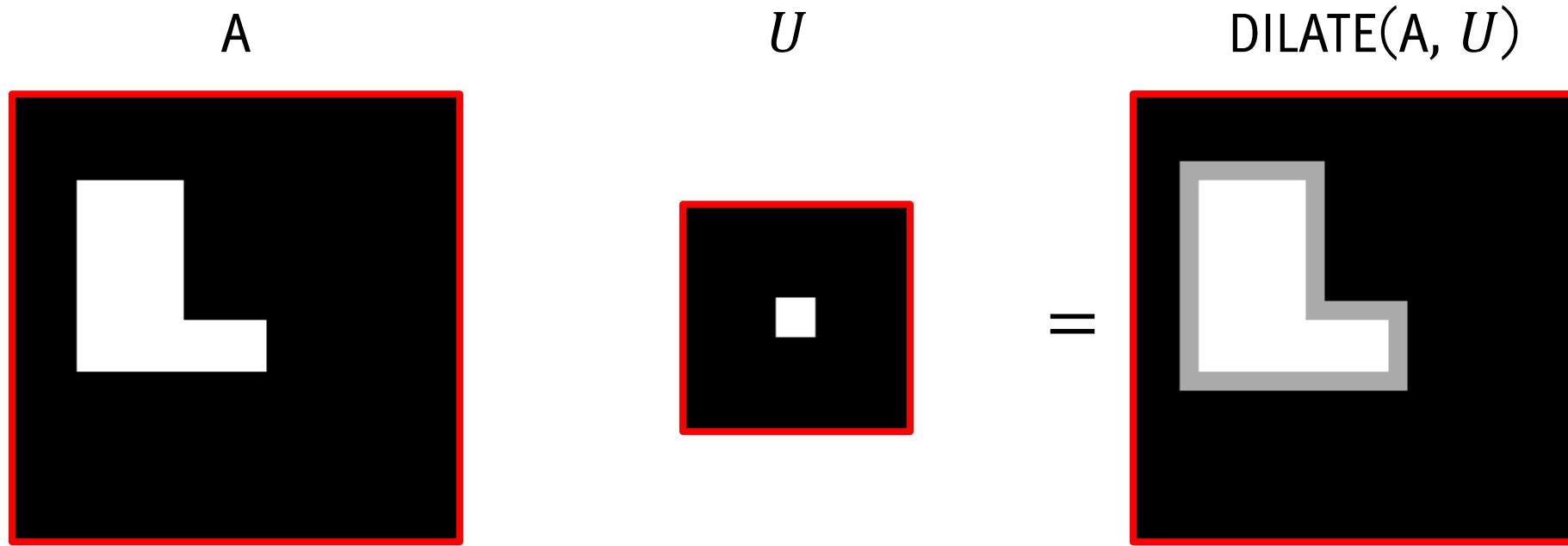
This operation grows fat the boundaries of binary images

It can be interpreted as an OR operation of the image and the neighbour overlapped at each pixel

Dilation



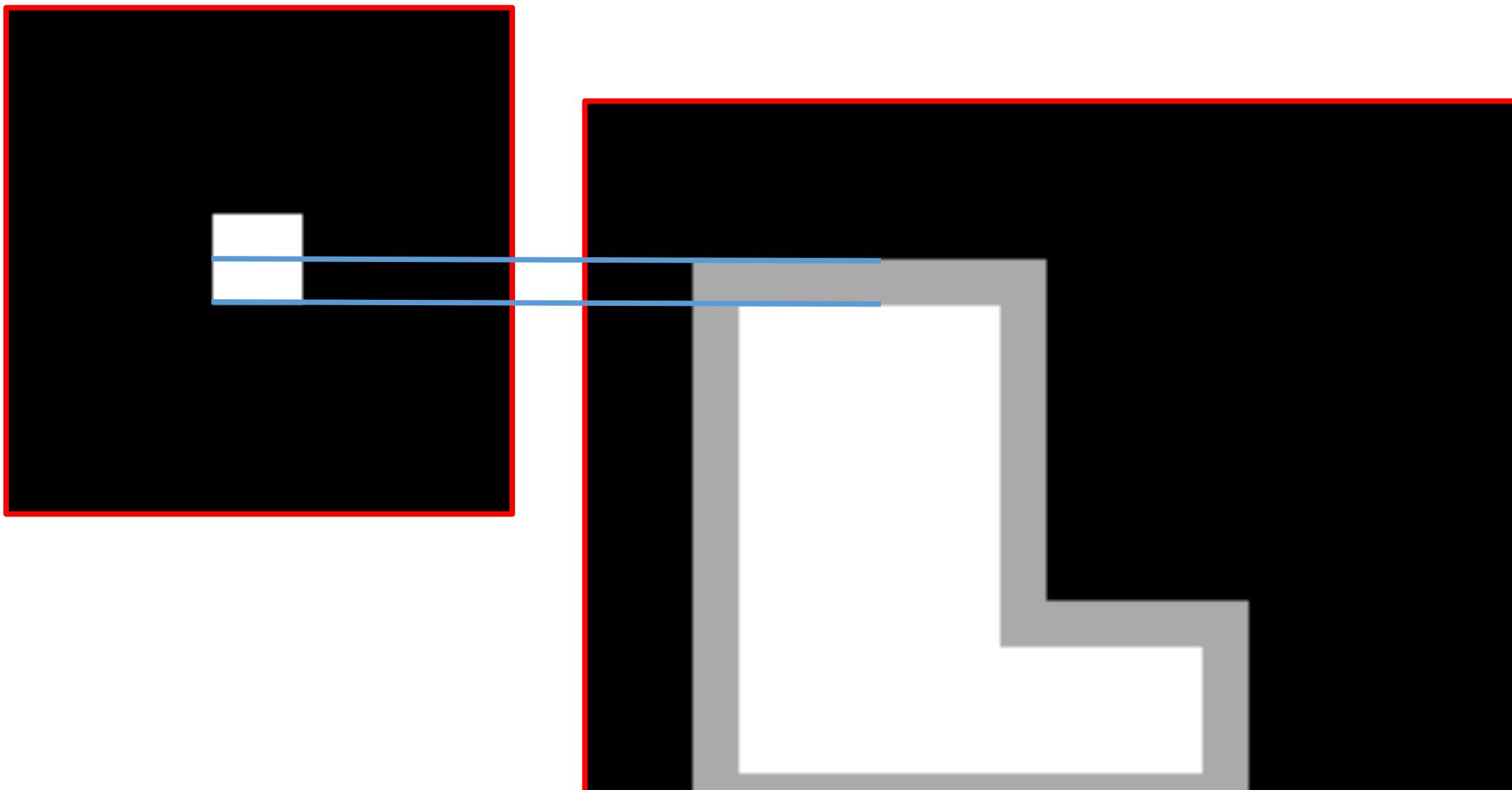
Dilation



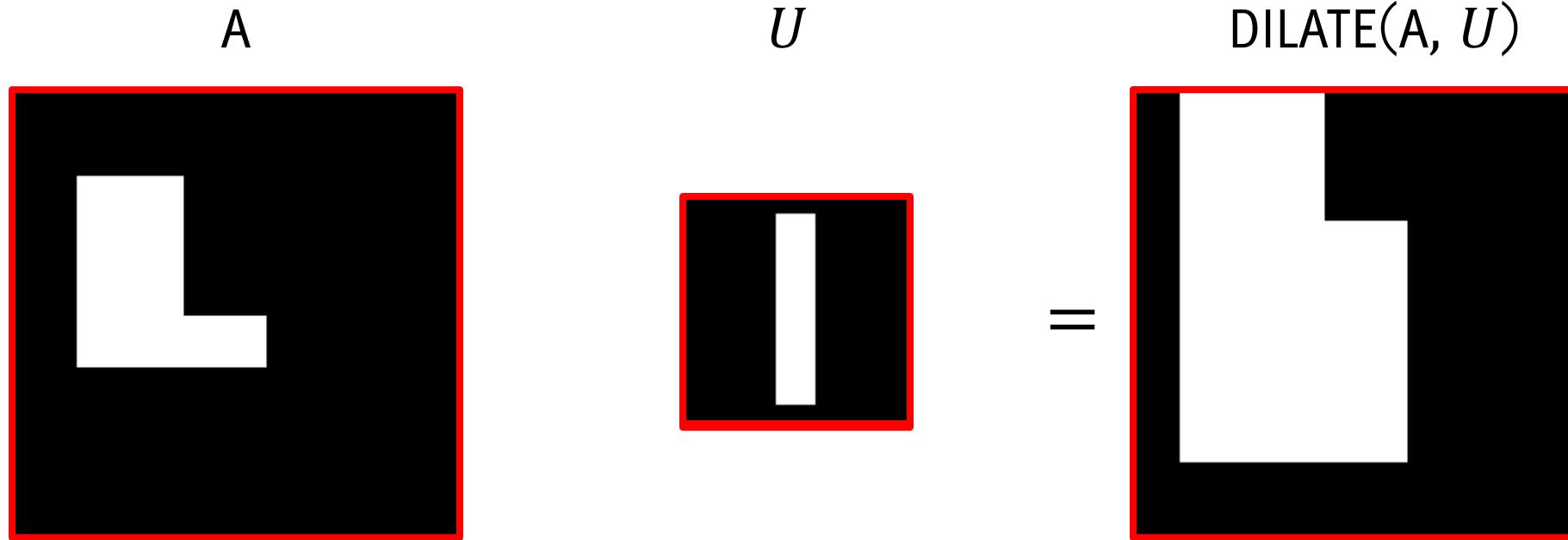
The brighter area now
corresponds to the input

Dilation

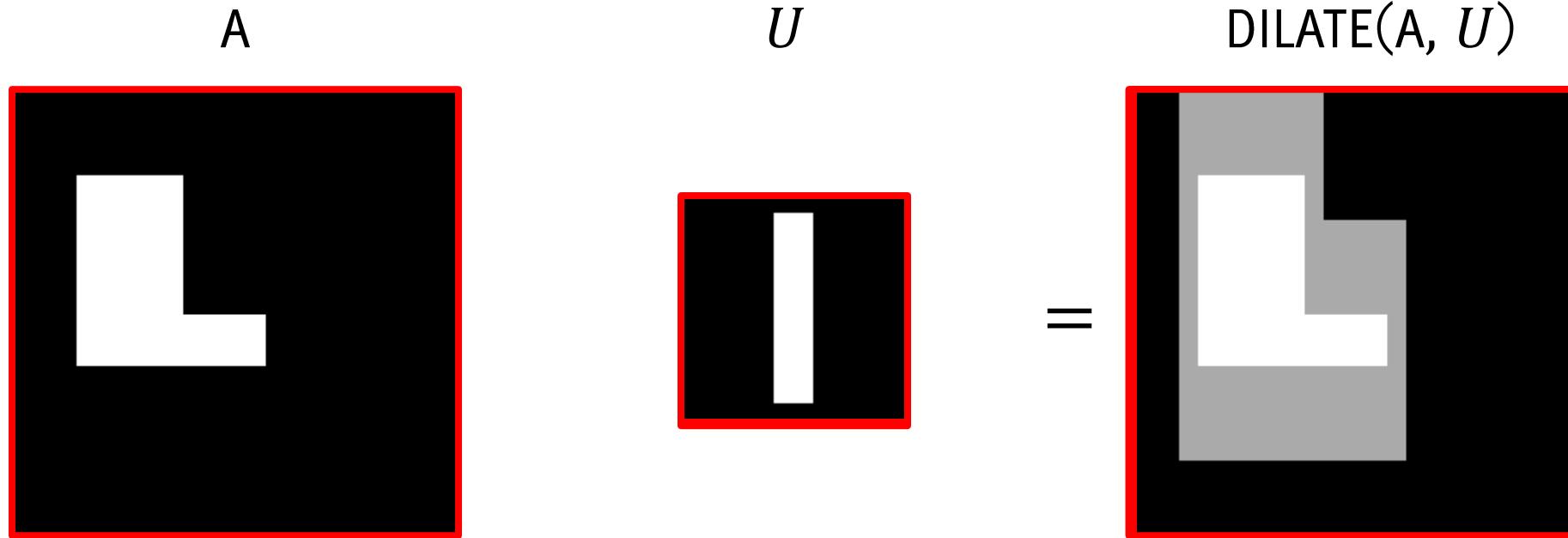
Dilation expands half size of the structuring element used as filter



Dilation

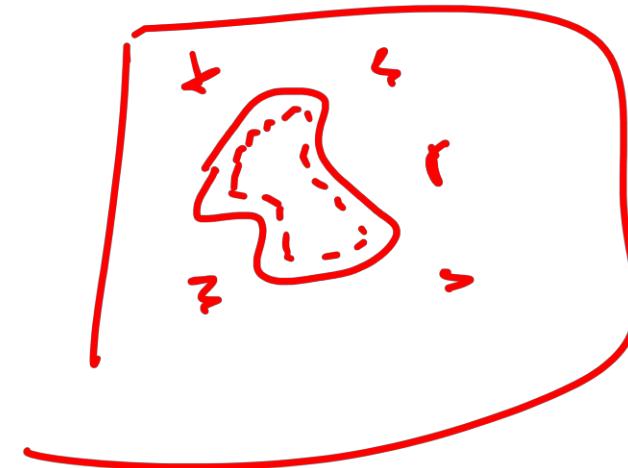


Dilation

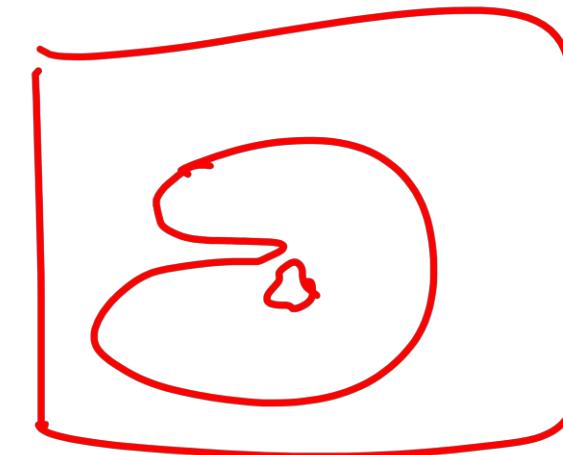


Open and Closure

Open Erosion followed by a Dilation



Closure Dilation followed by an Erosion



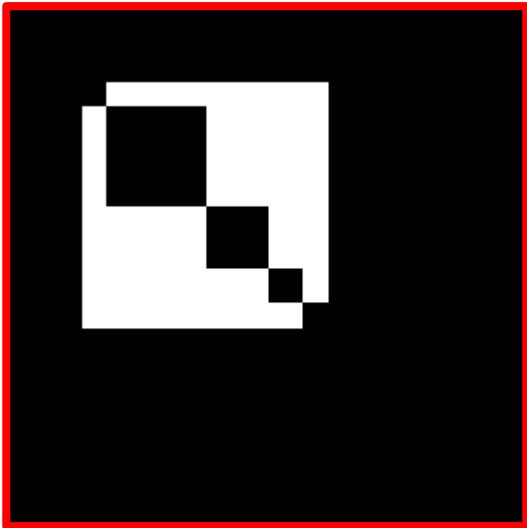
Open

Open Erosion followed by a Dilation

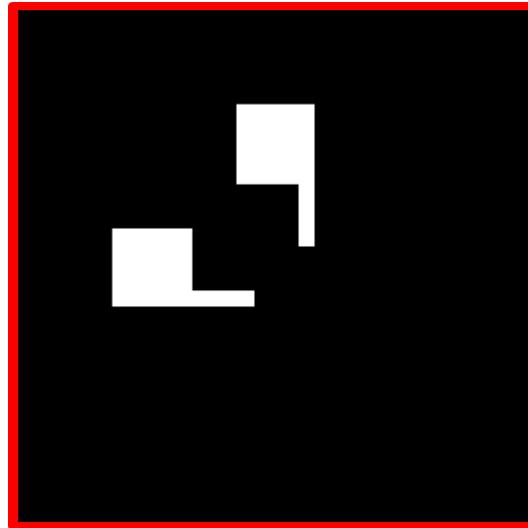
- Smooths the contours of an object
- Typically eliminates thin protrusions

Open

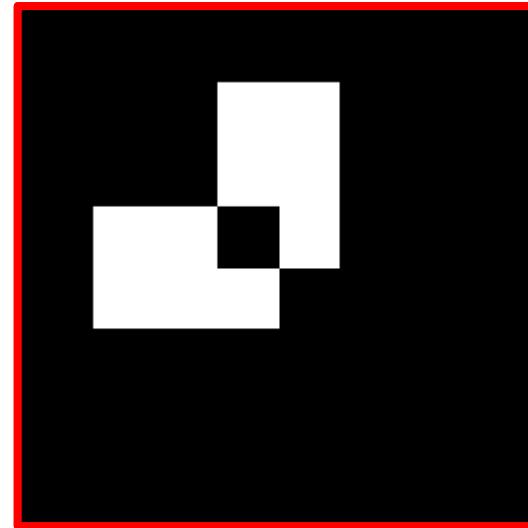
A



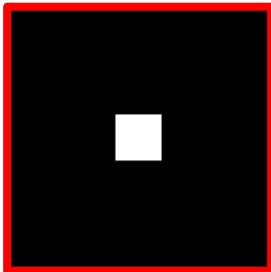
$O = \text{ERODE}(A, U)$



$O = \text{DILATE}(O, U)$

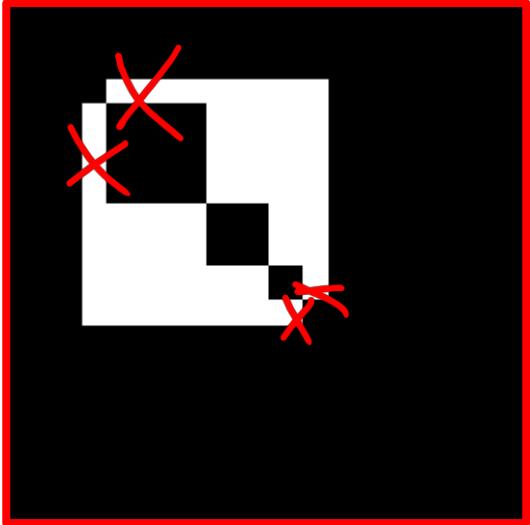


U

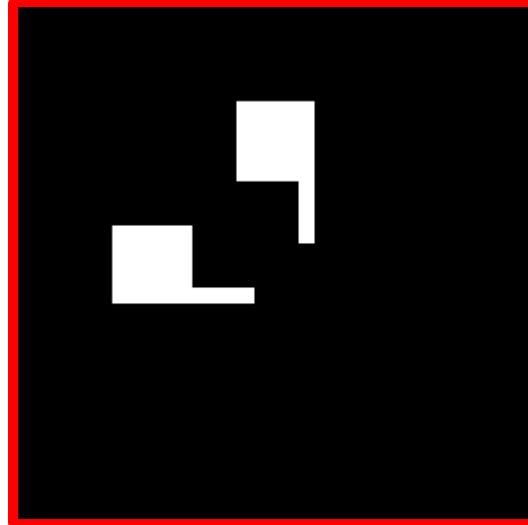


Open

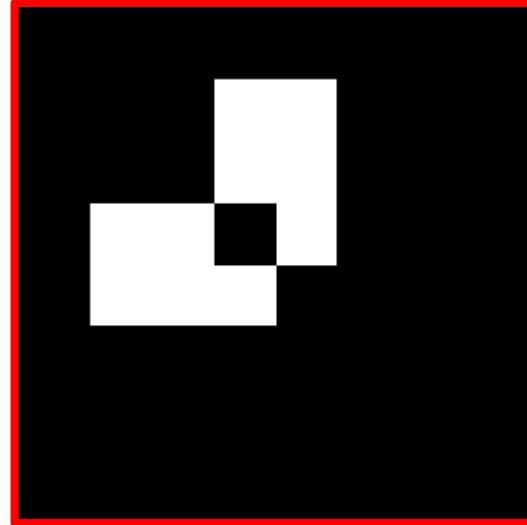
A



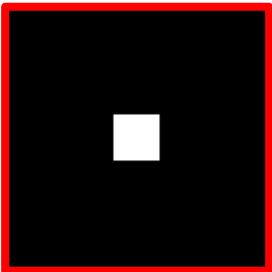
$O = \text{ERODE}(A, U)$



$O = \text{DILATE}(O, U)$

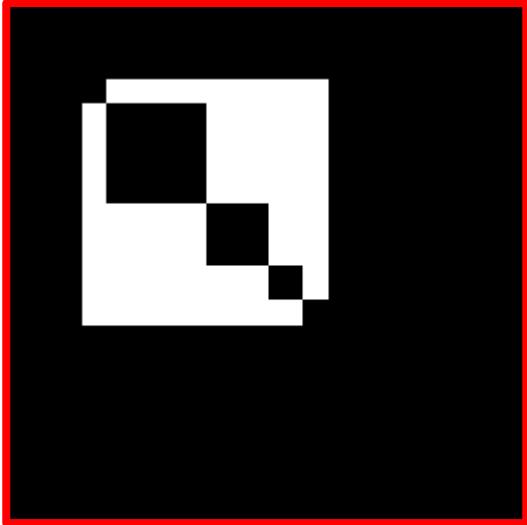


U

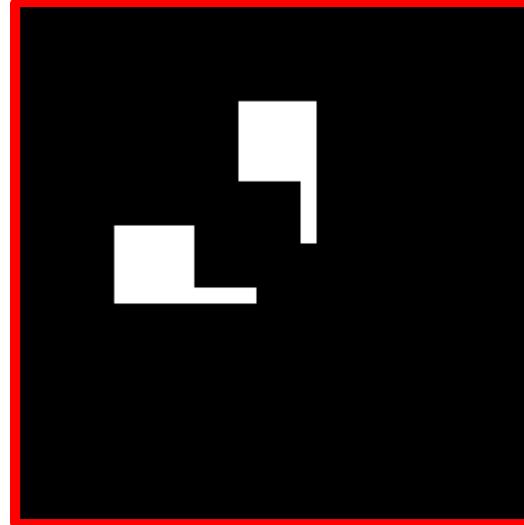


Open

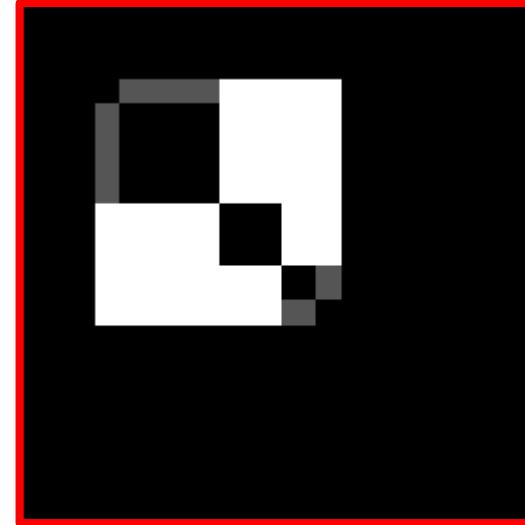
A



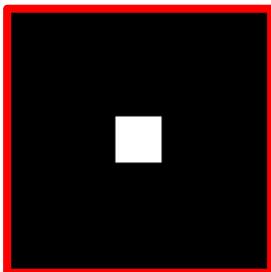
$O = \text{ERODE}(A, U)$



$O = \text{DILATE}(O, U)$



U



The gray area corresponds
to the input

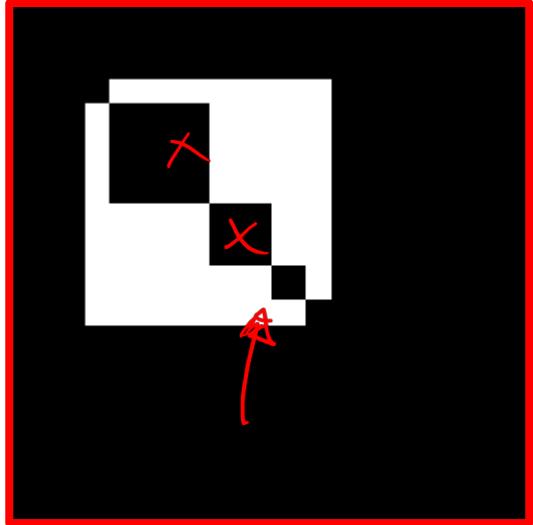
Closure

Closure Dilation followed by an Erosion

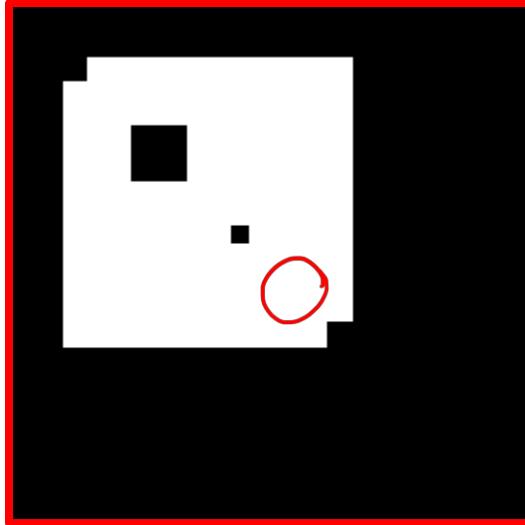
- Smooths the contours of an object, typically creates bridges
- Generally fuses narrow breaks

Close

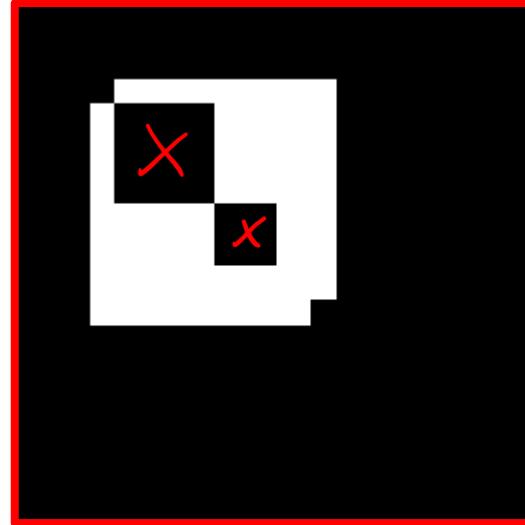
A



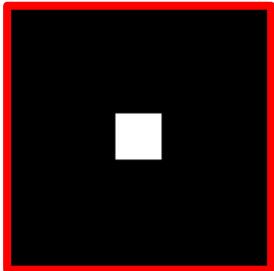
$O = \text{DILATE}(A, U)$



$O = \text{ERODE}(O, U)$

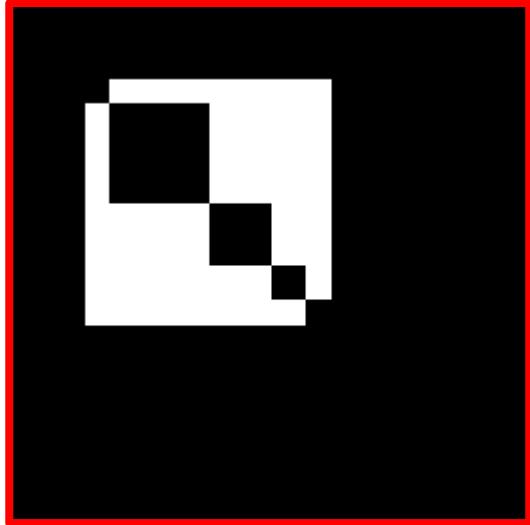


U

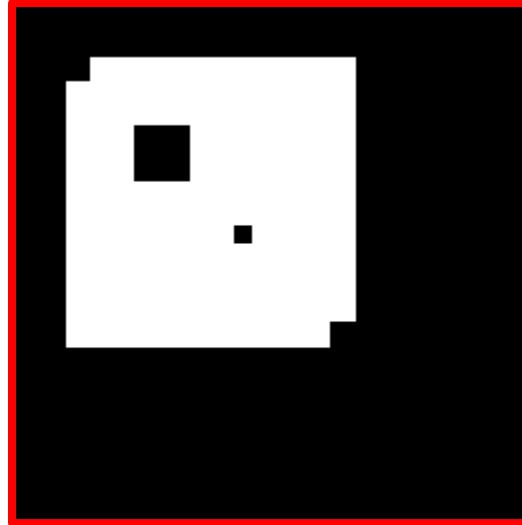


Close

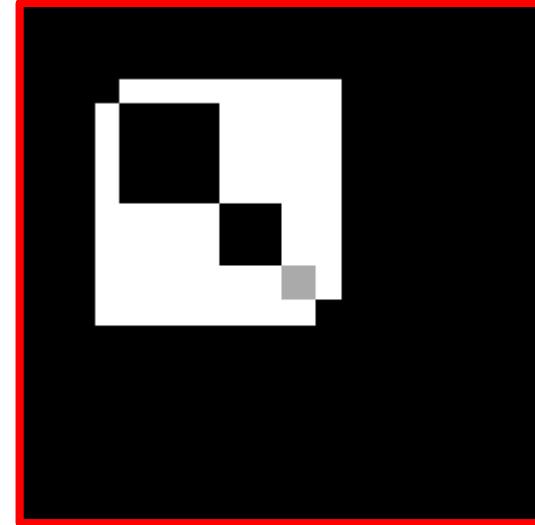
A



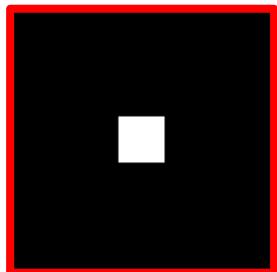
$0 = \text{DILATE}(A, U)$



$0 = \text{ERODE}(0, U)$



U



The gray spot was «false»
in the input

There are several other Non Linear Filters

Ordered Statistic based

- Median Filter
- Weight Ordered Statistic Filter (being erosion and dilation special cases)
- Trimmed Mean
- Hybrid Median

Ordered statistics filters (including erosion and dilation) can be applied to grayscale images as well, as their definition is general

In Python: **skimage.morphology**

Outline

A bit more on Nonlinear Filters

Edge Detection (Canny Edge Detector)

Digital Image Filters: Derivatives and Edges

Giacomo Boracchi

Image Analysis and Computer Vision

Politecnico di Milano

November 19, 2021

Book: GW chapters 3, 9, 10

Outline

Local Image Transformations

- **Derivatives estimation**
- Nonlinear Filters

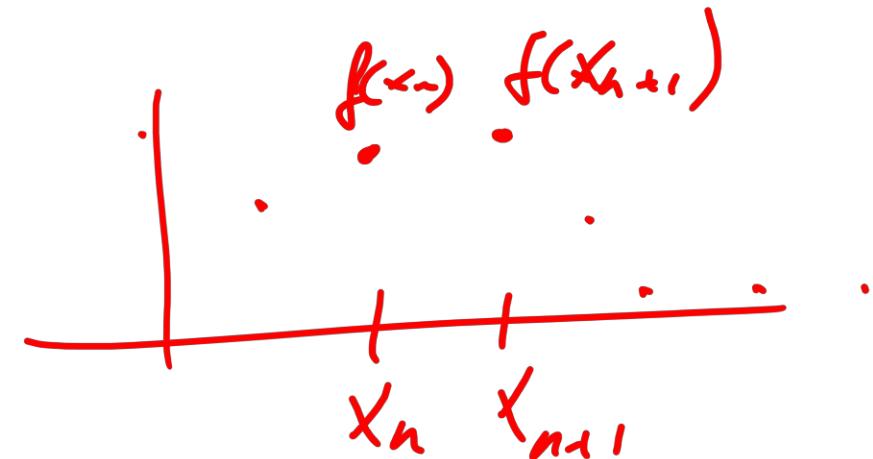
Edge Detection (Canny Edge Detector)

Derivatives Estimation

Differentiation and convolution

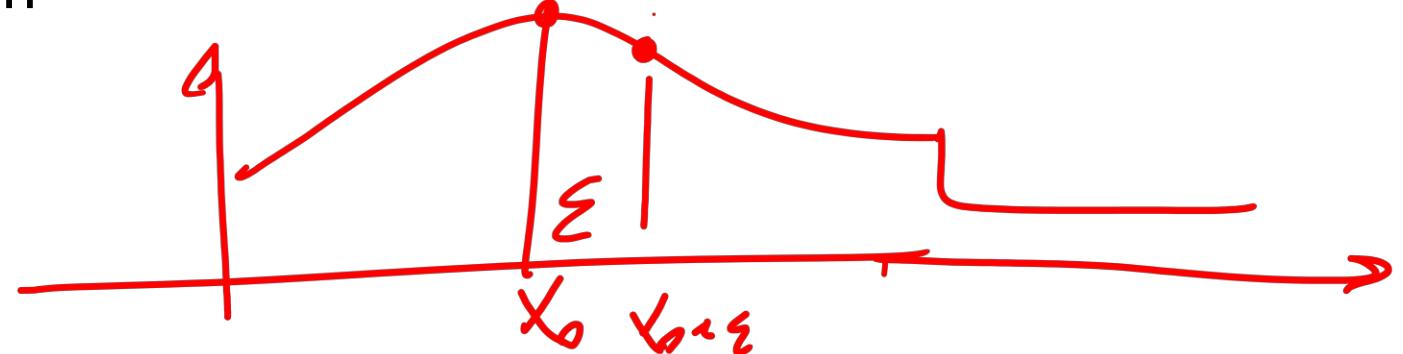
Recall the definition of derivative

$$\frac{\partial f(x_0)}{\partial x} = \lim_{\epsilon \rightarrow 0} \left(\frac{f(x_0 + \epsilon) - f(x_0)}{\epsilon} \right)$$



Now this is linear and shift invariant.

Therefore, in discrete domain, it will be represented as a convolution



Differentiation and convolution

Recall the definition of derivative

$$\frac{\partial f(x_0)}{\partial x} = \lim_{\epsilon \rightarrow 0} \left(\frac{f(x_0 + \epsilon) - f(x_0)}{\epsilon} \right)$$

We could approximate this as

$$\frac{\partial f(x_n)}{\partial x} \approx \frac{f(x_{n+1}) - f(x_n)}{\Delta x} = \textcolor{red}{7}$$

Now this is linear and shift invariant.

Therefore, in discrete domain, it will be represented as a convolution

which is obviously a convolution against the Kernel [1 -1];

$$(f * [-1, 1]) \quad \begin{matrix} [1 & -1] \\ \xrightarrow{x_n \quad x_{n-1}} \end{matrix}$$

Finite Differences in 2D (discrete) domain

$$\frac{\partial f(x, y)}{\partial x} = \lim_{\varepsilon \rightarrow 0} \left(\frac{f(x + \varepsilon, y) - f(x, y)}{\varepsilon} \right)$$

Horizontal

$$\frac{\partial f(x, y)}{\partial y} = \lim_{\varepsilon \rightarrow 0} \left(\frac{f(x, y + \varepsilon) - f(x, y)}{\varepsilon} \right)$$

[1 -1]

$$\frac{\partial f(x_n, y_m)}{\partial x} \approx \frac{f(x_{n+1}, y_m) - f(x_n, y_m)}{\Delta x}$$

Vertical

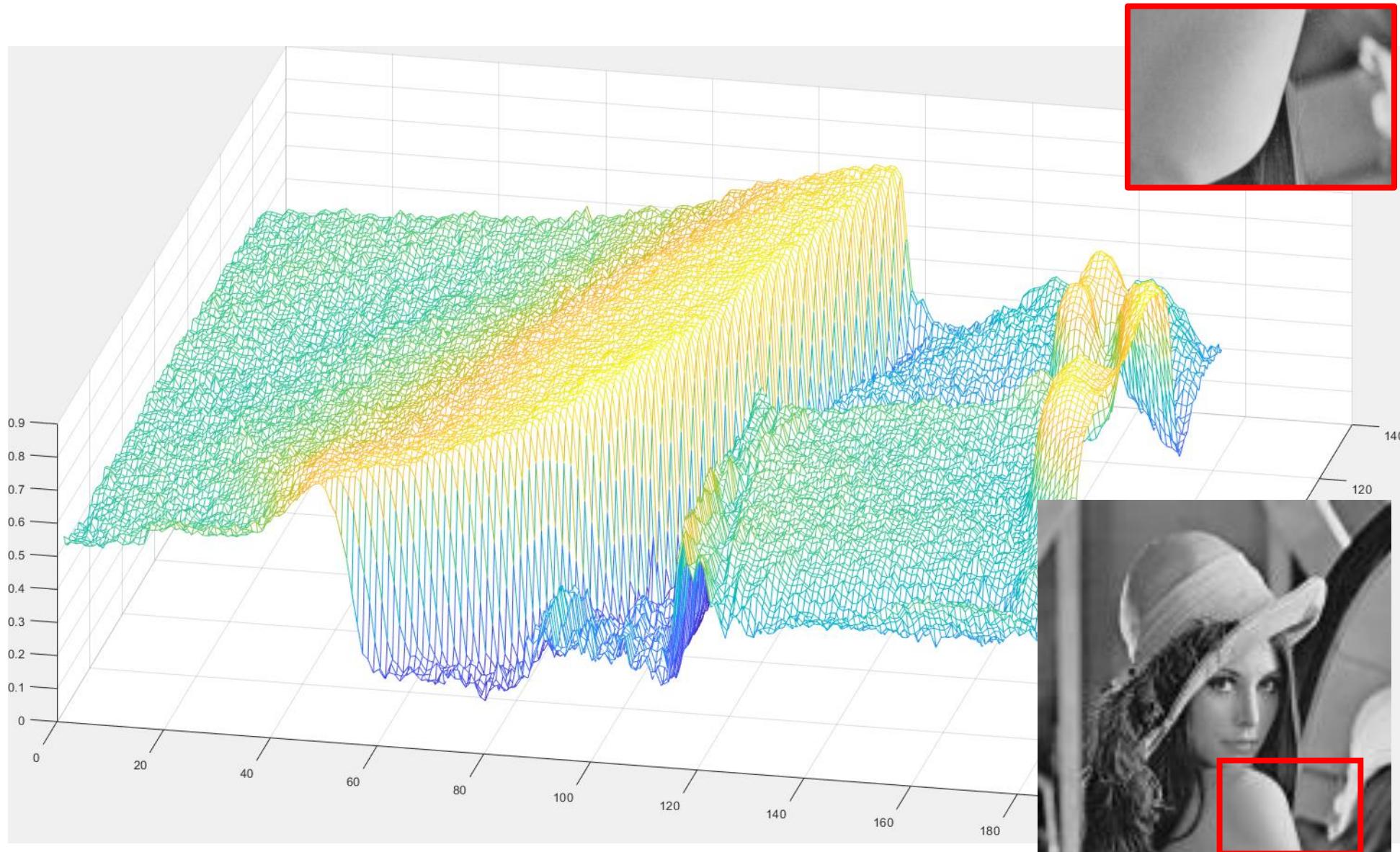
$$\frac{\partial f(x_n, y_m)}{\partial y} \approx \frac{f(x_n, y_{m+1}) - f(x_n, y_m)}{\Delta y}$$

$\begin{bmatrix} 1 \\ -1 \end{bmatrix}$

Discrete Approximation

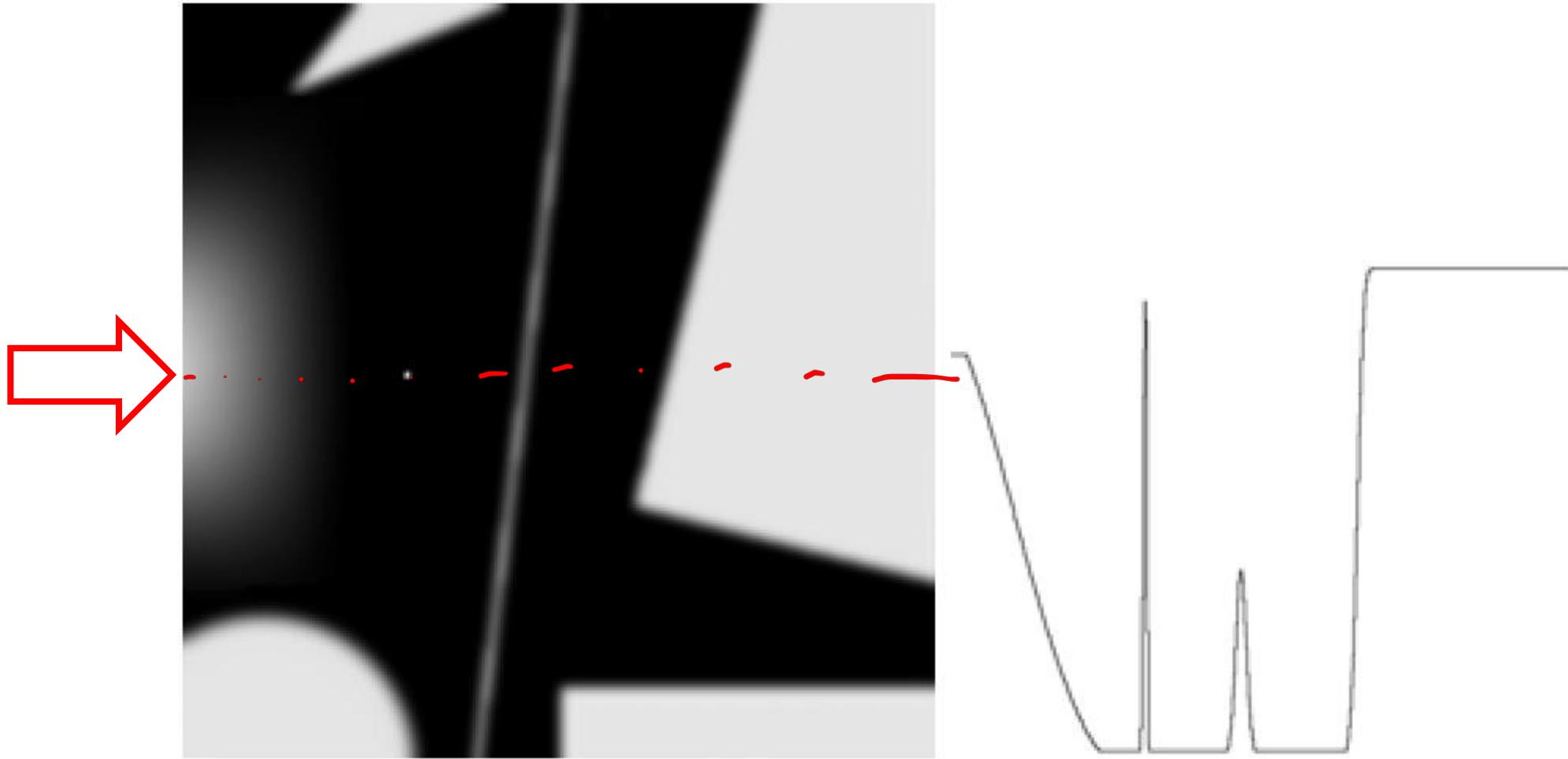
Convolution Kernels

Think of an image as a 2d, real-valued function



A 1D Example

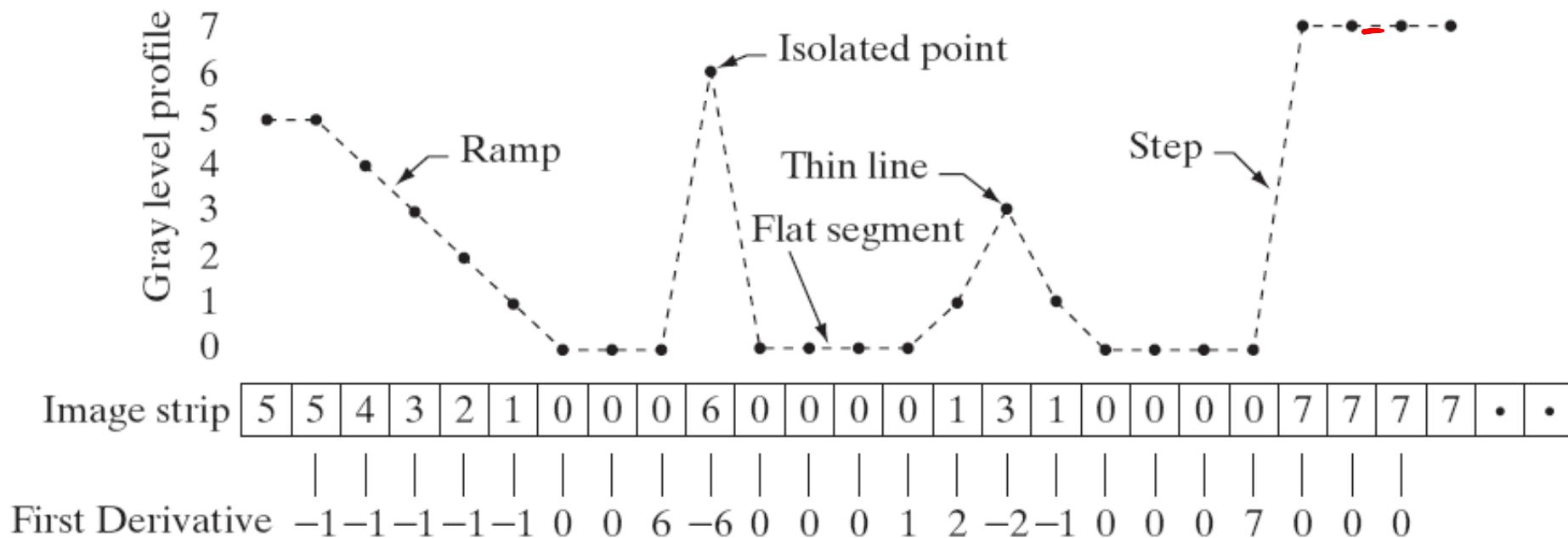
Take a line on a grayscale image



sw
Giacomo Boracchi

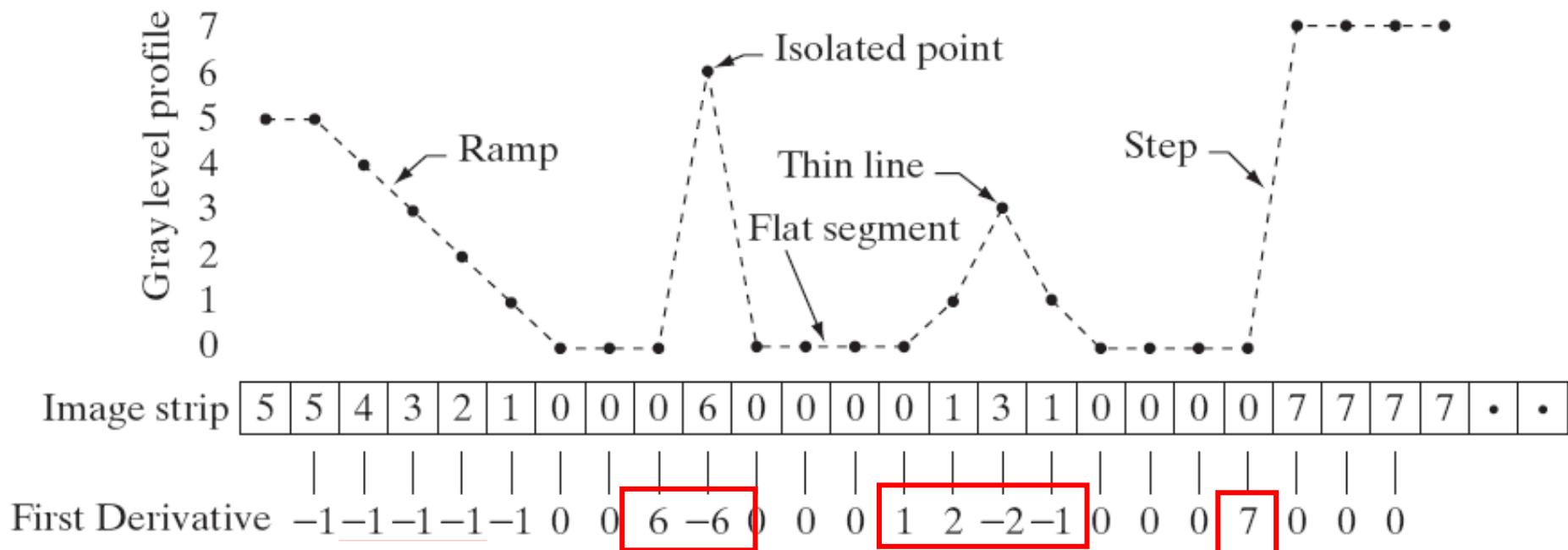
A 1D Example (II)

Filter the image values by a convolution against the filter [1 -1]



Derivatives

Derivatives are used to **highlight intensity discontinuities** in an image and to deemphasize regions with slowly varying intensity levels



Differentiating Filters

The derivatives can be also computed using centered filters:

$$f_x(x) = f(x - 1) - f(x + 1)$$

Such that the horizontal derivative is:

$$f_x = f \otimes \begin{array}{|c|c|c|} \hline 1 & 0 & -1 \\ \hline \end{array}$$

While the vertical derivative is:

$$f_y = f \otimes \begin{array}{|c|c|c|} \hline 1 & 0 & -1 \\ \hline \end{array} t$$

Classical Operators: Prewitt

Horizontal derivative

$$s = \begin{bmatrix} 1 & 1 \\ 1 & 1 \\ 1 & 1 \end{bmatrix} \quad dx = [1 \quad -1]$$

Smooth Differentiate

$$\begin{aligned} I \star \text{Prewitt} &= \\ I \star (s \star dx) &= (I \star s) \star dx \end{aligned}$$

$$h_x = s \odot dx = \begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix}$$

Vertical derivative

$$s = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \quad dy = \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$
$$h_y = s \odot dy = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}$$

Classical Operators: Sobel

Horizontal derivative

$$s = \begin{bmatrix} 1 & 1 \\ 2 & 2 \\ 1 & 1 \end{bmatrix} \quad dx = [1 \quad -1] \quad h_x = s \odot dx = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix}$$

Smooth Differentiate

Vertical derivative

$$s = \begin{bmatrix} 1 & 2 & 1 \\ 1 & 2 & 1 \end{bmatrix} \quad dy = \begin{bmatrix} 1 \\ -1 \end{bmatrix} \quad h_y = s \odot dy = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

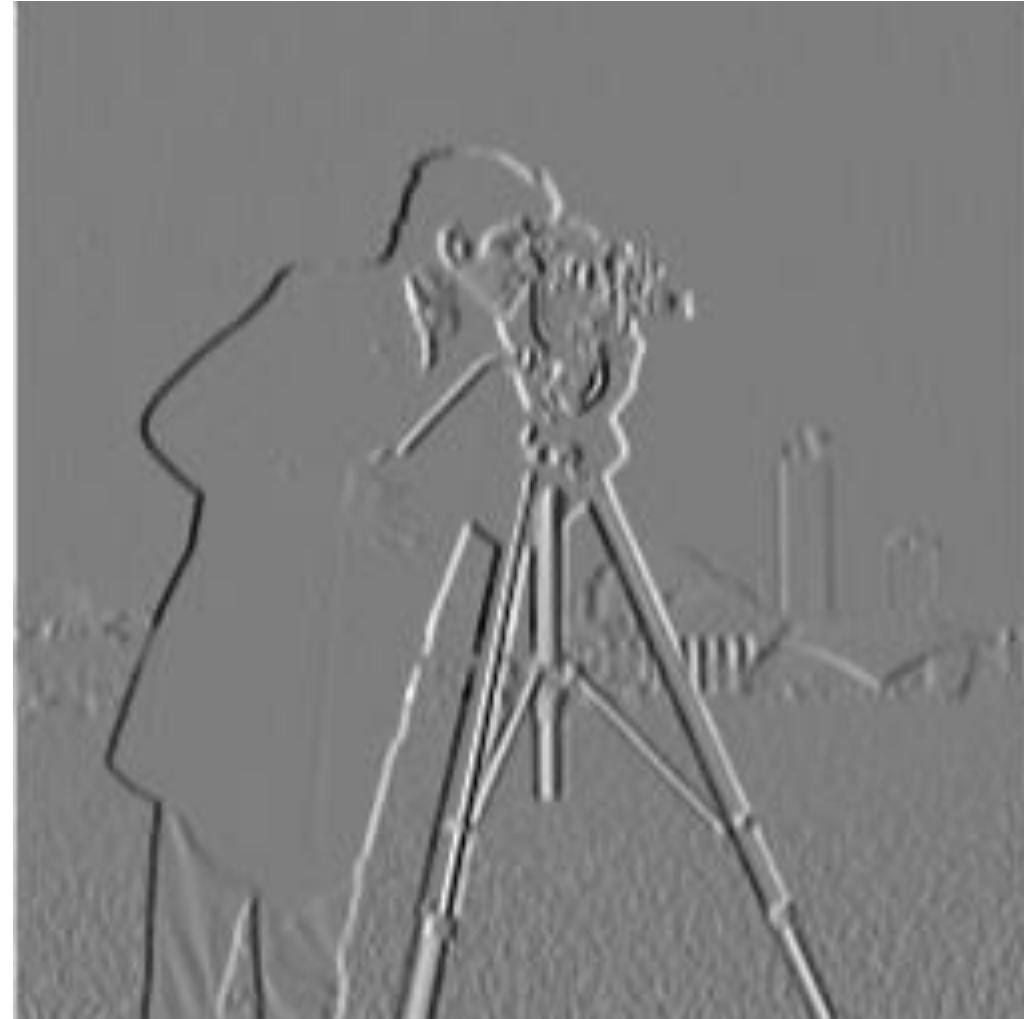
Another famous test image - cameraman



Horizontal Derivatives using Sobel

$$\nabla I_x = (I \odot d_x)$$

$$\nabla I(r, c) = \begin{bmatrix} \nabla I_x(r, c) \\ \nabla I_y(r, c) \end{bmatrix}$$

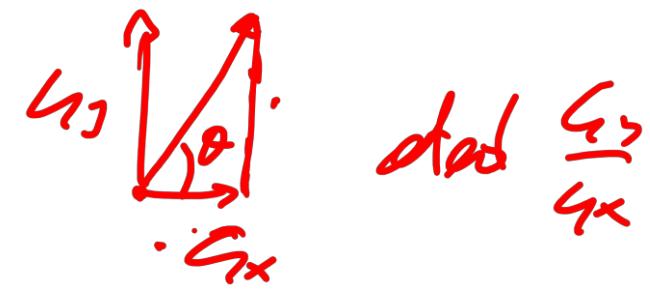
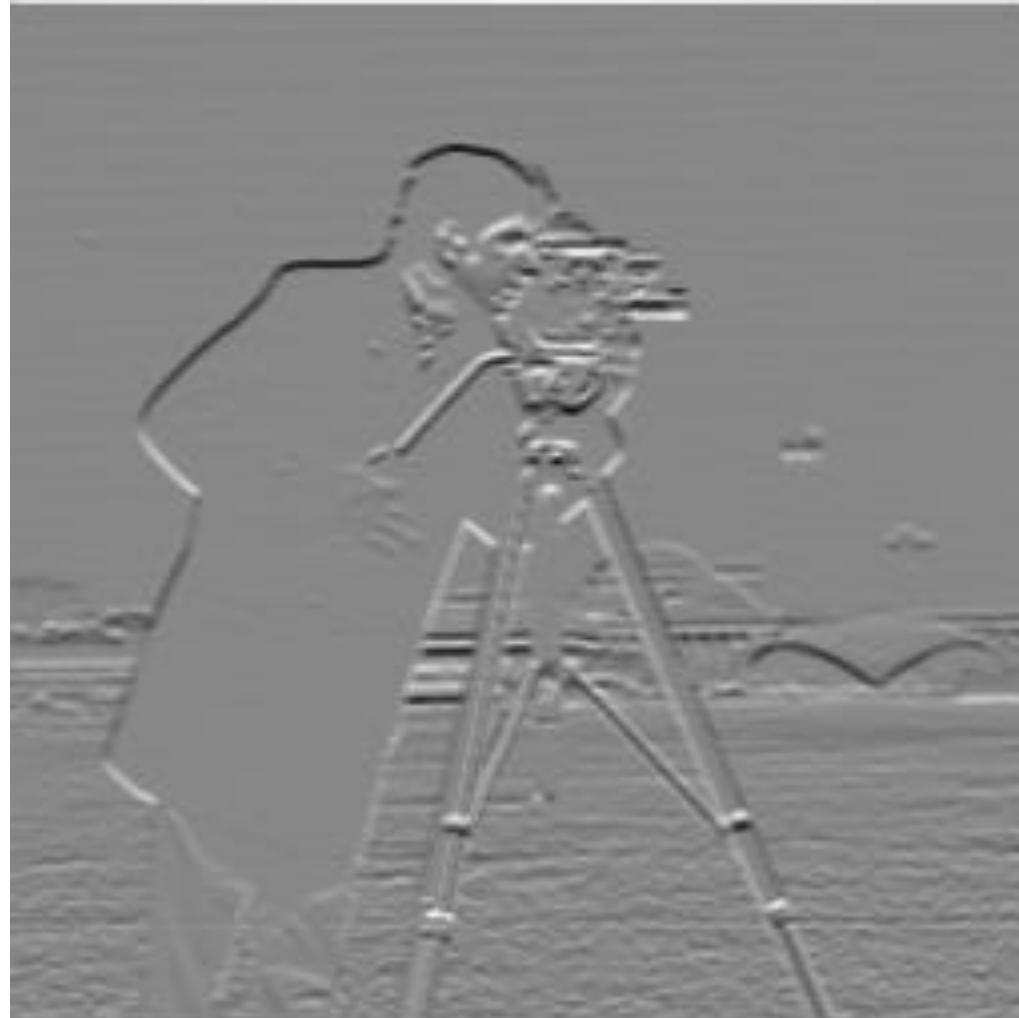


Vertical Derivatives using Sobel

$$\nabla I_y = (I \odot d_y)$$

$$d_y = d_x'$$

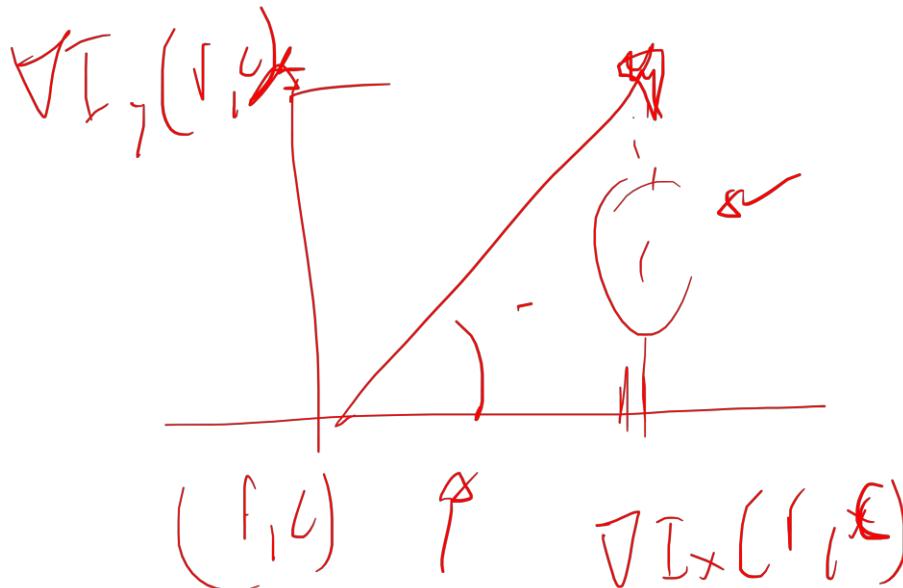
$$\nabla I(r, c) = \begin{bmatrix} \nabla I_x(r, c) \\ \nabla I_y(r, c) \end{bmatrix}$$



Gradient Magnitude

$$\|\nabla I\| = \sqrt{(I \odot d_x)^2 + (I \odot d_y)^2}$$

$$\nabla I(r, c) = \begin{bmatrix} \nabla I_x(r, c) \\ \nabla I_y(r, c) \end{bmatrix}$$



The Gradient Orientation

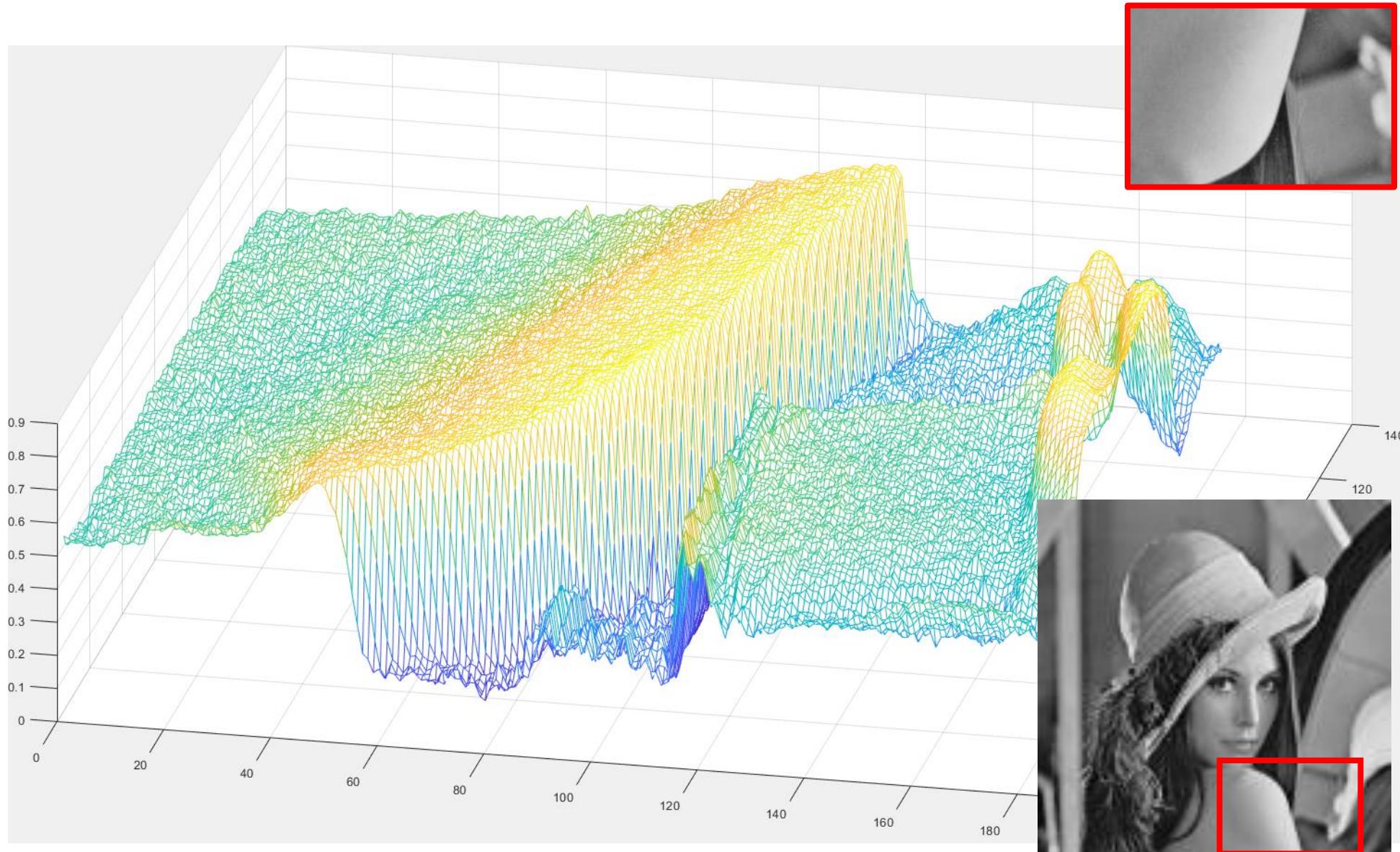
Like for continuous function, the gradient in each pixel points at the **steepest growth/decrease direction**.

$$\angle \nabla I(r, c) = \text{atan} \left(\frac{\nabla I_y(r, c)}{\nabla I_x(r, c)} \right) = \text{atan} \left(\frac{(I \odot d_y)(r, c)}{(I \odot d_x)(r, c)} \right)$$

The gradient norm indicates the strength of the intensity variation

Let's switch to Matlab....

Think of an image as a 2d, real-valued function



The Image Gradient

Image Gradient is the gradient of a real-valued 2D function

$$\nabla I(r, c) = \begin{bmatrix} I \circledast d_x \\ I \circledast d_y \end{bmatrix}(r, c)$$

where principal derivatives are computed through convolution against the derivative filters (e.g. Prewitt)

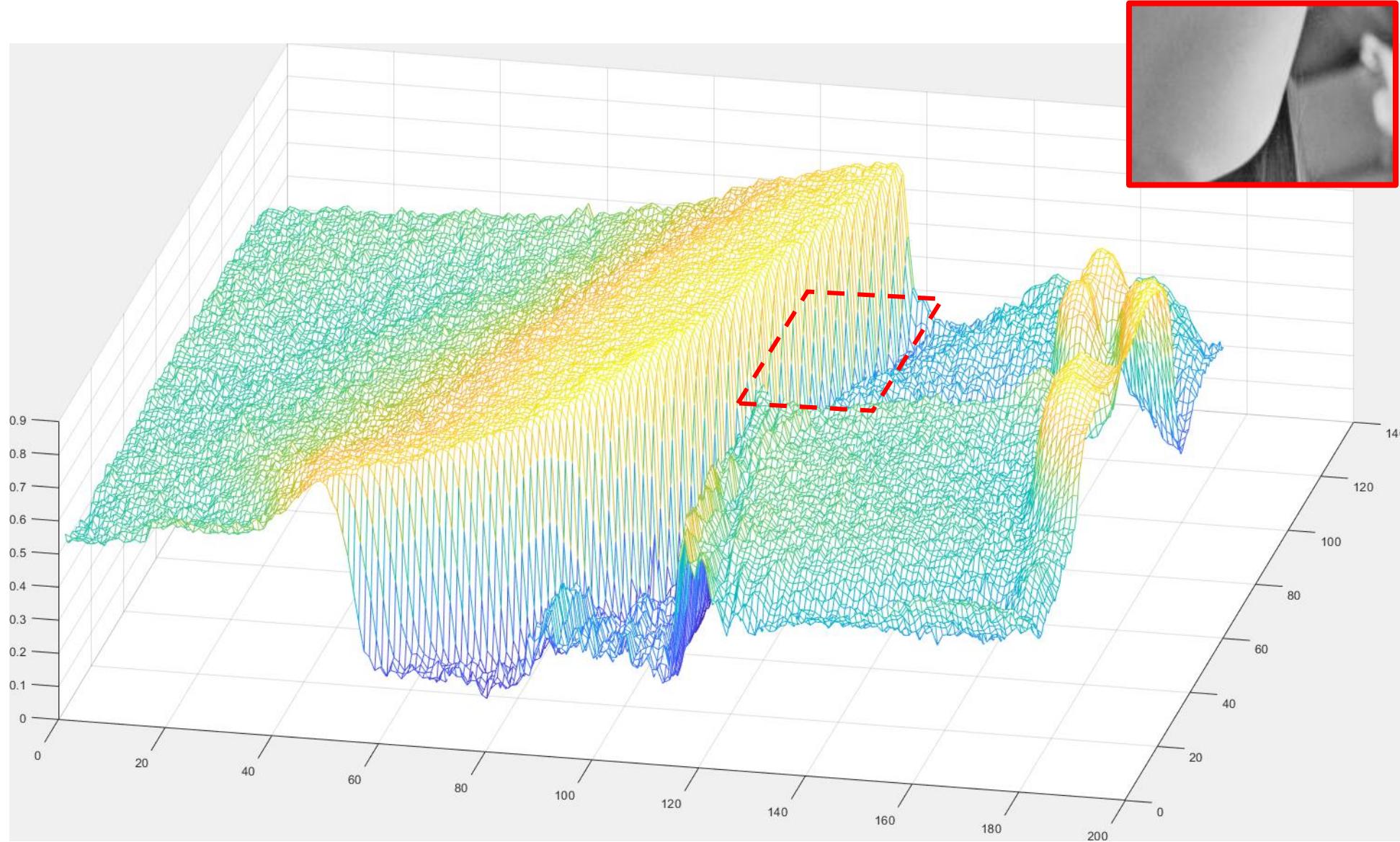
$$dx = \begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix}, \quad dy = dx'$$

Image gradient behaves like the gradient of a function:

$|\nabla I(r, c)|$ is large where there are large variations

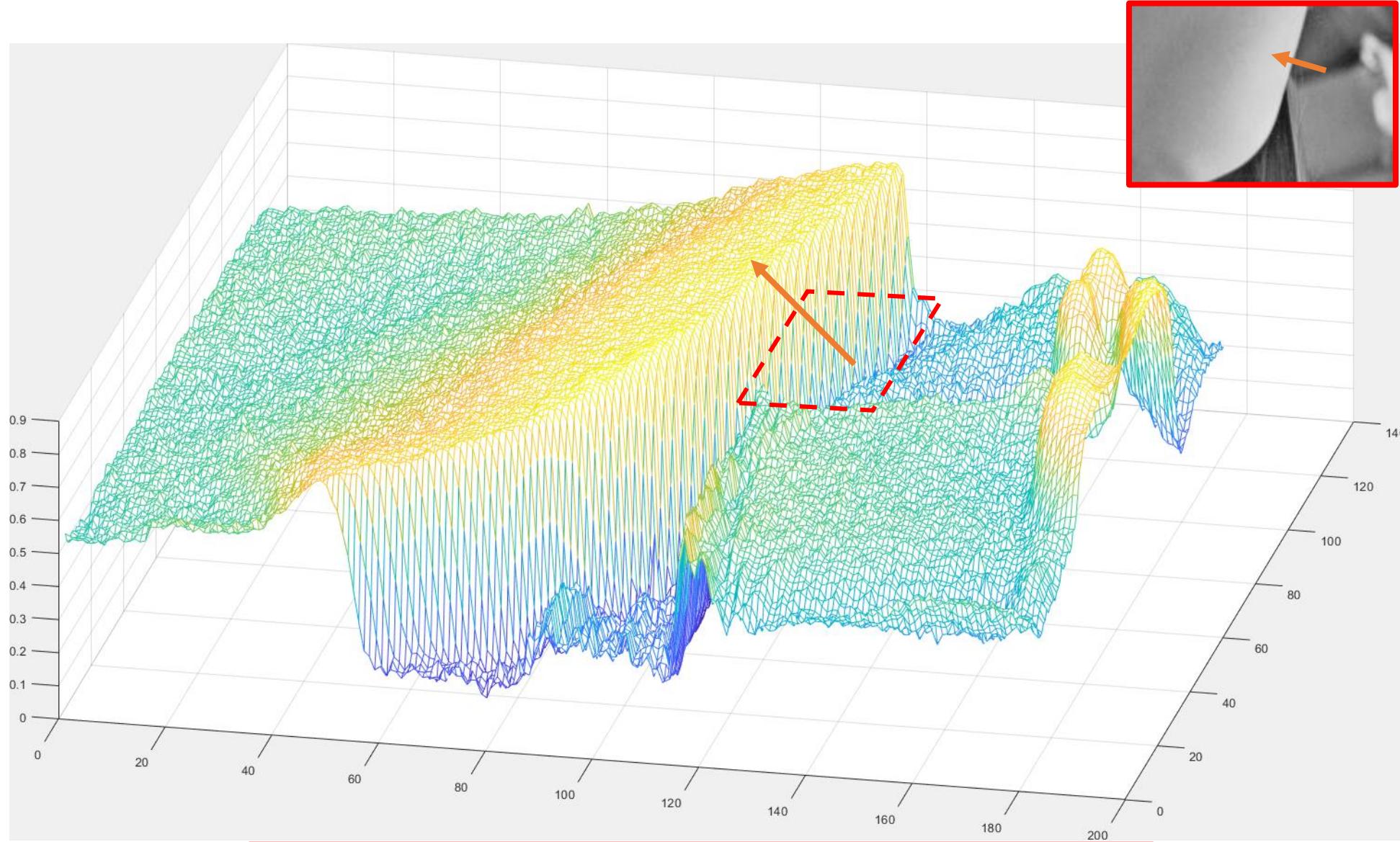
$\angle \nabla I(r, c)$ is the direction of the steepest variation

Think of an image as a 2d, real-valued function



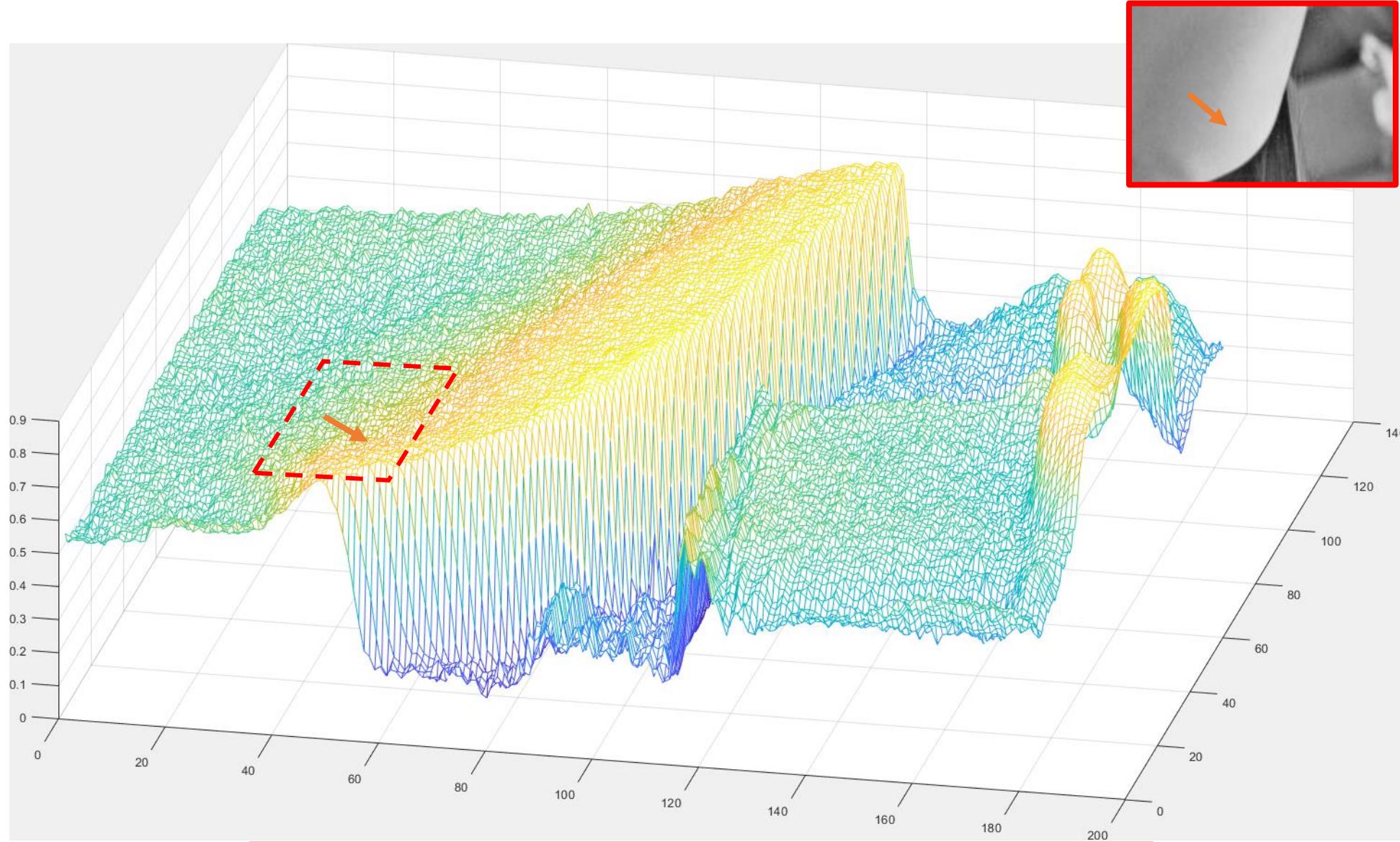
Local spatial transformations are defined over neighborhood like this

Think of an image as a 2d, real-valued function



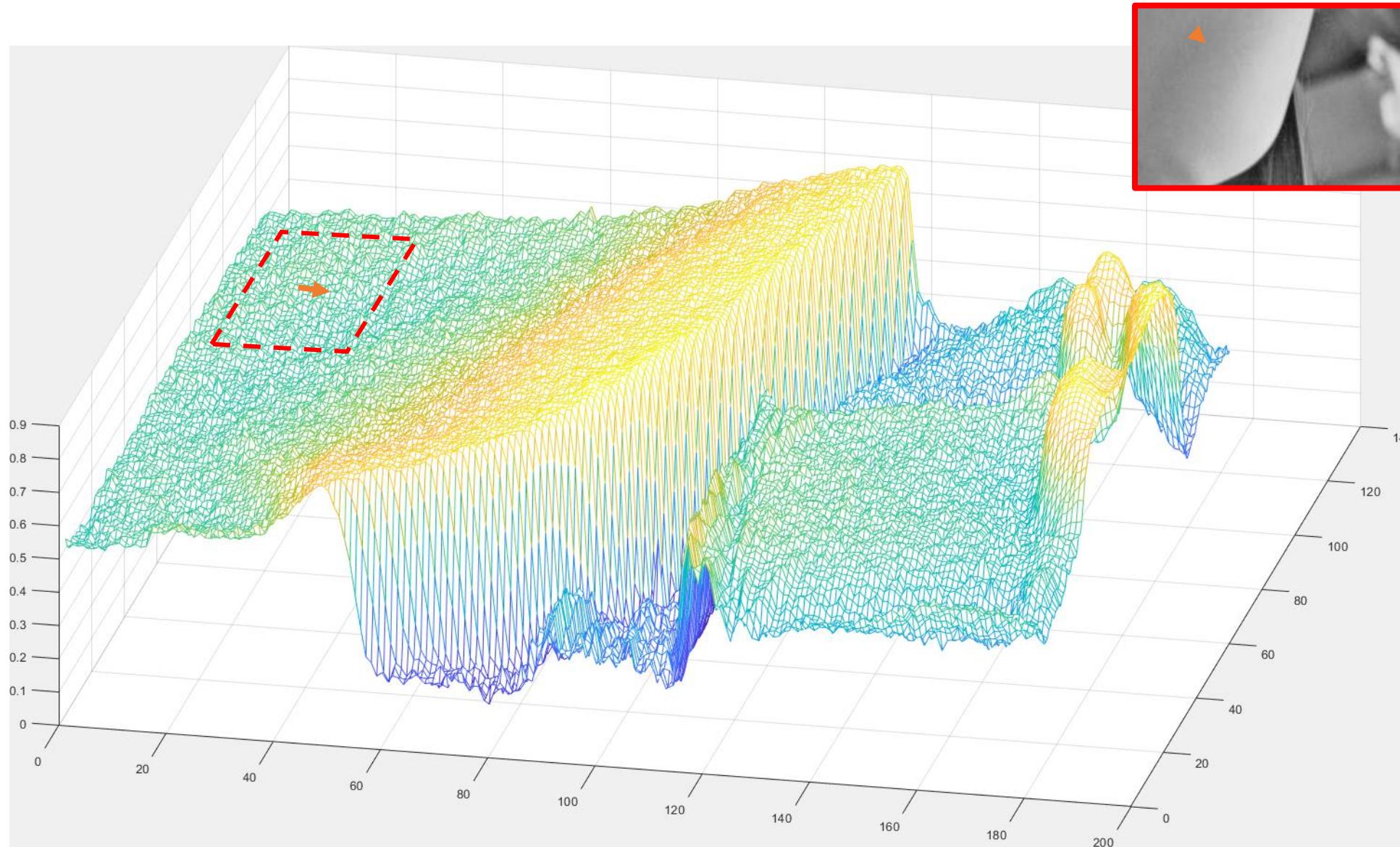
What about the gradient in this neighborhood?

Think of an image as a 2d, real-valued function



What about the gradient in this neighborhood?

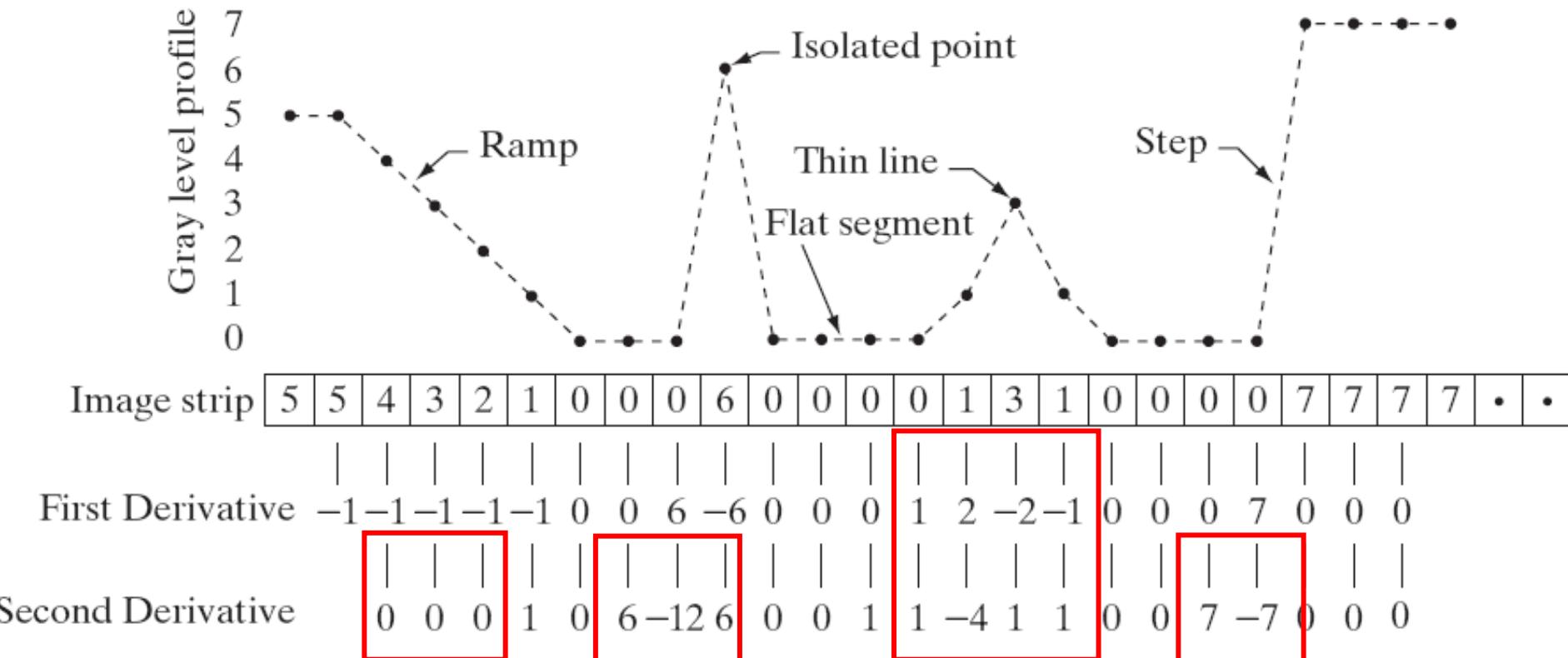
Think of an image as a 2d, real-valued function



Higher Order Derivatives

Derivatives

Derivatives are used to highlight intensity discontinuities in an image and to deemphasize regions with slowly varying intensity levels



Second Order Derivatives

The Laplacian of the second order derivative is defined as

$$\nabla^2 I = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2}$$

where

$$\frac{\partial^2 I}{\partial x^2} = I(x+1, y) + I(x-1, y) - 2I(x, y)$$

$$\frac{\partial^2 I}{\partial y^2} = I(x, y-1) + I(x, y+1) - 2I(x, y), \text{ thus}$$

$$\nabla^2 I = I(x+1, y) + I(x-1, y) + I(x, y-1) + I(x, y+1) - 4I(x, y)$$

It's a linear operator \rightarrow it can be implemented as a convolution

TODO: prove that the second order derivative (computed as the convolution of the first order derivative) is like this

Filter for Digital Laplacian

The Laplacian of the second order derivative is defined as

$$\nabla^2 I = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2}$$

0	1	0
1	-4	1
0	1	0

Standard
definition, invariant
to 90° rotation

1	1	1
1	-8	1
1	1	1

Alternative
definition, invariant
to 45° rotation

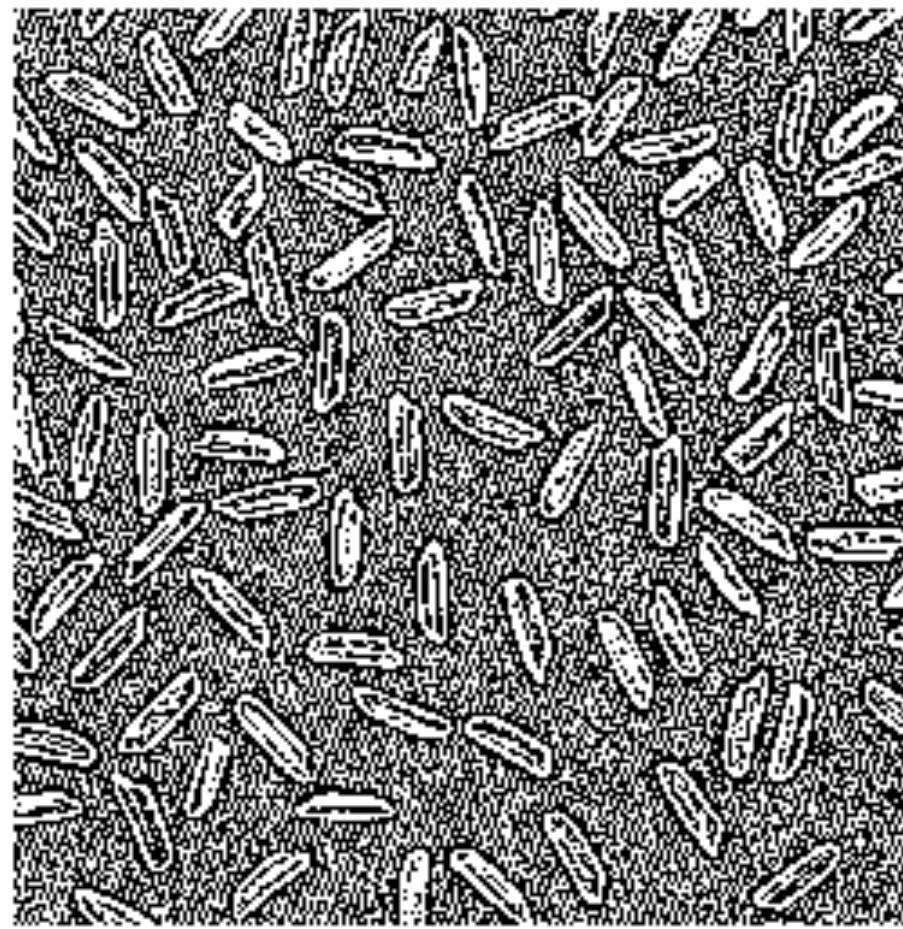
The Laplacian: Image Sharpening

The Laplacian of an image have grayish edge lines and other discontinuities, all superimposed on a dark, featureless background.



The Laplacian: Image Sharpening

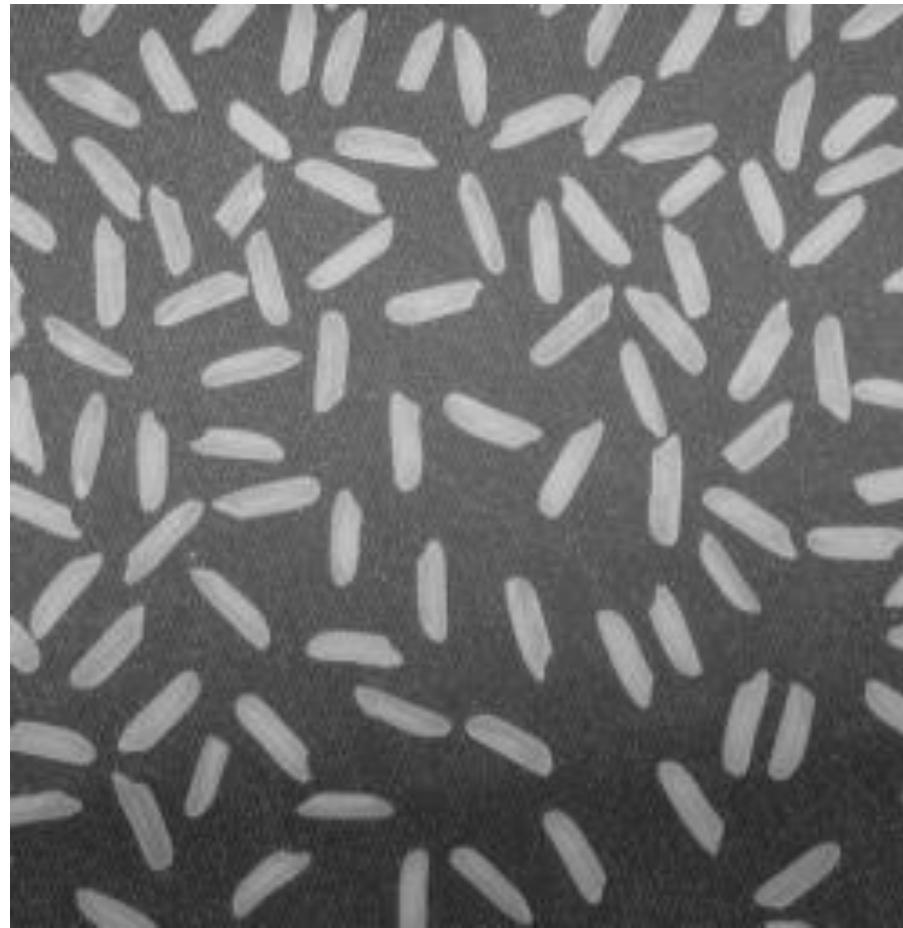
The Laplacian of an image have grayish edge lines and other discontinuities, all superimposed on a dark, featureless background.



The Laplacian: Image Sharpening

Background features can be “recovered” simply by adding the Laplacian image to the original (provided suitable rescaling)

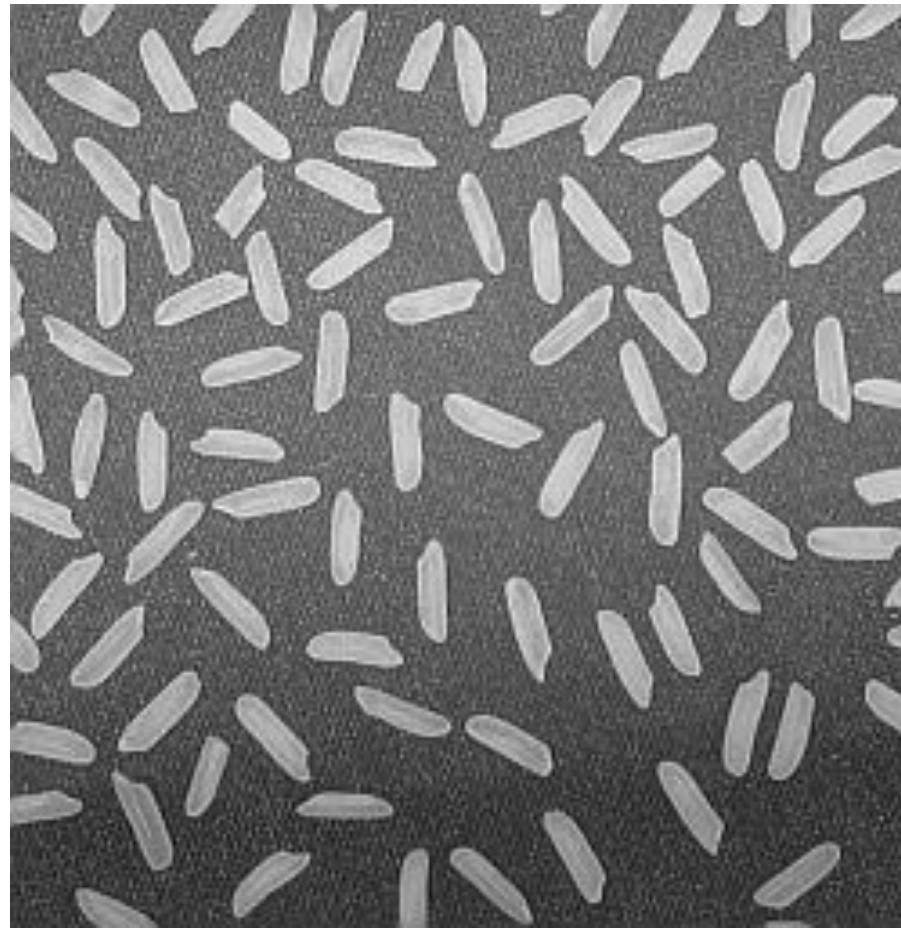
$$G(r, c) = I(r, c) + k[\nabla^2 I(r, c)]$$



The Laplacian: Image Sharpening

Background features can be “recovered” simply by adding the Laplacian image to the original (provided suitable rescaling)

$$G(r, c) = I(r, c) + k[\nabla^2 I(r, c)]$$



Edges in Images

Edge Detection in Images

Goal: Automatically find the contour of objects in a scene.

What For: Edges are significant for scene understanding, enhancement compression...



Typically the edge mask is «flipped», 1 at edges and 0 elsewhere

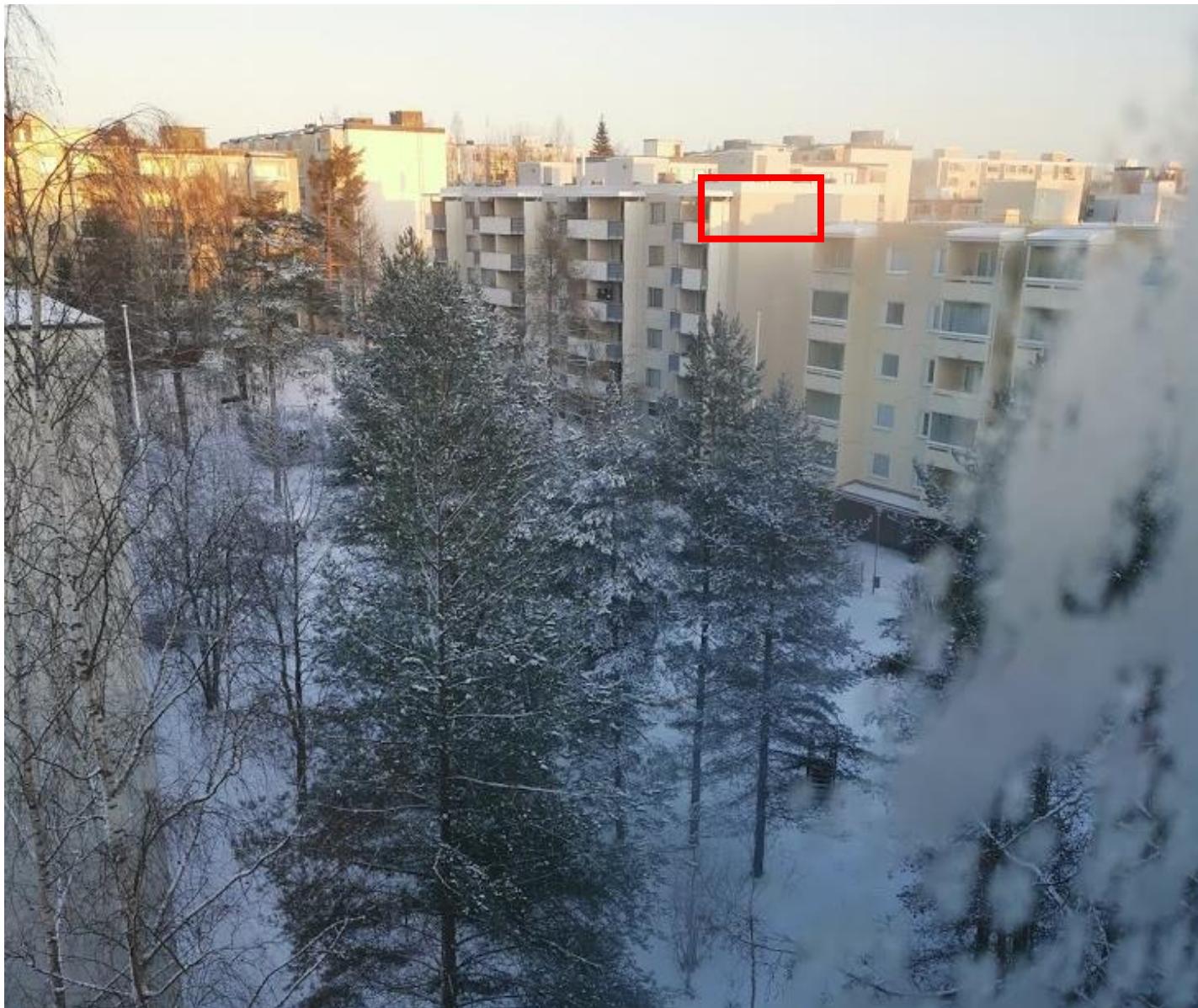
Edges in Images



Depth discontinuities



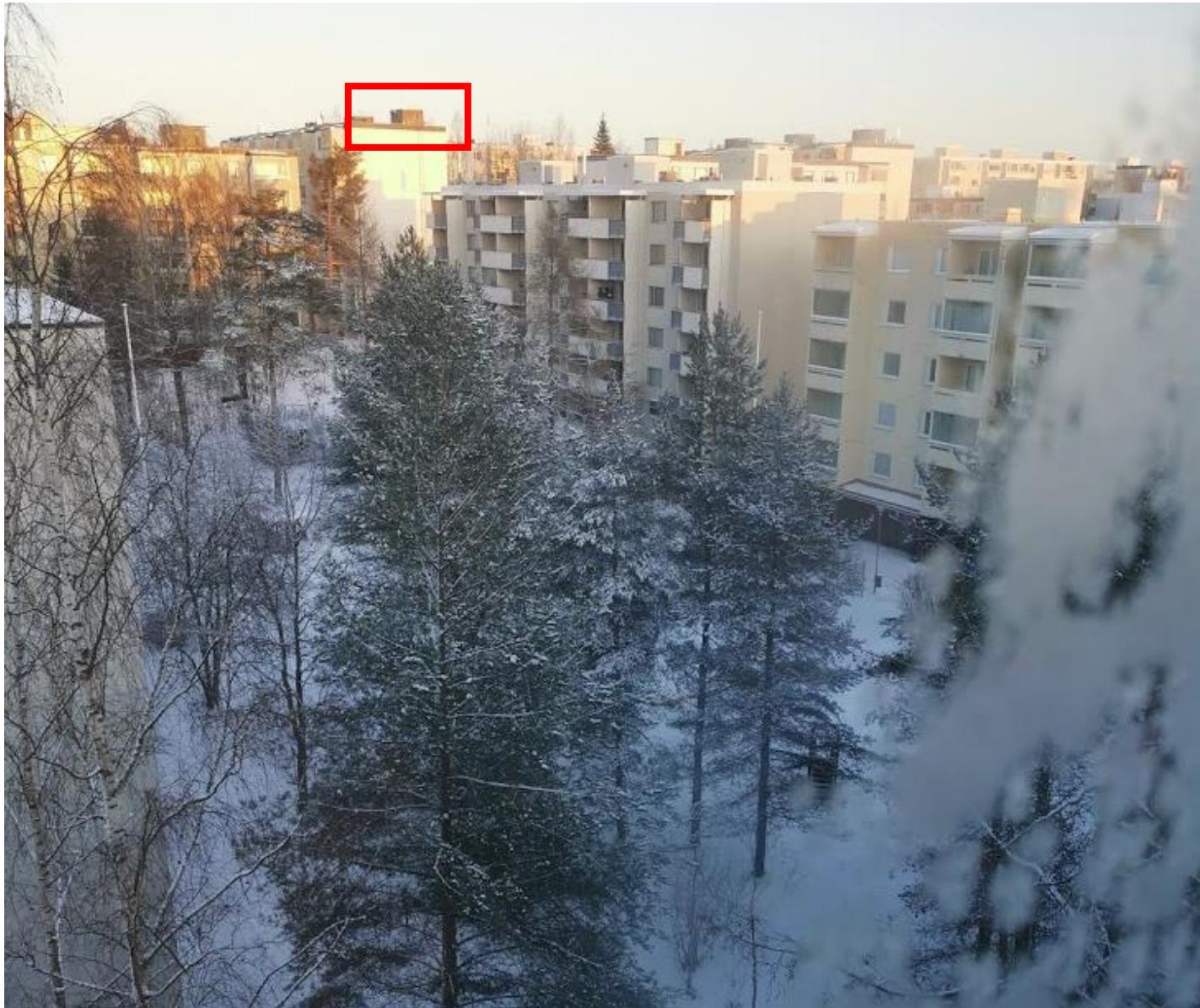
Edges in Images



Shadows



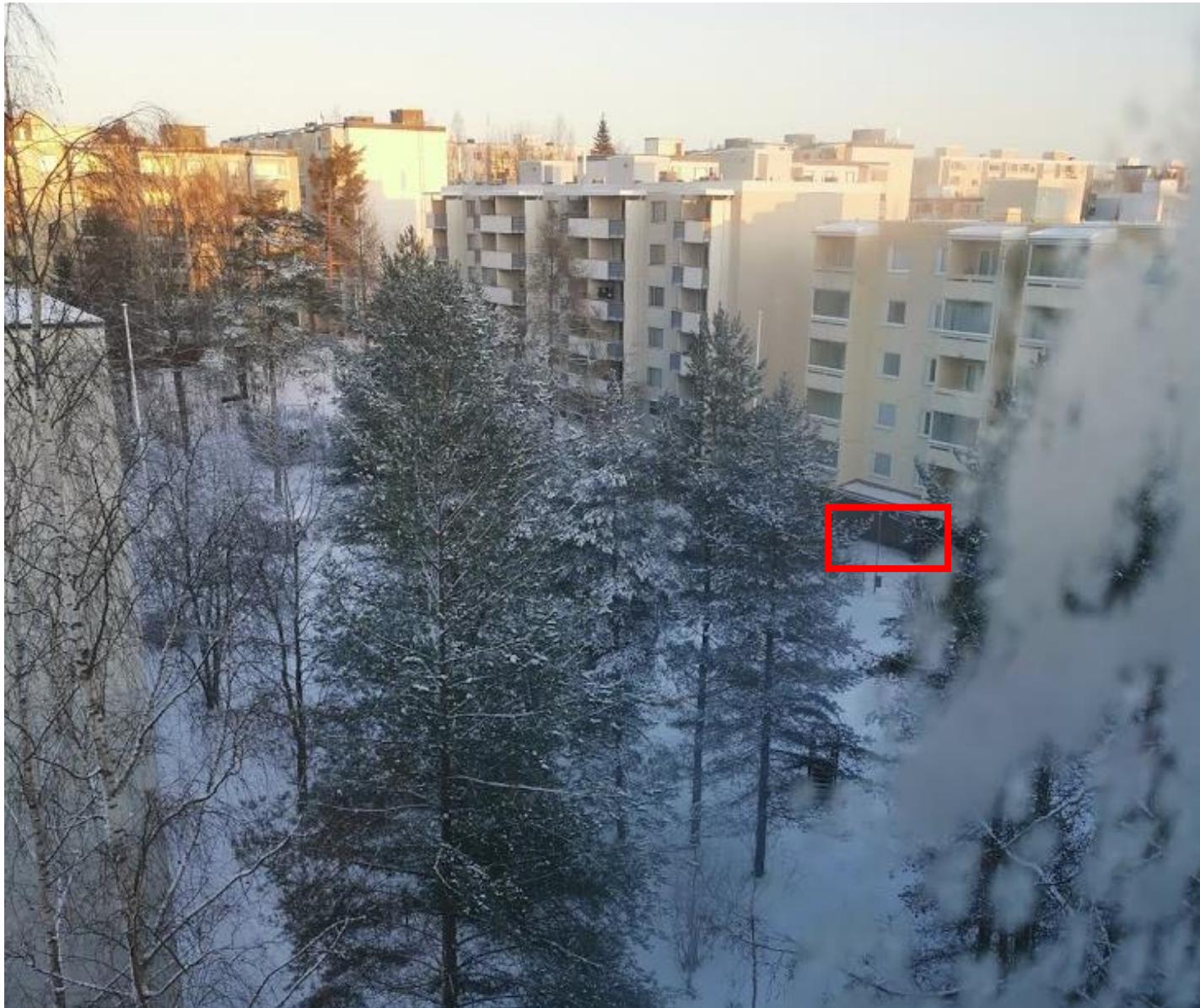
Edges in Images



Discontinuities in
the surface color,
Color changes



Edges in Images



Discontinuities in
the surface
normal



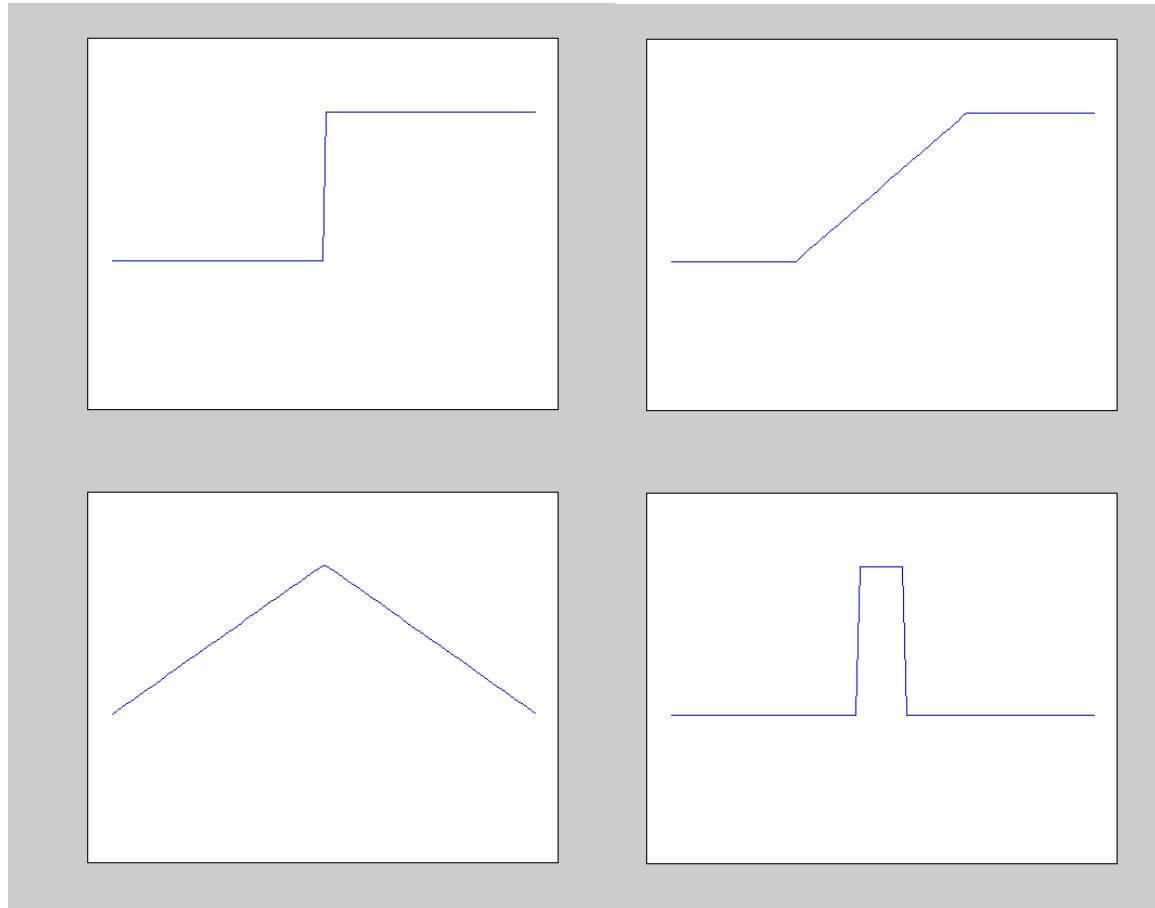
What is an Edge

Lets define an edge to be a **discontinuity** in image intensity function.

Several Models

- Step Edge
- Ramp Edge
- Roof Edge
- Spike Edge

They can be
thus detected as
discontinuities
of image
Derivatives



Edge Detection

Gradient Magnitude and edge detectors

Gradient Magnitude is not a binary image

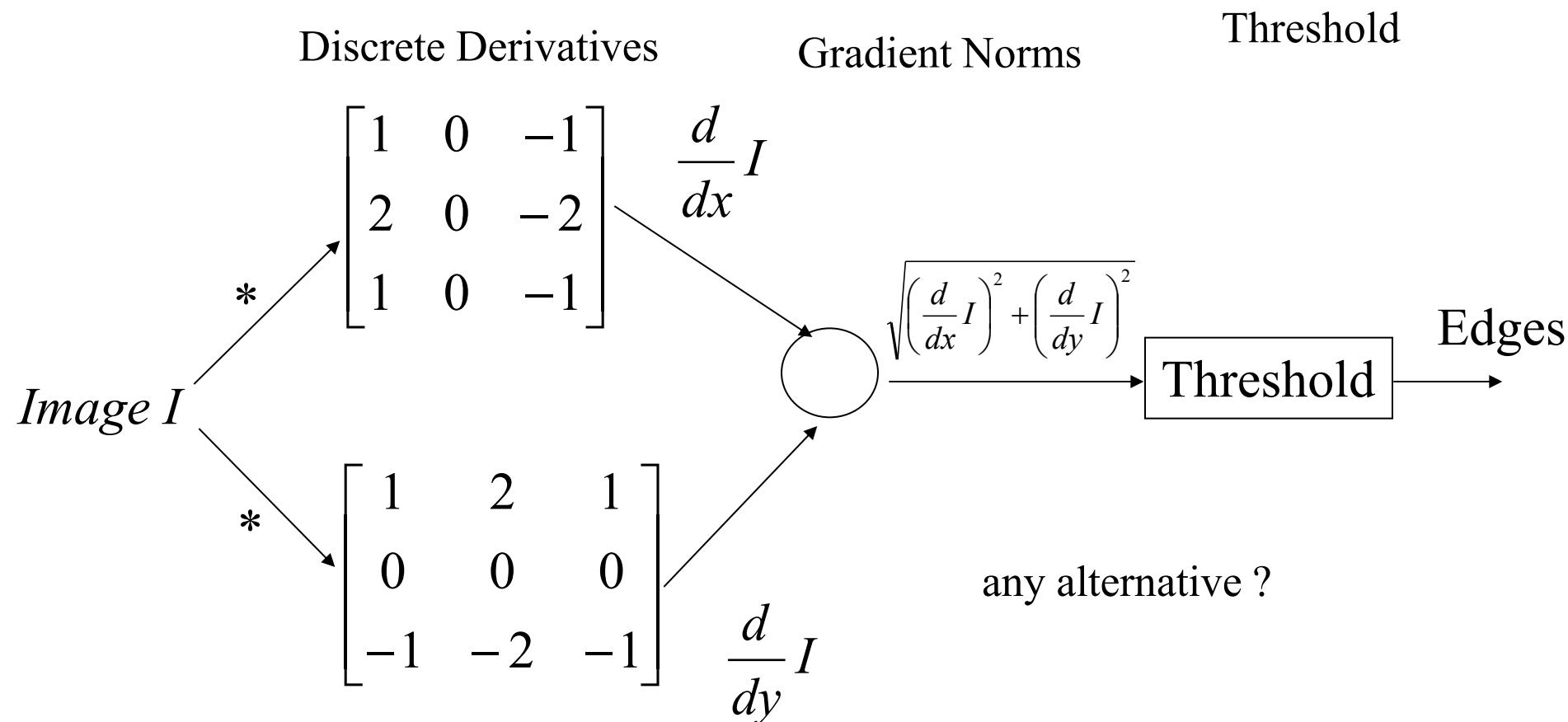
We can see edges but we cannot identify them, yet

$$\|\nabla I\| = \sqrt{(I \odot d_x)^2 + (I \odot d_y)^2}$$



Detecting Edges in Image

Sobel Edge Detector

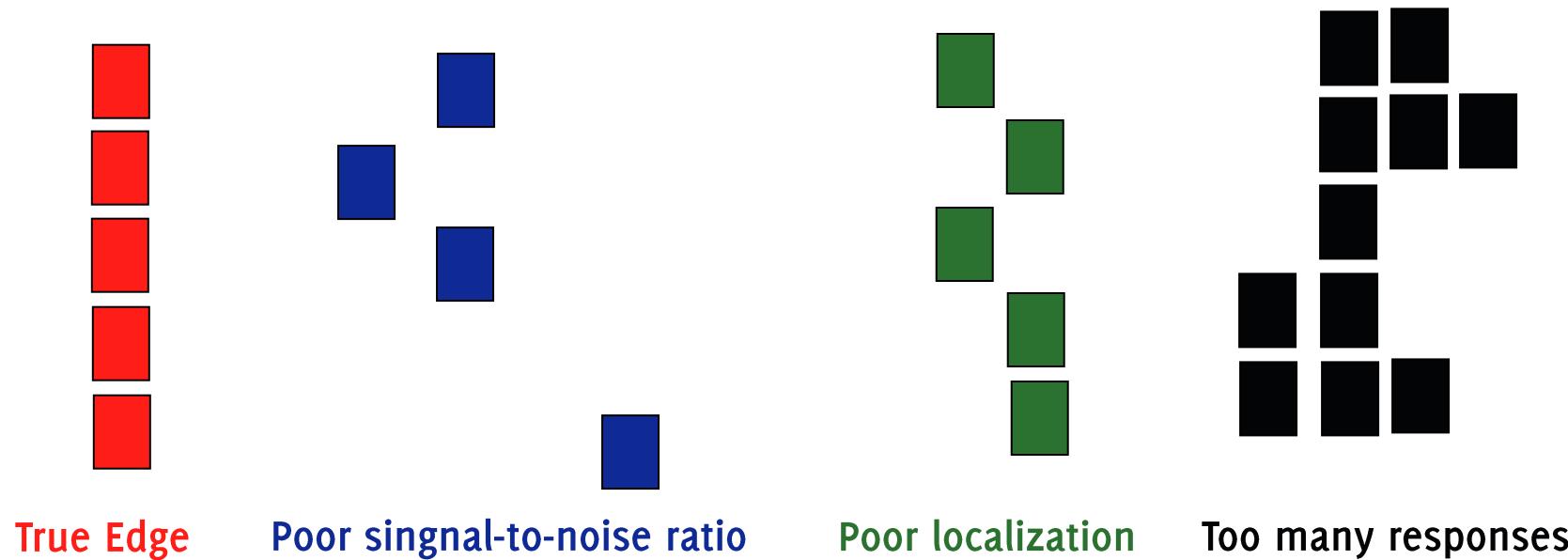


Canny Edge Detector Criteria

Good Detection: The optimal detector must minimize the probability of false positives as well as false negatives.

Good Localization: The edges detected must be as close as possible to the true edges.

Single Response Constraint: The detector must return one point only for each edge point. similar to good detection but requires an ad-hoc formulation to get rid of multiple responses to a single edge



Canny Edge Detector

It is characterized by 3 important steps

- Convolution with smoothing Gaussian filter before computing image derivatives
- Non-maximum Suppression
- Hysteresis Thresholding

Canny Edge Detector

Smooth by Gaussian (smoothing regulated by σ)

$$S = G_\sigma * I \quad G_\sigma = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

Compute x and y derivatives

$$\Delta S = \begin{bmatrix} \frac{\partial}{\partial x} S & \frac{\partial}{\partial y} S \end{bmatrix}^T = [S_x \quad S_y]^T$$

Compute gradient magnitude and orientation

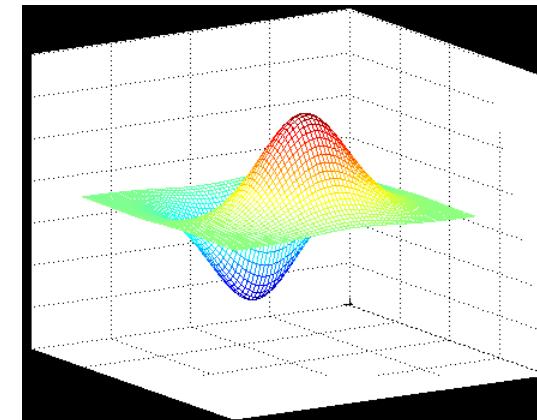
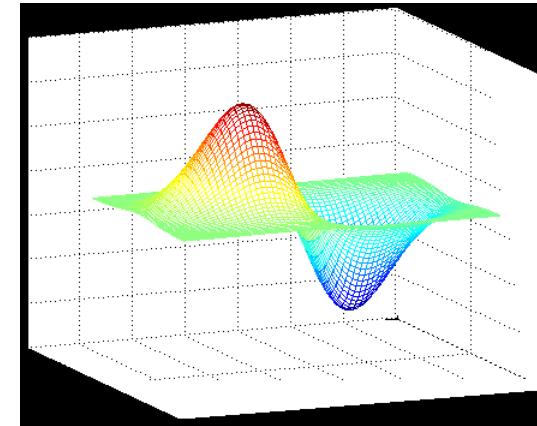
$$|\Delta S| = \sqrt{S_x^2 + S_y^2} \quad \theta = \tan^{-1} \frac{S_y}{S_x}$$

Canny Edge Operator (derivatives)

$$\Delta S = \Delta(G_\sigma * I) = \Delta G_\sigma * I$$

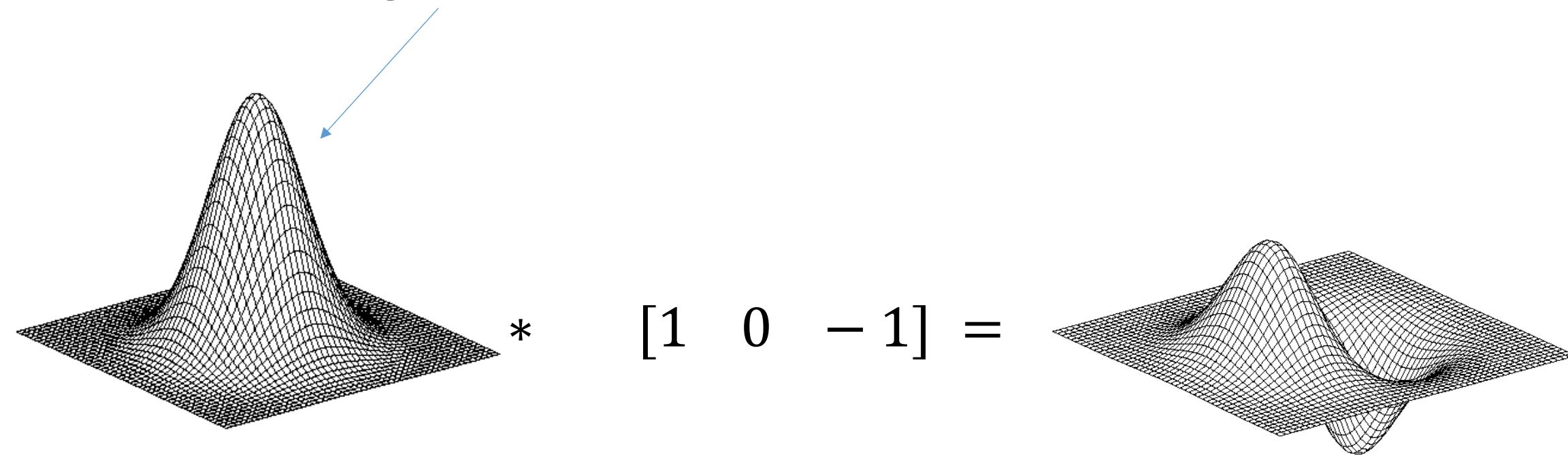
$$\Delta G_\sigma = \begin{bmatrix} \frac{\partial G_\sigma}{\partial x} & \frac{\partial G_\sigma}{\partial y} \end{bmatrix}^T$$

$$\Delta S = \begin{bmatrix} \frac{\partial G_\sigma}{\partial x} * I & \frac{\partial G_\sigma}{\partial y} * I \end{bmatrix}^T$$



Convolution is associative

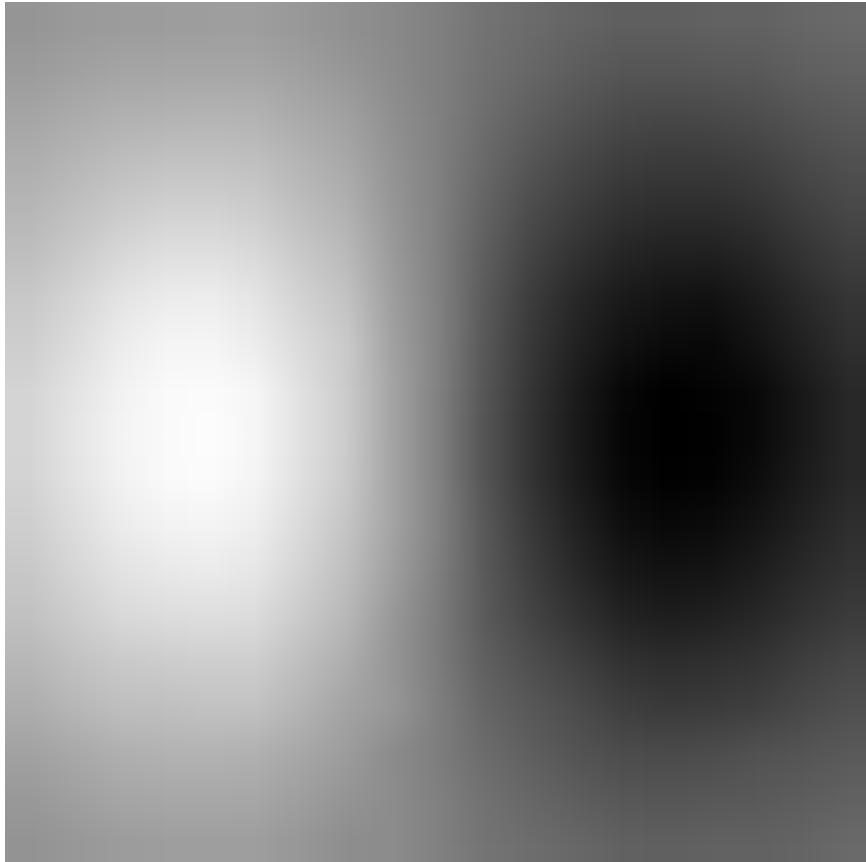
$$I \otimes (g \otimes dx)$$



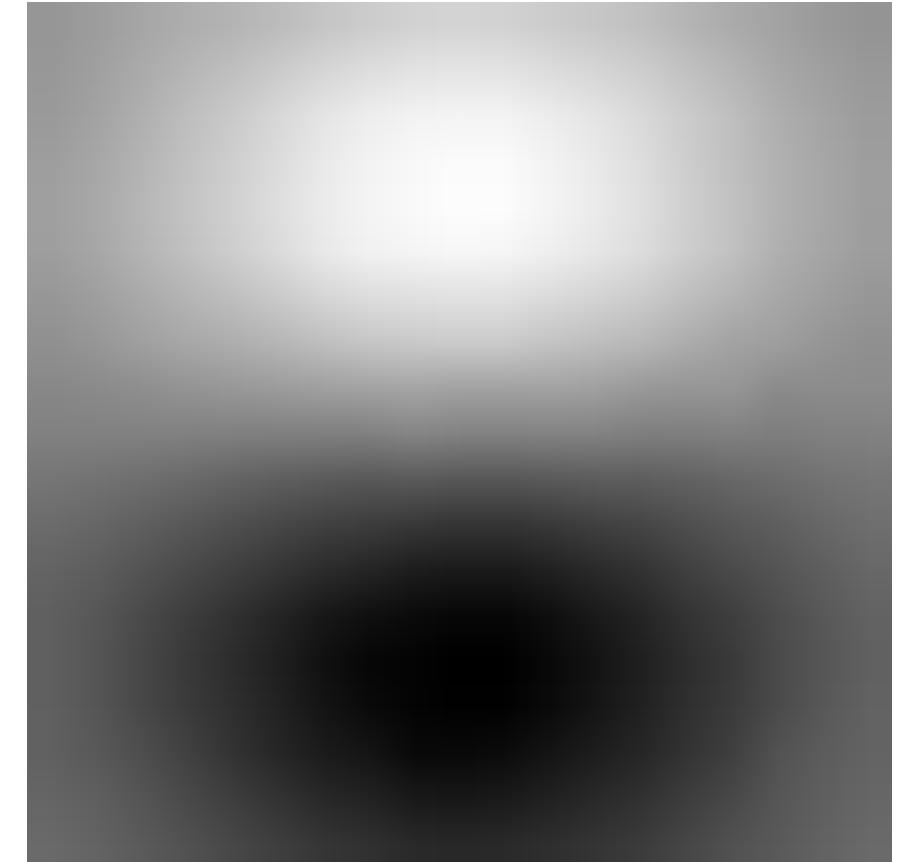
2D-Gaussian

Gaussian Derivative Filters

The amount of smoothing is regulated by a parameter σ



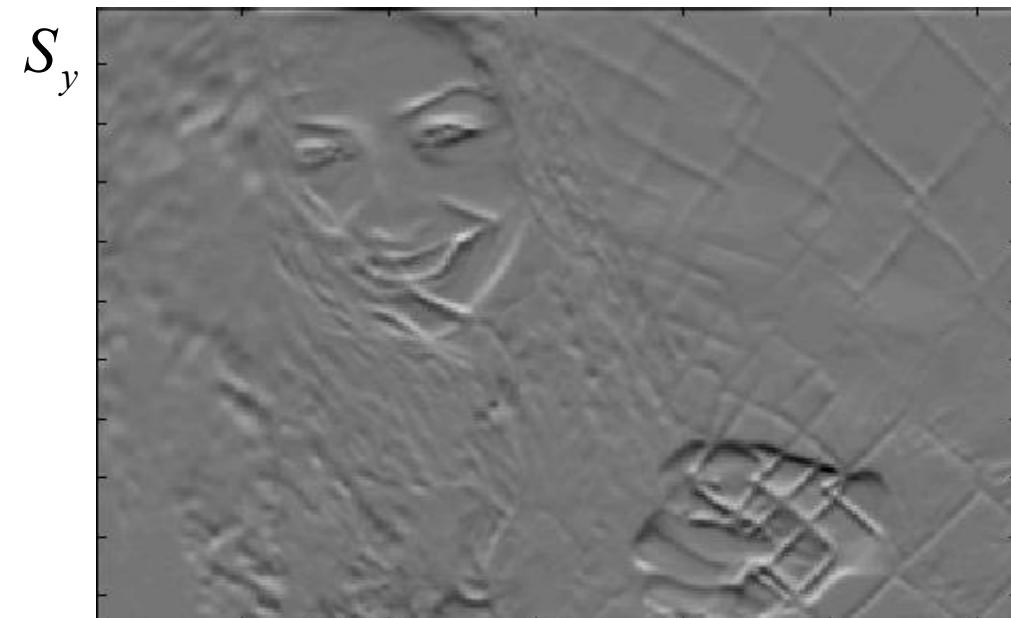
x-direction



y-direction

Canny Edge Detector

I



Canny Edge Detector

$$|\Delta S| = \sqrt{S_x^2 + S_y^2}$$

Gradient Magnitude

I



$$|\Delta S| \geq \text{Threshold} = 25$$

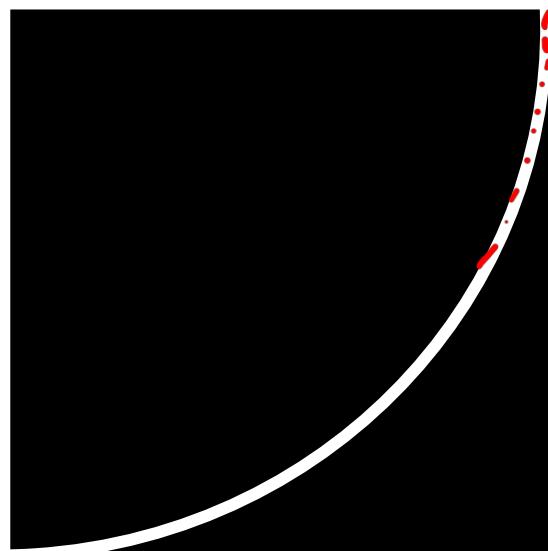
Thresholded Gradient
Magnitude



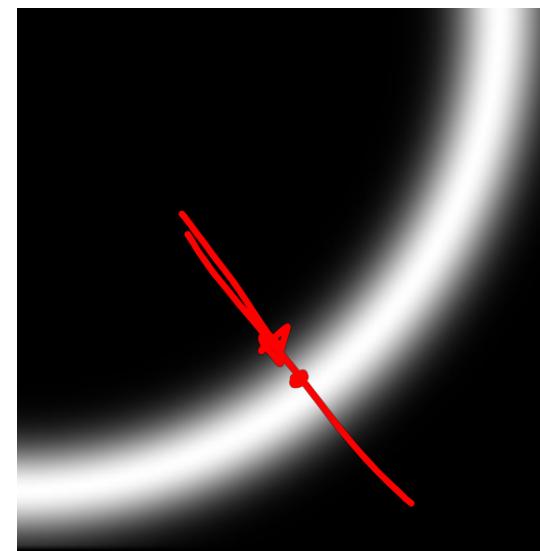
Non-Maximum Suppression: The Idea

We wish to determine the points along the curve where the gradient magnitude is largest.

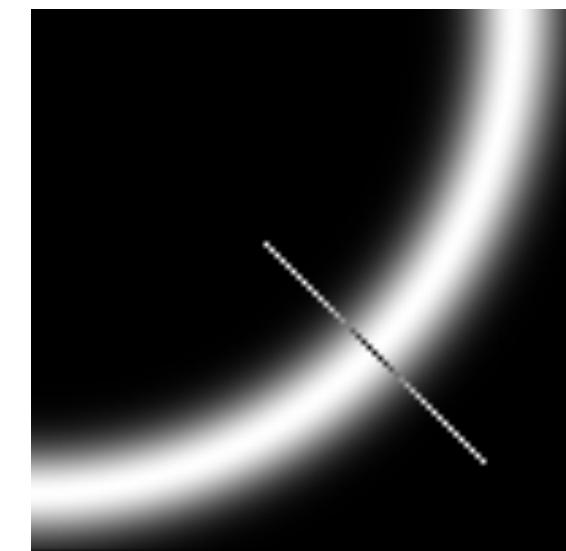
Non-maximum suppression: we look for a maximum along a slice orthogonal to the curve. These points form a 1D signal.



Original Image

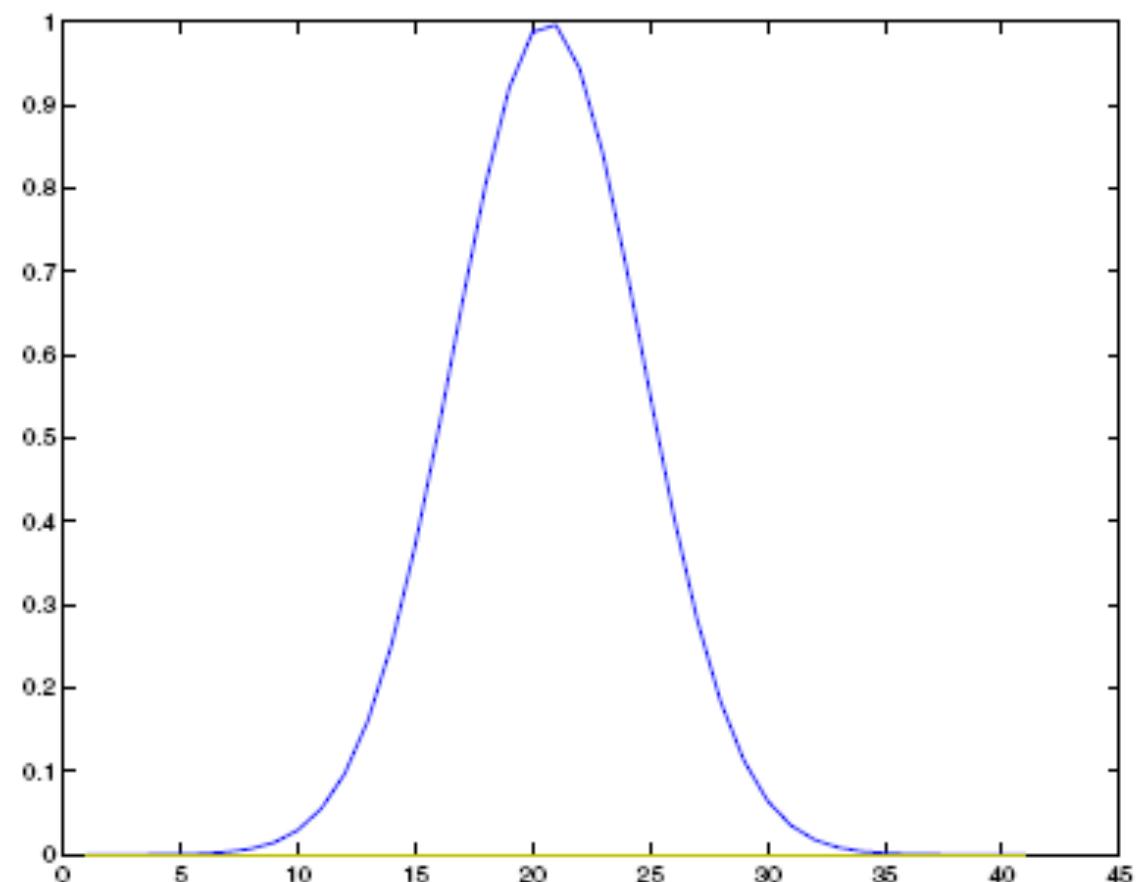
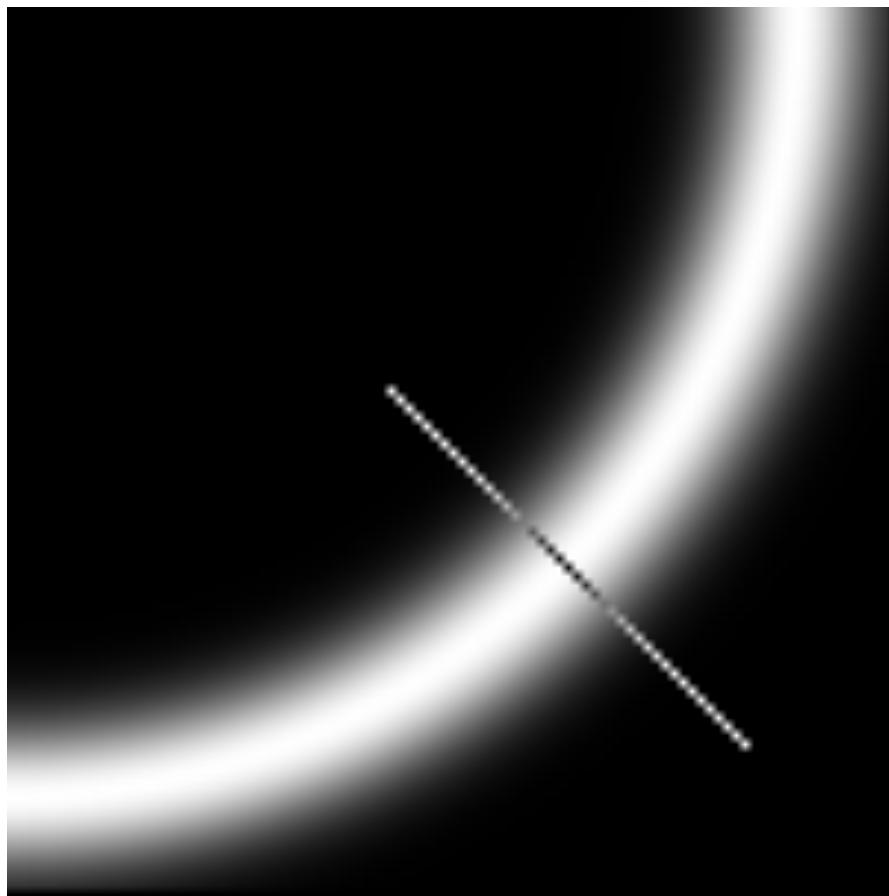


Gradient Magnitude
(after thresholding)



Segment orthogonal

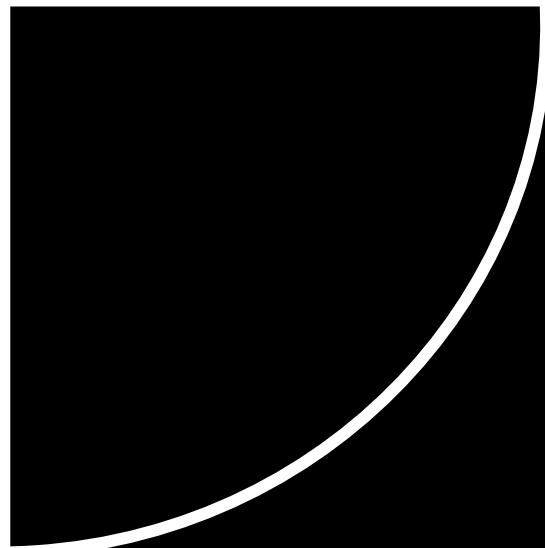
Non-Maximum Suppression



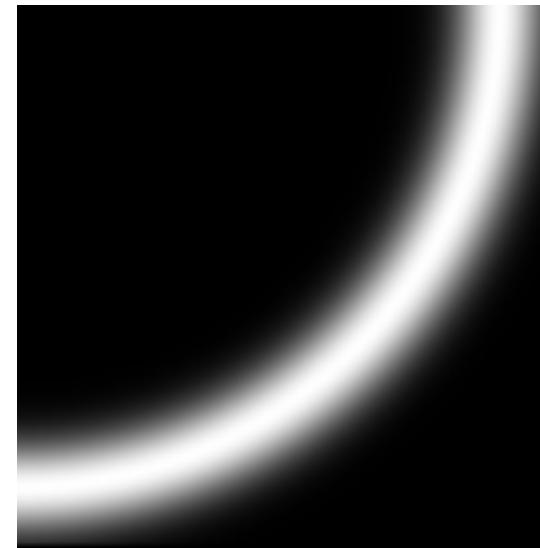
Non-Maximum Suppression: The Idea

There are two issues:

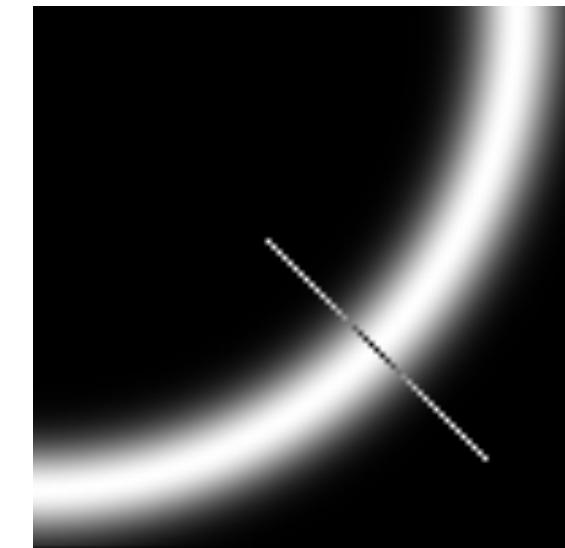
- i. which slice to select to extract the maximum?
- ii. once an edge pixel has been found, which pixel to test next?



Original Image

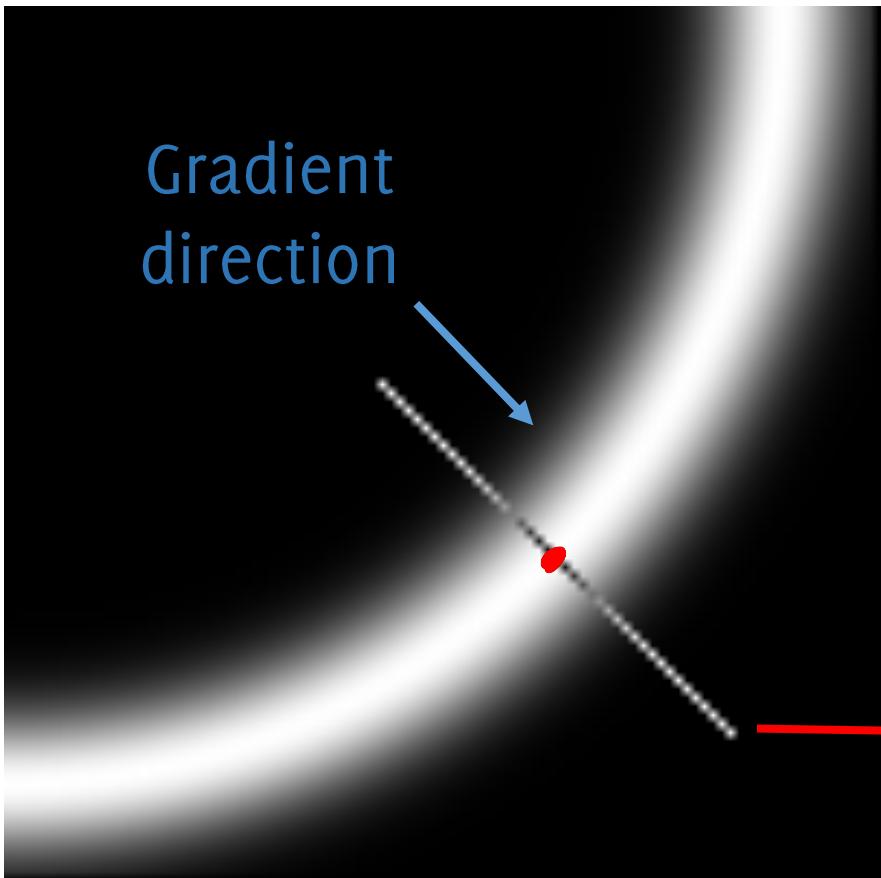


Gradient Magnitude
(after thresholding)

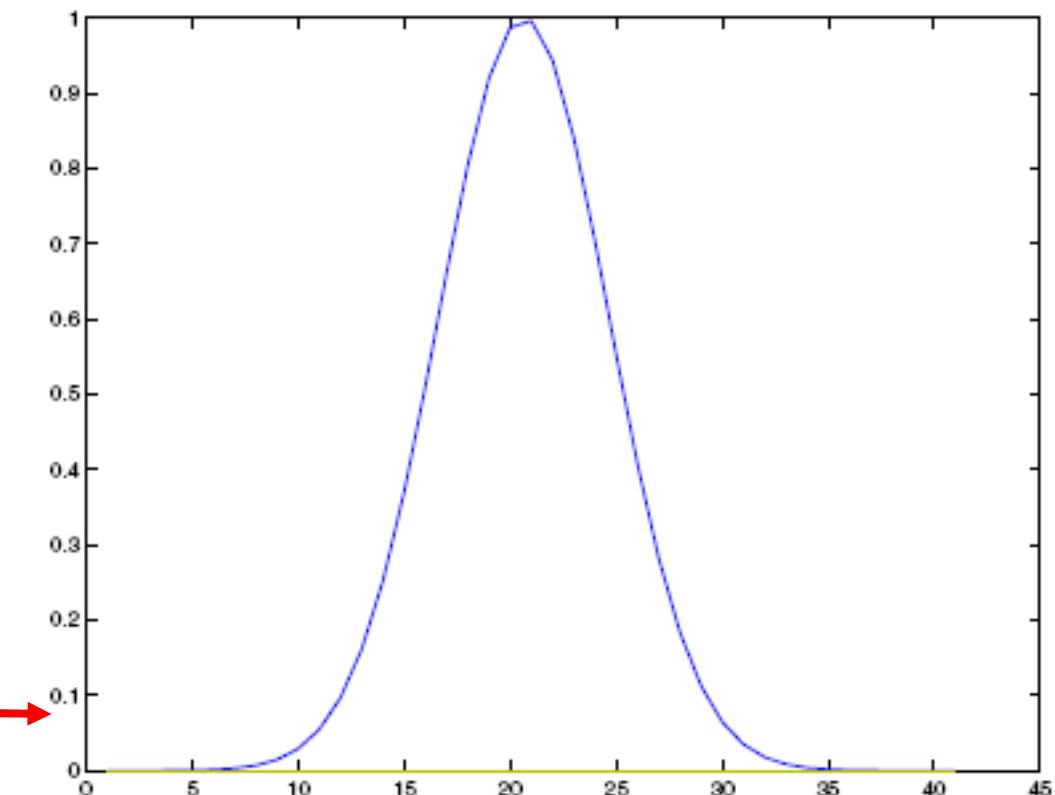


Segment orthogonal

Non-Maximum Suppression – Idea (II)



In each pixel, the gradient indicates the direction of the steepest variation: thus, the gradient is orthogonal to the edge direction (no variation along the edge). We have to consider pixels on a segment following the gradient direction

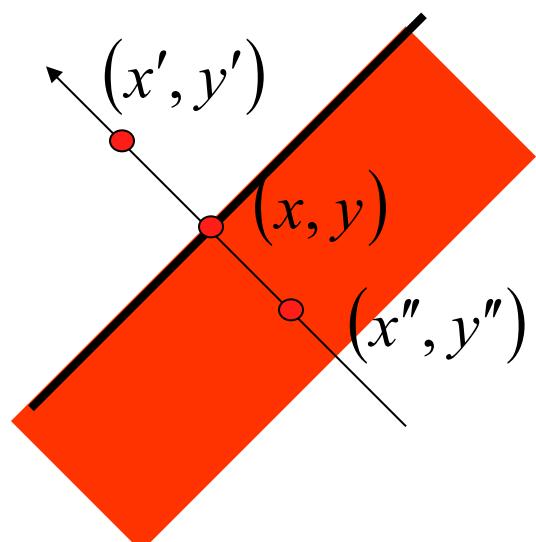


The intensity profile along the segment. We can easily identify the location of the maximum.

Non-Maximum Suppression - Threshold

Suppress the pixels in ‘Gradient Magnitude Image’ which are not local maximum

$$M(x, y) = \begin{cases} |\Delta S|(x, y) & \text{if } |\Delta S|(x, y) > |\Delta S|(x', y') \\ & \quad \& |\Delta S|(x, y) > |\Delta S|(x'', y'') \\ 0 & \text{otherwise} \end{cases}$$



(x', y') and (x'', y'') are the neighbors of (x, y) in $|\Delta S|$

These have to be taken on a line along the gradient direction in (x, y)

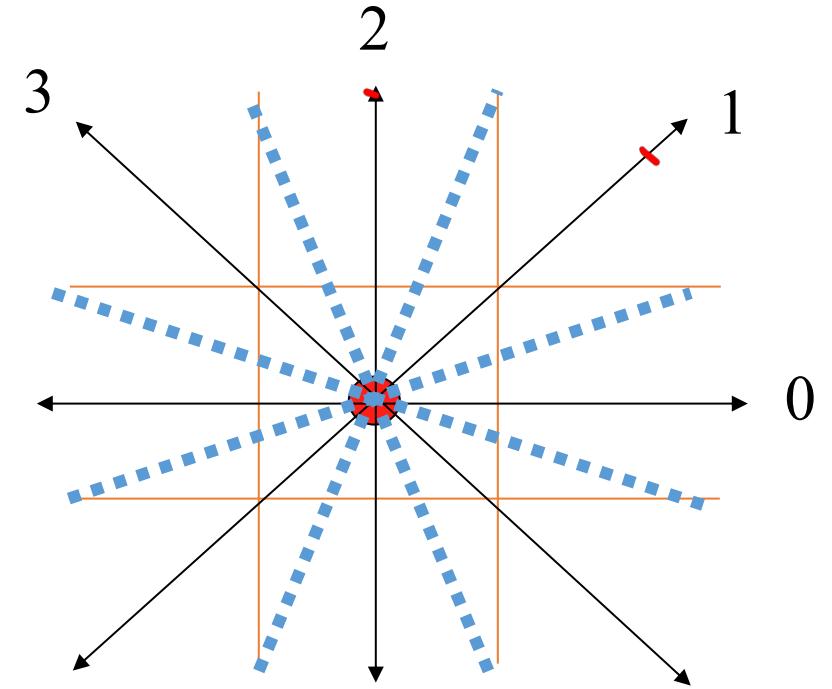
Non-Maximum Suppression: Quantize Gradient Directions

In practice the gradient directions are quantized according to 4 main directions, each covering 45° (orientation is not considered)

- Thus, only diagonal, horizontal, vertical line segments are considered

We consider 4 quantized directions 0,1,2, 3

$$\theta(x_0) = \text{atan} \left(\frac{\partial/\partial y I(x_0)}{\partial/\partial x I(x_0)} \right)$$



Orientation is irrelevant since this is meant for segment extraction

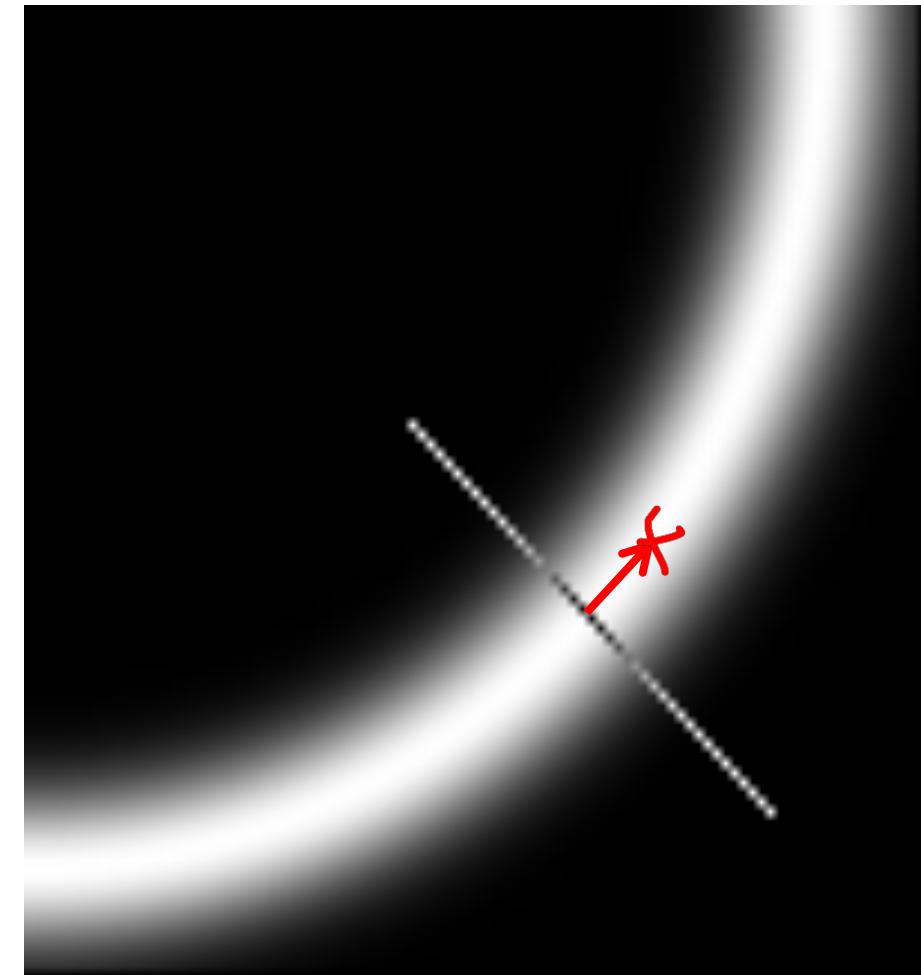
Tracking the edge direction

The direction orthogonal to the gradient follows the edge

Once a local maxima is found, we consider the direction orthogonal to the gradient in that pixel,

The direction is quantized as for extracting the 1D segment for nonmaximum suppression

We move one step in the quantized direction to determine another point where to extract 1D segments



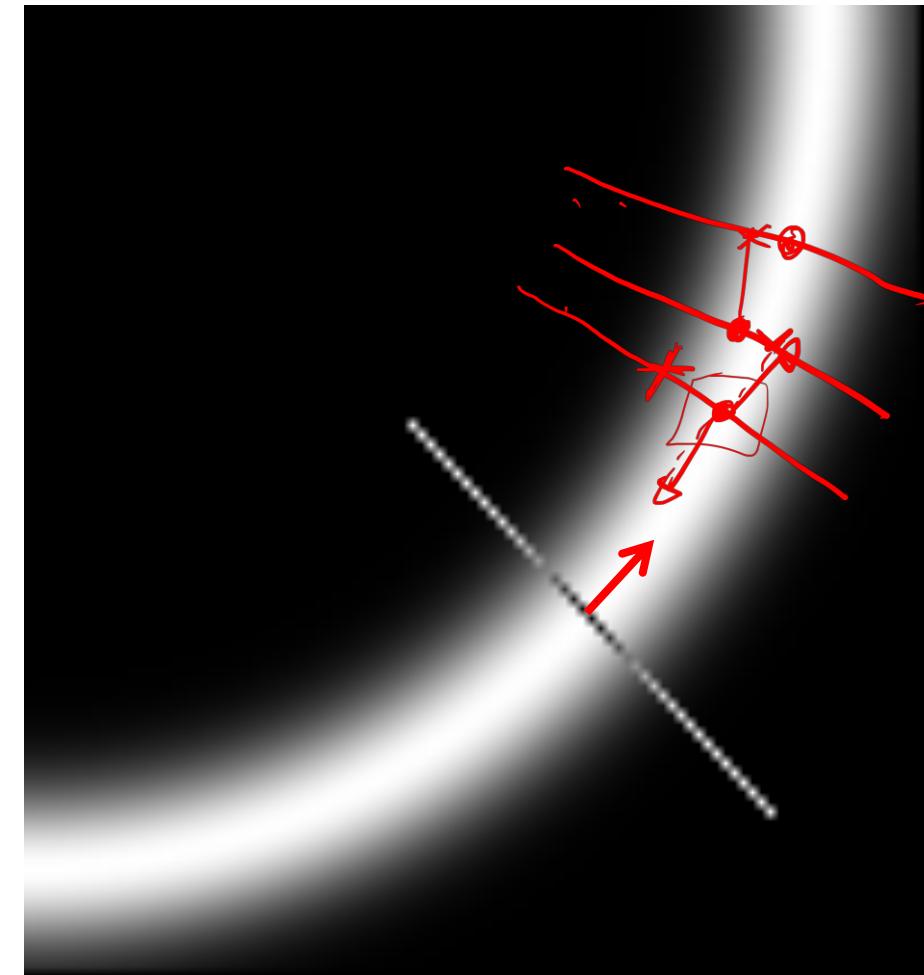
Tracking the edge direction

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The direction is quantized as for extracting the 1D segment for nonmaximum suppression

We move one step in the quantized direction to determine another point where to extract 1D segments



Non-Maximum Suppression



$$|\Delta S| = \sqrt{S_x^2 + S_y^2}$$

Results from
nonmaximum
suppression

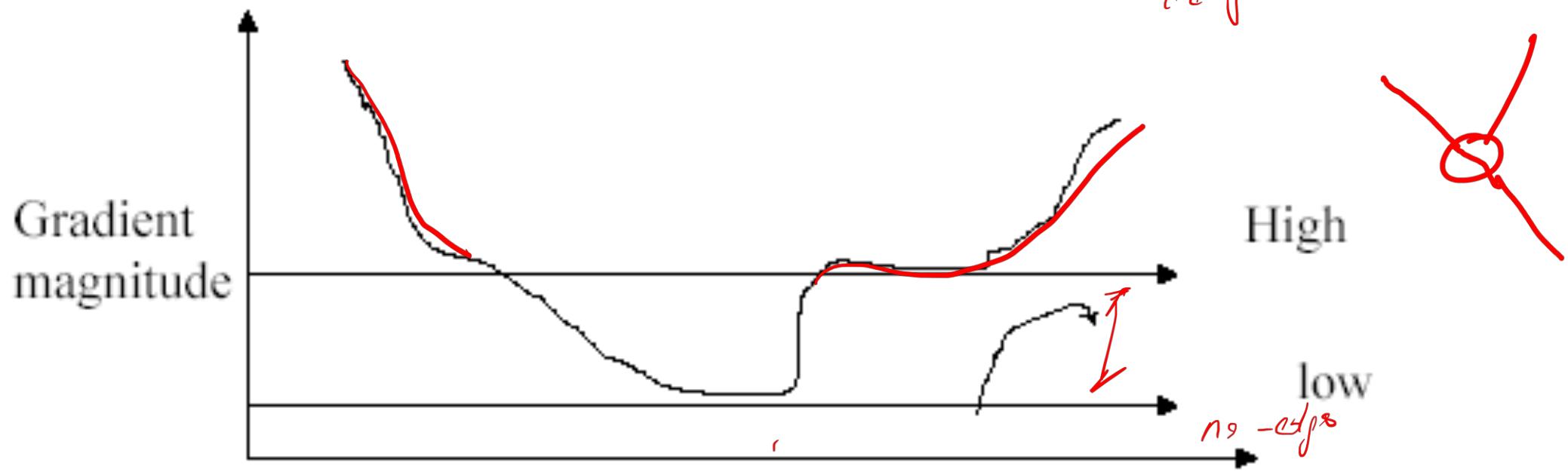
$$M \geq \text{Threshold} = 25$$



Hysteresis Thresholding

Use of two different threshold High and Low for

- For new edge starting point
- For continuing edges



In such a way the edges continuity is preserved

Hysteresis Thresholding

If the gradient at a pixel is **above ‘High’ threshold**,

- declare it an ‘edge pixel’.

If the gradient at a pixel is **below ‘Low’ threshold**

- declare it a ‘non-edge-pixel’.

If the gradient at a pixel is **between ‘Low’ and ‘High’ thresholds**

- then declare it an ‘edge pixel’ if and only if can be directly connected to an ‘edge pixel’ or connected via pixels between ‘Low’ and ‘High’.

Hysteresis Thresholding

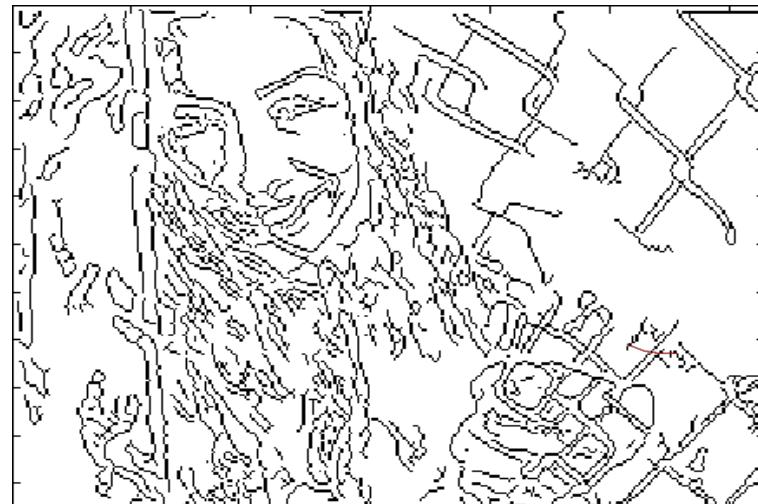


M



$M \geq \text{Threshold} = 25$

$\text{High} = 35$
 $\text{Low} = 15$



Hysteresis Thresholding

$M \geq \text{Threshold} = 25$

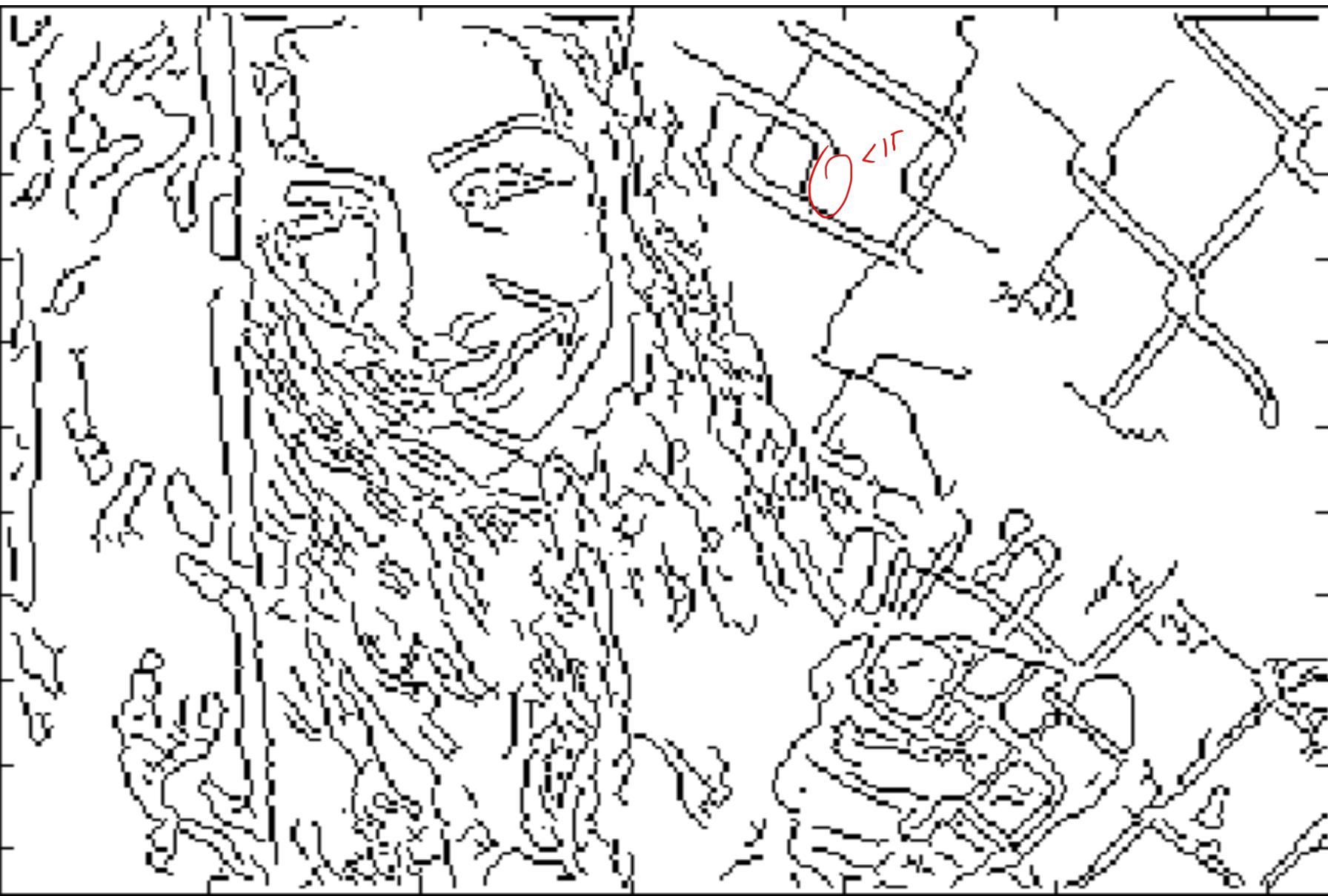
$$G_{ij}(DII_{ij}) < L_{ij}^{High}$$



Hysteresis Thresholding

High = 35

Low = 15

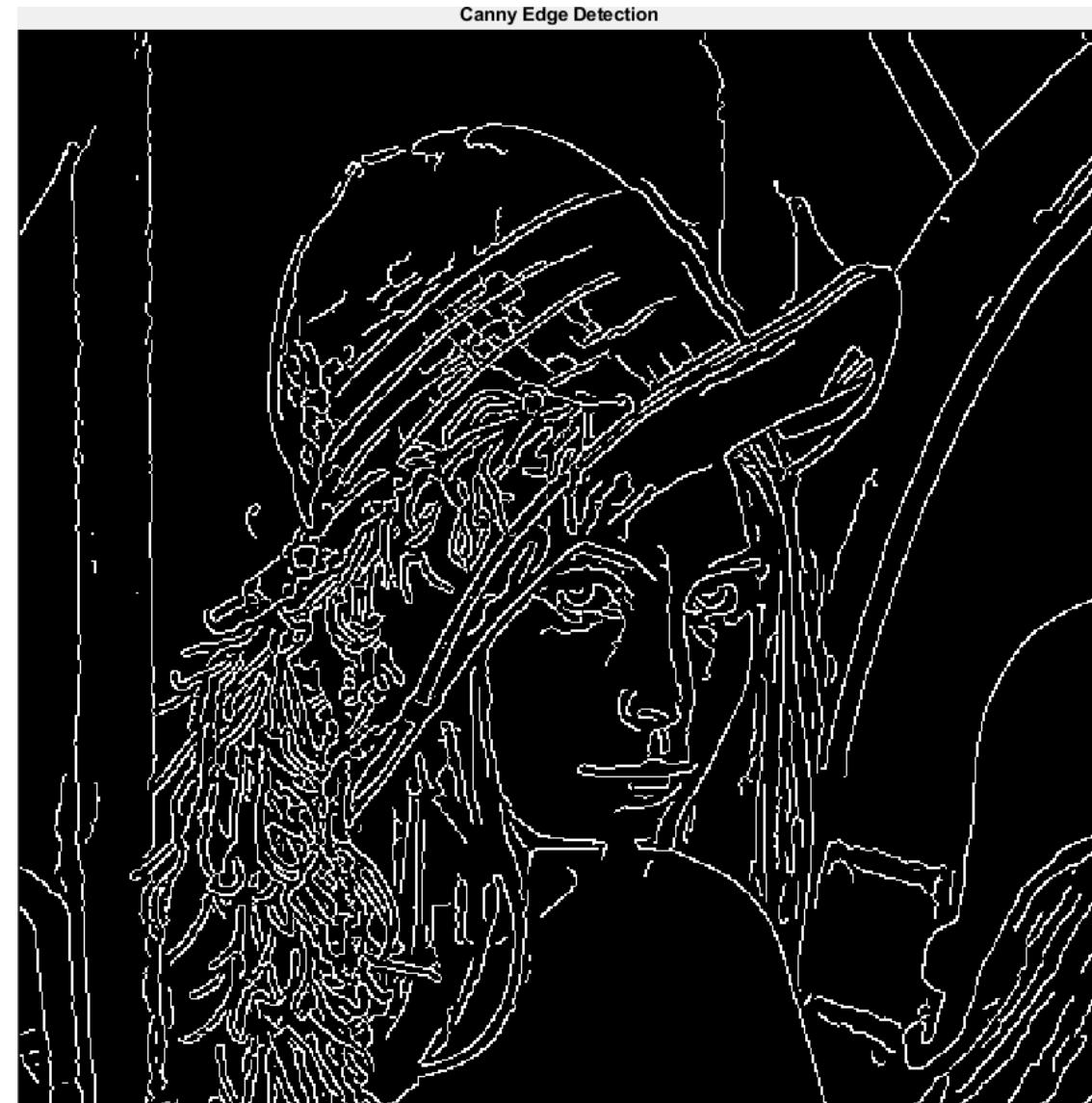


Canny Edge Detection



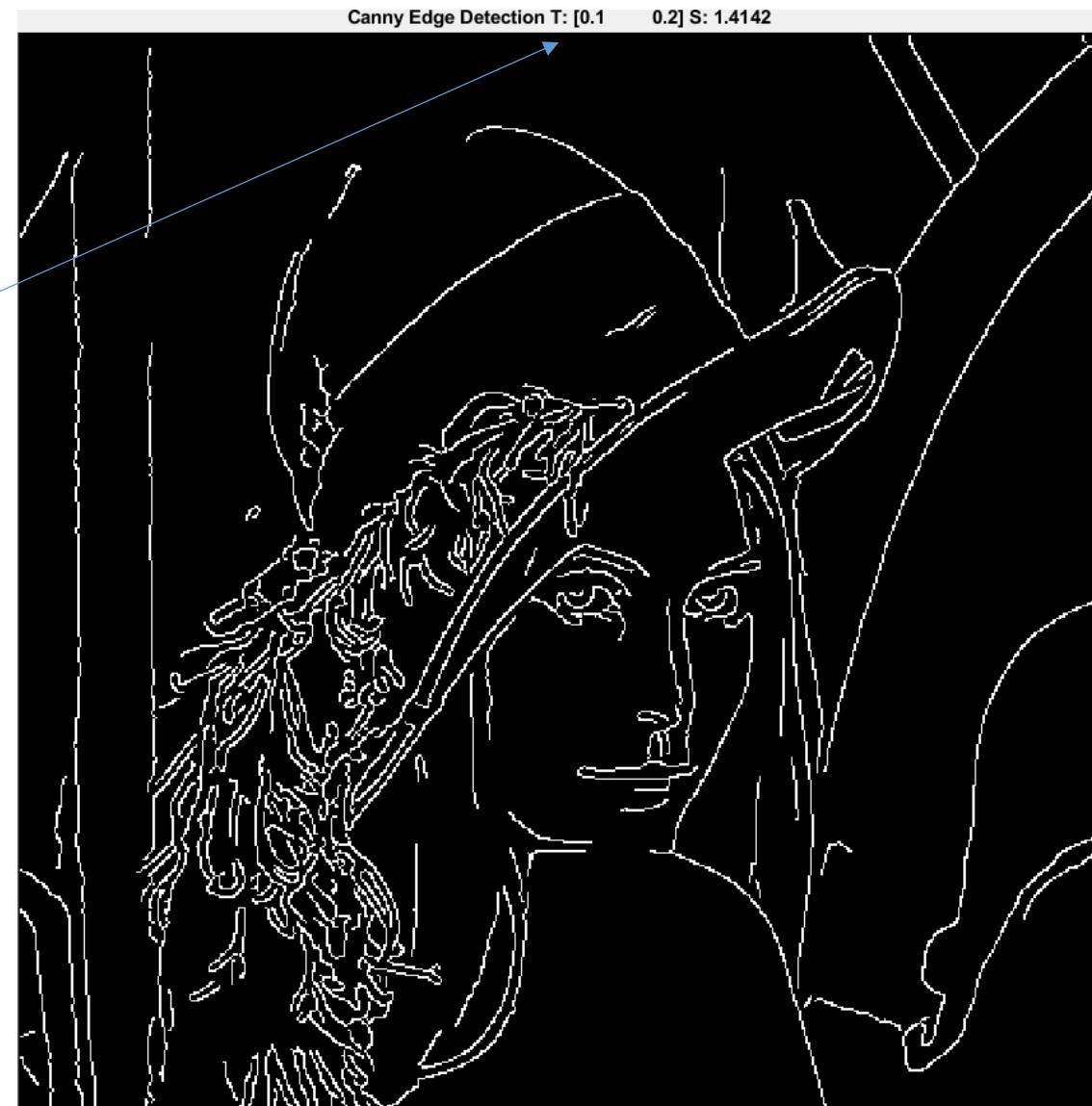
Canny Edge Detection

$$\sigma = \sqrt{2}$$



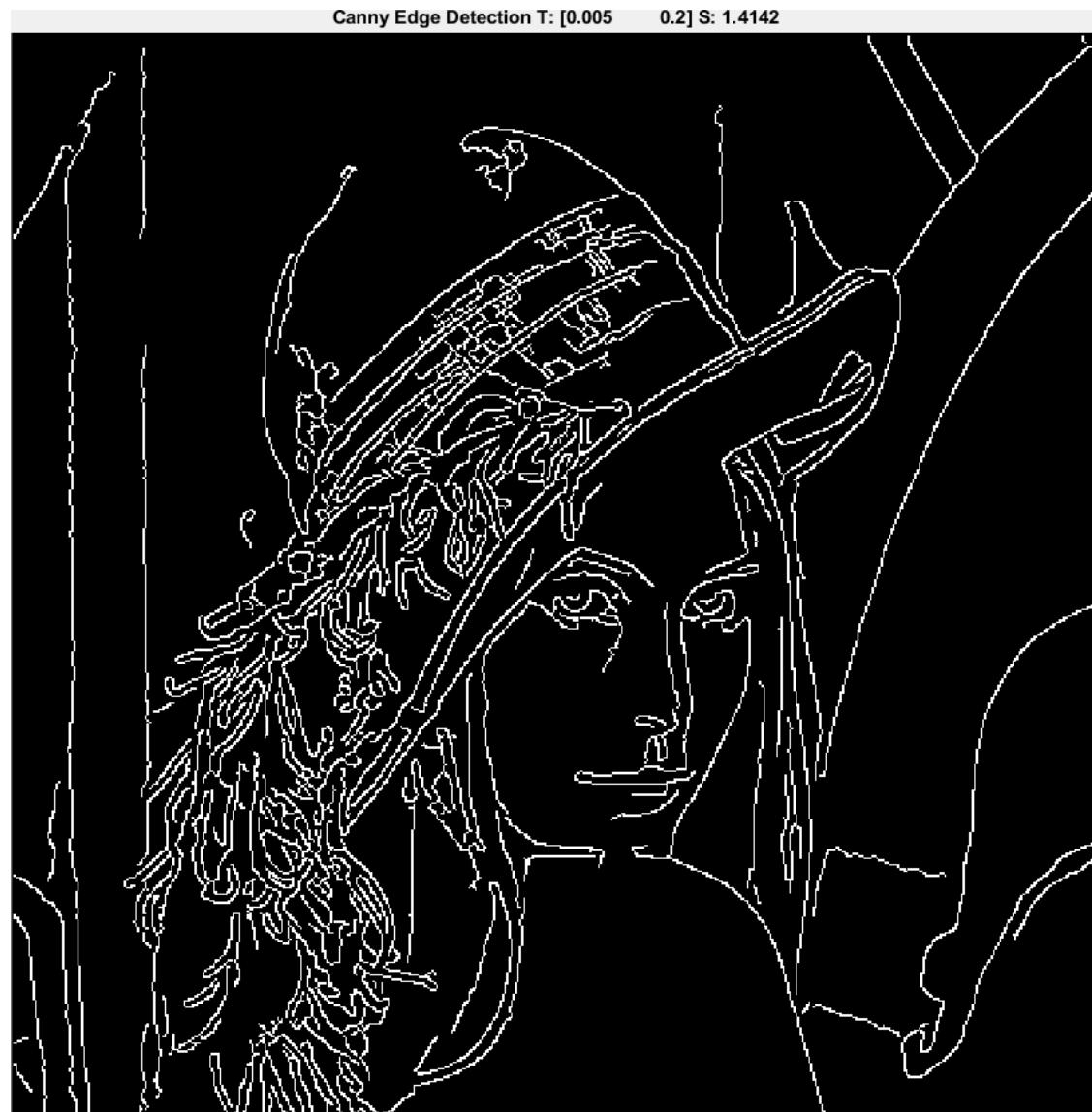
Canny Edge Detection – changing hysteresis thresholds

Threshold: [Low, High], Sigma



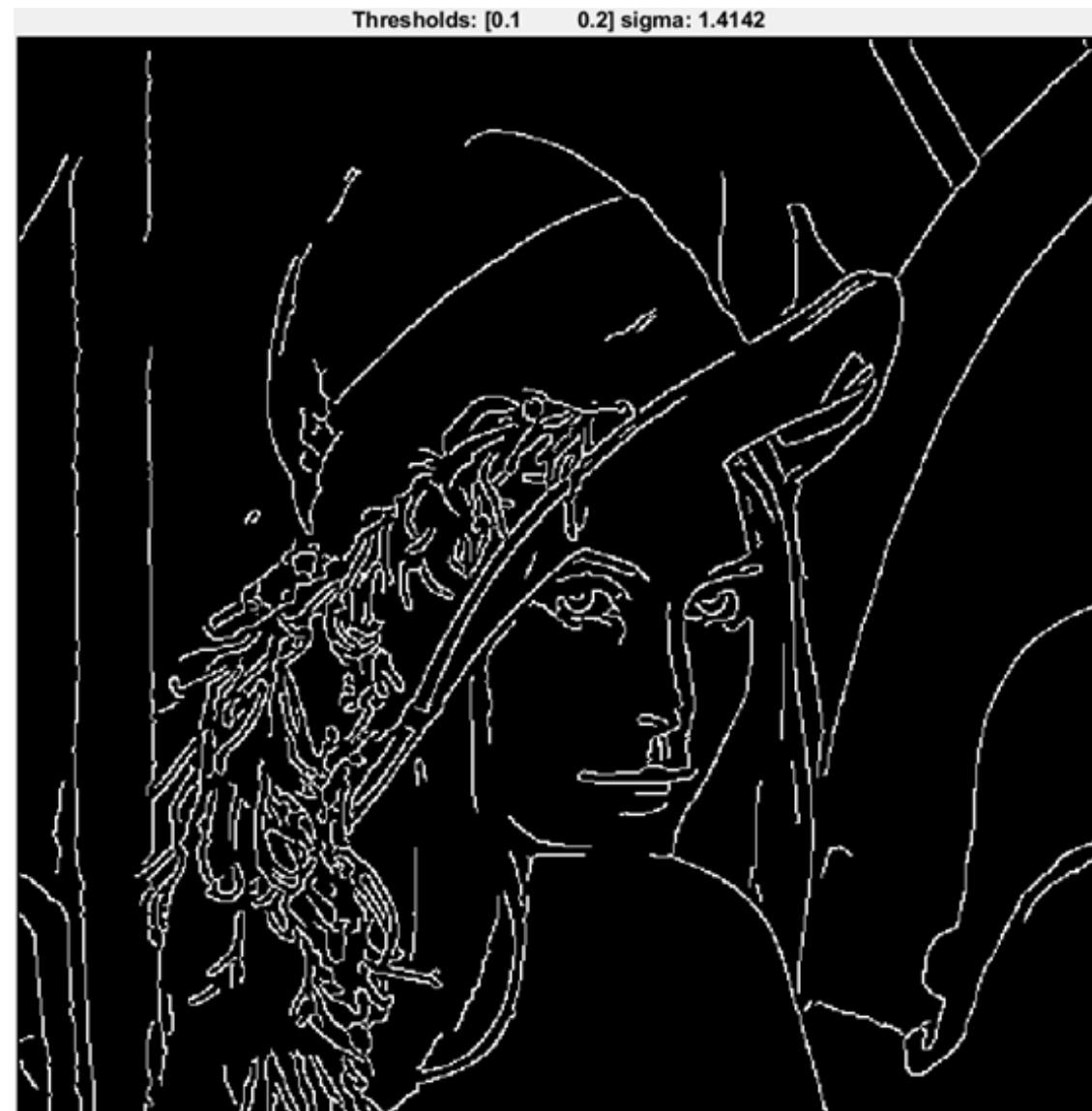
Canny Edge Detection – changing hysteresis thresholds

Decreasing the low threshold extends the length of existing edges



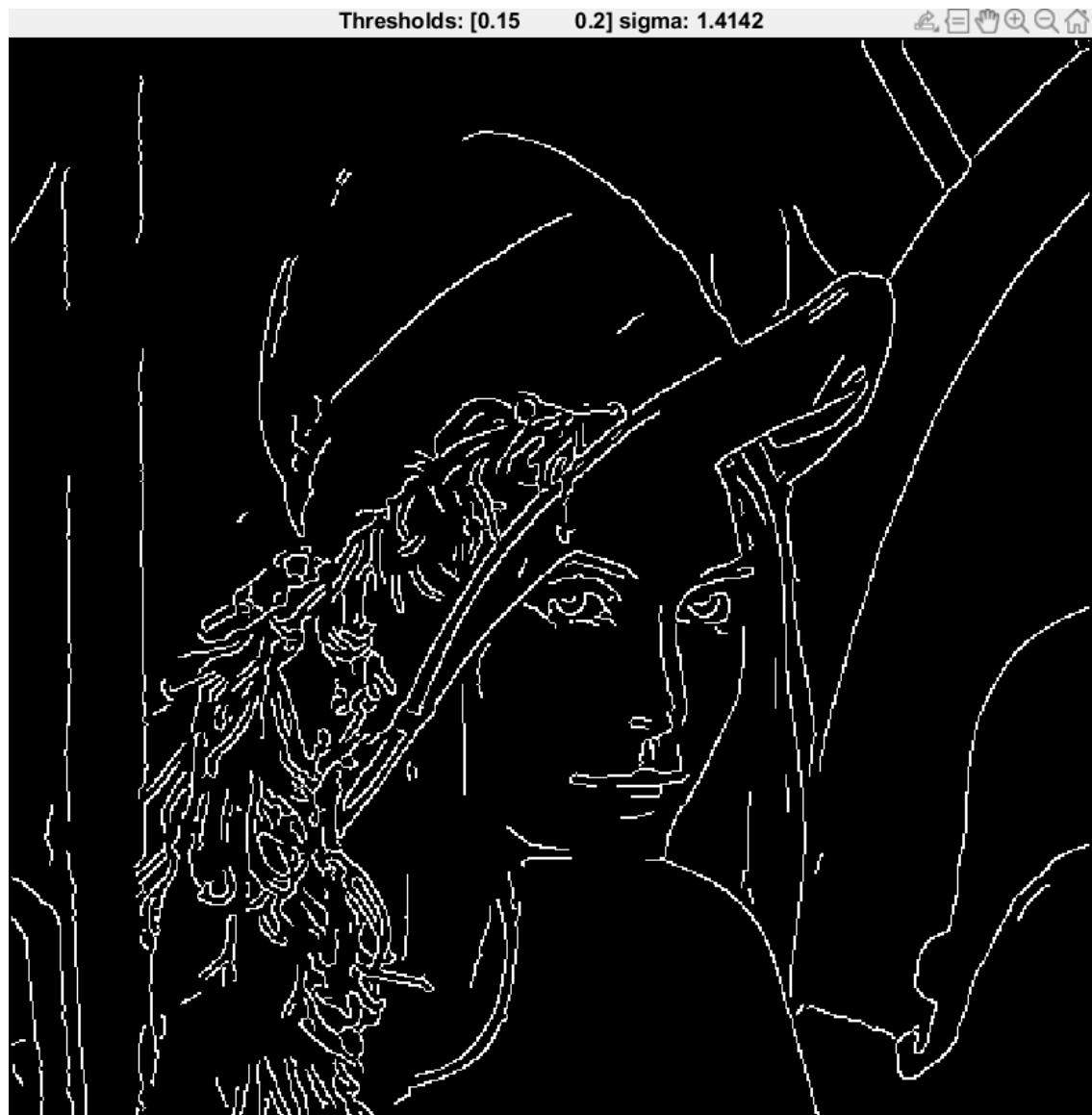
Canny Edge Detection – changing hysteresis thresholds

Reference thresholds



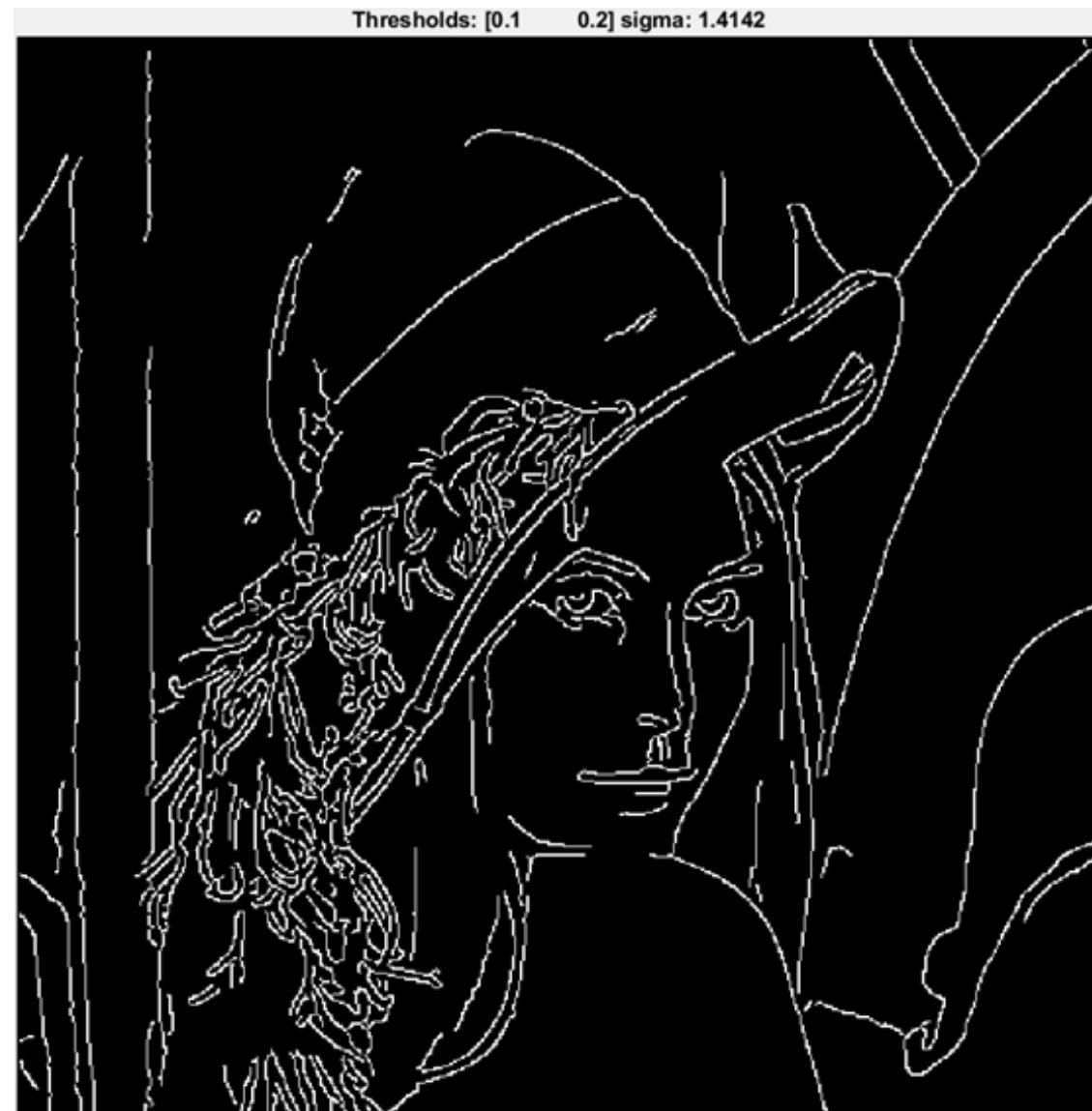
Canny Edge Detection – changing hysteresis thresholds

Increasing the low threshold shorten edges



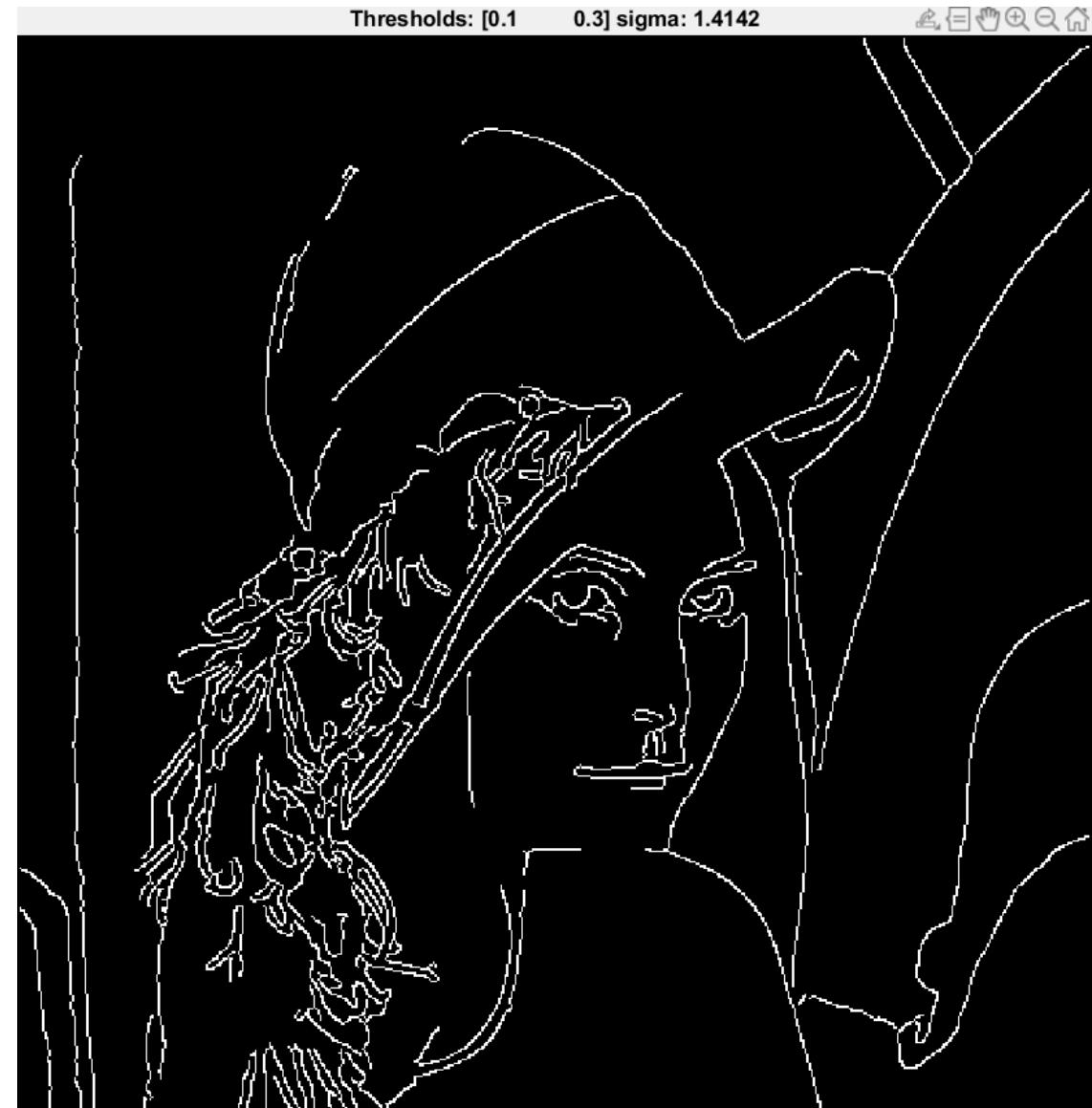
Canny Edge Detection – changing hysteresis thresholds

Reference thresholds



Canny Edge Detection – changing hysteresis thresholds

Increasing the high threshold reduces the number of edges



Canny Edge Detection - changing the smoothing

Increasing sigma reduces the number of returned edges and makes these poorly localized

