MEDICAL IMAGE COMPUTING (CAP 5937)

LECTURE 3: Pre-Processing Medical Images (I)

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Outline

- CAVA: Computer Aided Visualization and Analysis
- CAD: Computer Aided Diagnosis
- Definitions and Terminologies
- Coordinate Systems
- Pre-Processing Images
  - Volume of Interest
  - Region of Interest
  - Intensity of Interest
  - Image Enhancement
    - Filtering
    - Smoothing

CAVA: Computer Aided Visualization and Analysis

- **Definition:**
  - The science of underlying computerized methods of image processing, analysis, and visualizations to facilitate new therapeutic strategies, basic clinical research, education, and training.

CAD: Computer Aided Diagnosis

- **Definition:**
  - The science of underlying computerized methods of image processing, analysis for the diagnosis of diseases via images.

Purpose of CAVA and CAD

Multiple multimodality
Multidimensional images
Of an object system

→ **CAVA/CAD** →

Qualitative/Quantitative
Information of the objects
In the object system

Object System: a collection of rigid, deformable, static, or dynamic objects inside the body of or conceptual objects.

CAVA/CAD Operations

- **Pre (Image) Processing**
  - For enhancing information about and defining object system.
- **Visualization**
  - For viewing and comprehending object system
- **Manipulation**
  - For altering object system (virtual surgery)
- **Analysis**
  - For quantifying information about object system.

CAVA/CAD Operations

- **Pre (Image) Processing**
  – For enhancing information about and defining object system.

Today's lecture

- **Visualization**
  – For viewing and comprehending object system
- **Manipulation**
  – For altering object system (virtual surgery)
- **Analysis**
  – For quantifying information about object system.

Terminology-I

- **Object:**
  - An entity that is imaged and studied. May be rigid, deformable, static, or dynamic, physical or conceptual.
- **Object system:**
  - A collection of related objects.
- **Scanner:**
  - Any imaging device-real or conceptual.
- **Body region:**
  - The support region of the imaged object system.
- **Voxels (3D):**
  - Cuboidal elements into which body region is digitized by the imaging device.

Terminology-II

- **Scene:**
  - Multidimensional (2D, 3D, 4D, …) image of the body regions; $S=(C,f)$
- **Scene Domain:**
  - Rectangular array of voxels on which scene is defined; C
- **Scene Intensity:**
  - Values assigned to voxels; $f(c)$
- **Binary Scene:**
  - A scene with intensities 0 and 1 only.
- **Structure:**
  - Geometric representation of an object in the object system derived from scenes.

Terminology-III

- **Structure System:**
  - A collection of structures representing the objects in an object system
- **Rendition:**
  - A 2D image depicting a structure system
- **Body Coordinate System:**
  - A coordinate system associated with the imaged body region
- **Scanner Coordinate System:**
  - A coordinate system affixed to the scanner
- **Scene Coordinate System:**
  - A coordinate system affixed to the scene
- **Structure Coordinate System:**
  - A coordinate system determined for structures
- **Display Coordinate System:**
  - A coordinate system associated with the display device

Coordinate Systems

$\alpha\beta\gamma$: body coordinate system

⇓

abc: scanner coordinate system

⇓

xyz: scene coordinate system

⇓

uvw: structure coordinate system

⇓

rst: display coordinate system

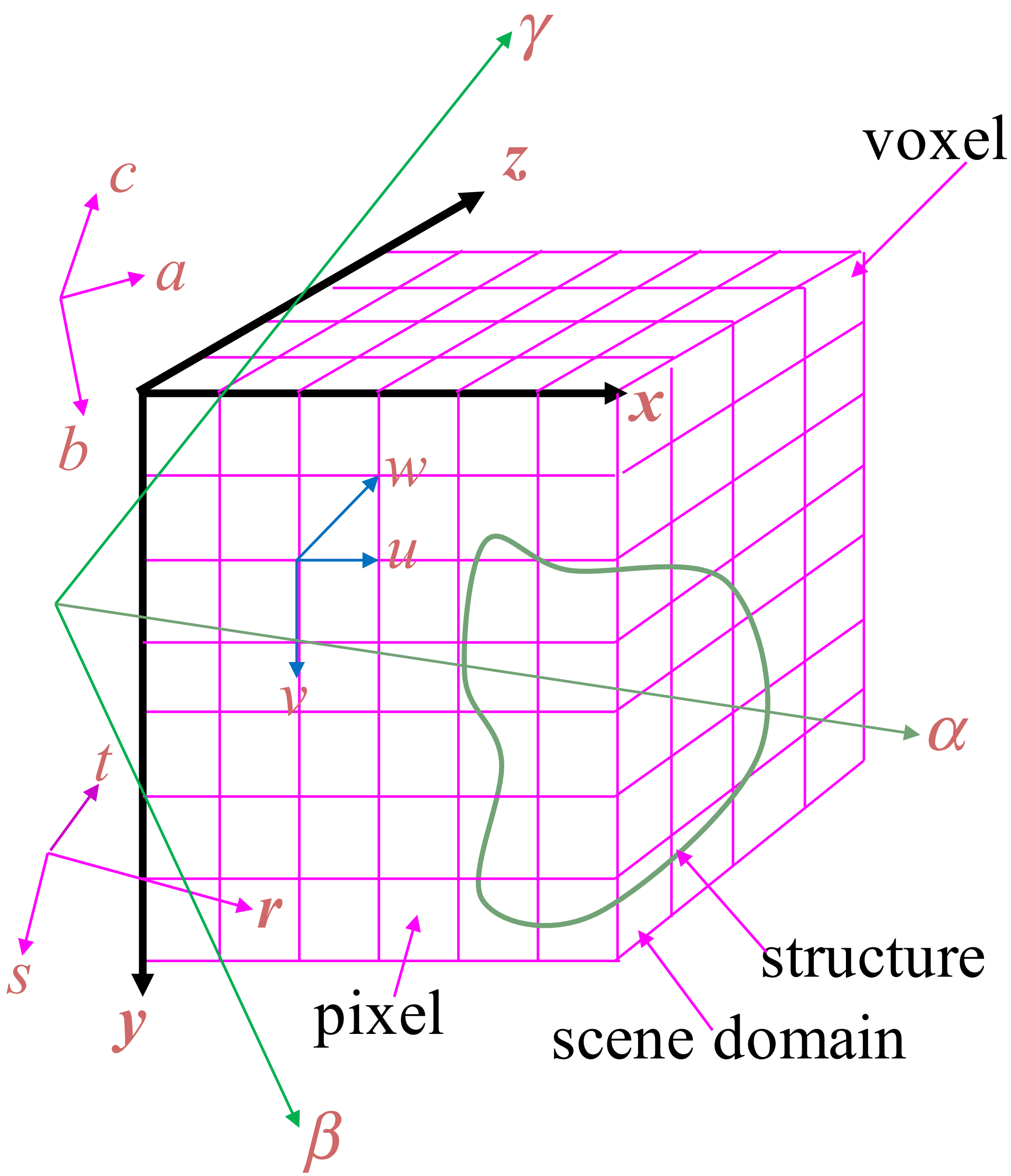

Image Pre-Processing

- **Volume of Interest (VOI):**
  - Purpose: to reduce data for speeding up CAVA operations.

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Image Pre-Processing

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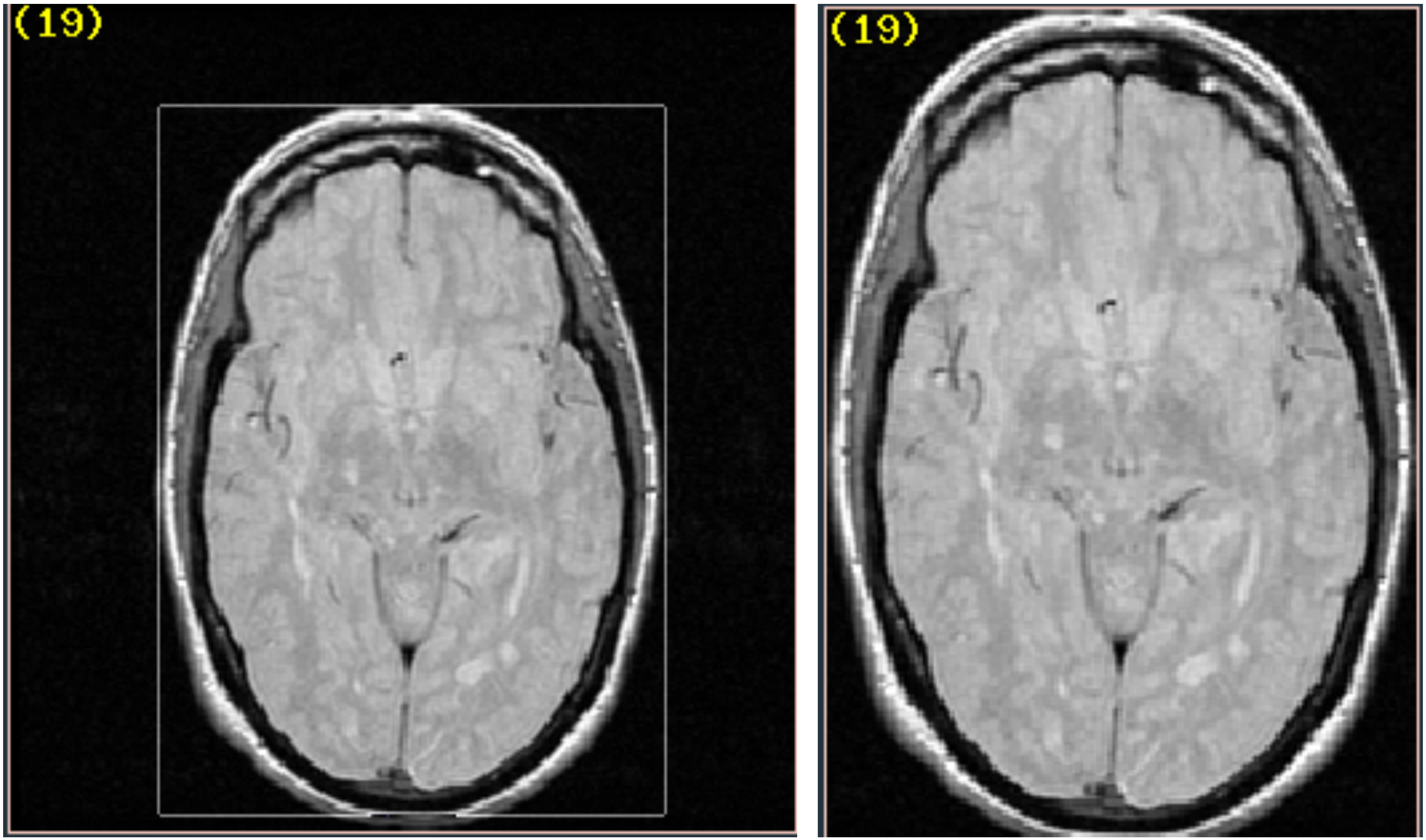
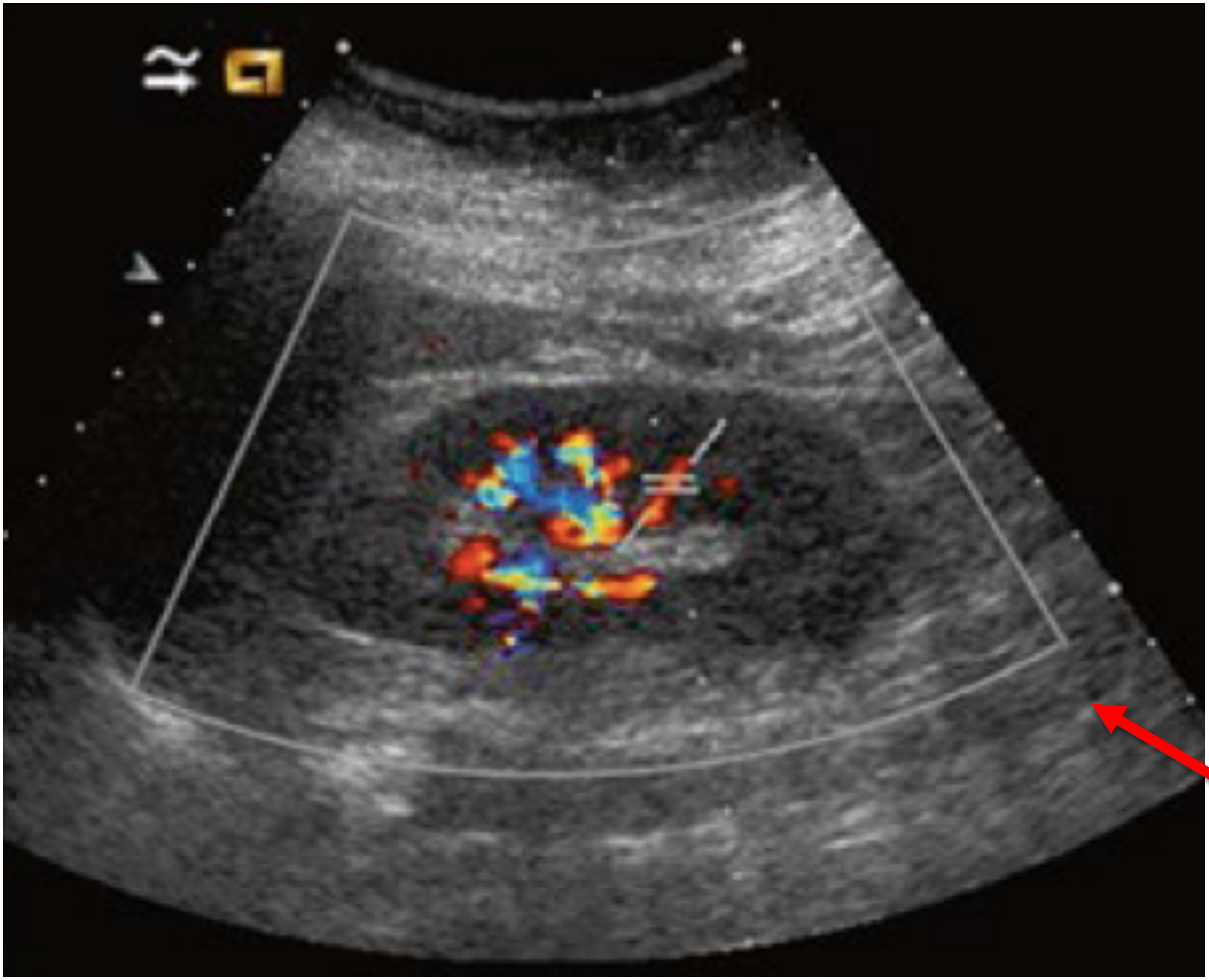
Storage requirement can be reduced by a factor of 2-10

VOI / ROI (volume/region of interest)



VOI / ROI (volume/region of interest)



Kidney region

Image Filtering

Scene → Scene

$S=(C,f) \rightarrow S_F=(C,f_F)$

Purpose: To suppress unwanted (non-object) info.
To enhance wanted (object) information.

Enhancive: For enhancing edges, regions.
For intensity scale standardization.
For correcting background variation.

Suppressive: Mainly for suppressing random noise.

Medical Image Enhancement

- Medical images are often deteriorated by noise due to various sources of interference
  - affect measurement process in imaging and data acquisition systems

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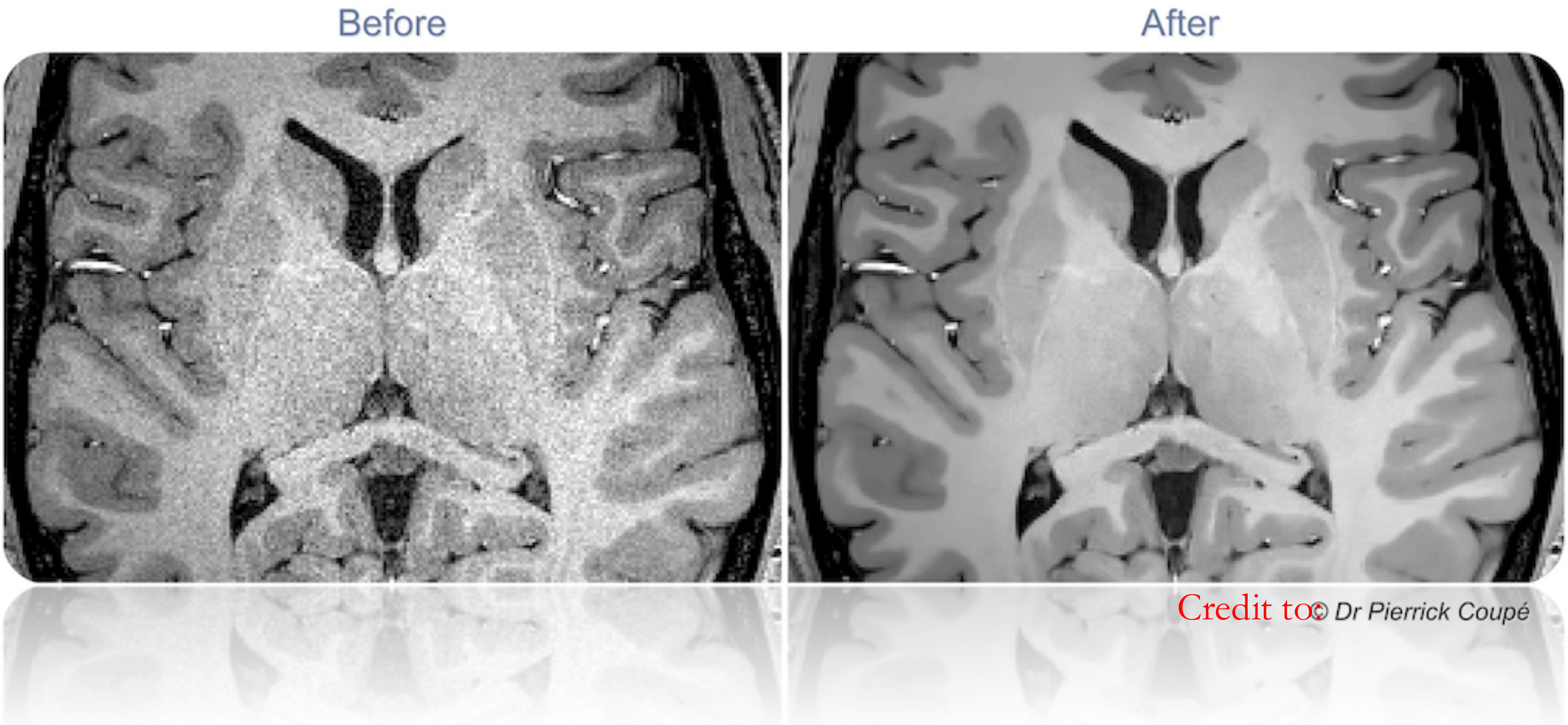
- Some enhancement algorithms are developed for deriving images that are meant for use by a subsequent algorithm for computer processing!
  - Edge detection, object segmentation, etc.

Inappropriate use of Enhancement Methods

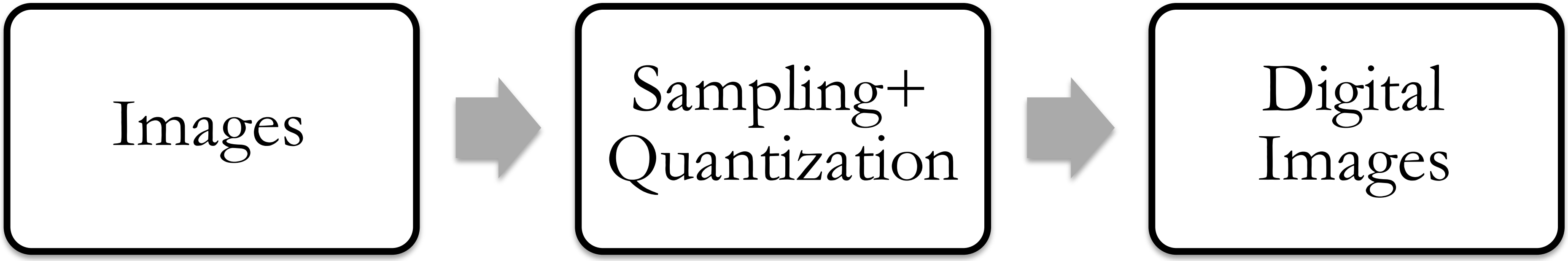
- Enhancement methods themselves may increase noise while improving contrast!
- They may eliminate small details and edge sharpness while removing noise
- They may produce artifacts in general.

Smoothing MRI

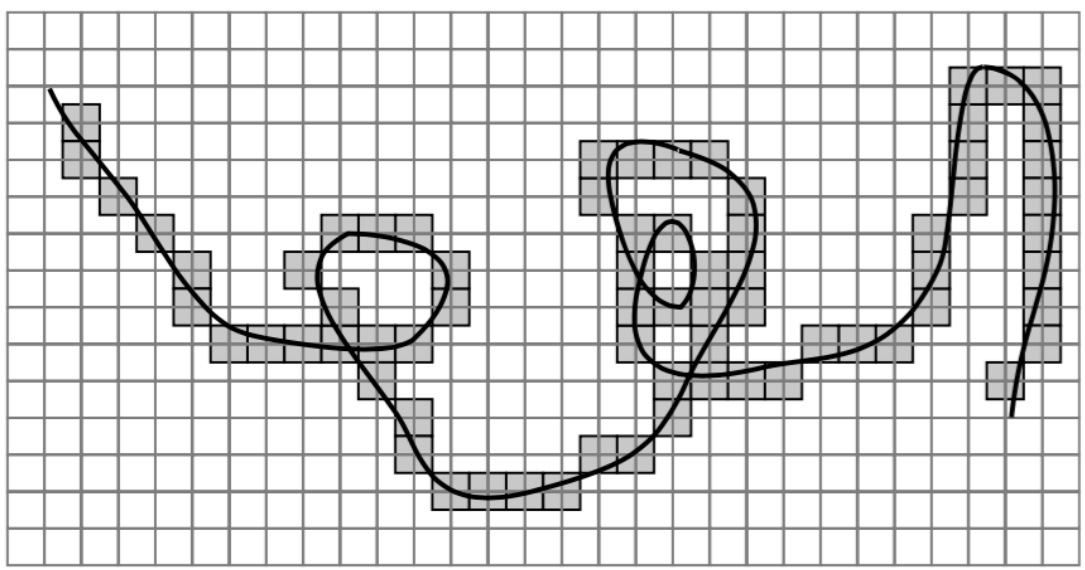


P. Coupé et al. An Optimized Blockwise NonLocal Means Denoising Filter for 3-D Magnetic Resonance Images. IEEE TMI 2008

REMARKS

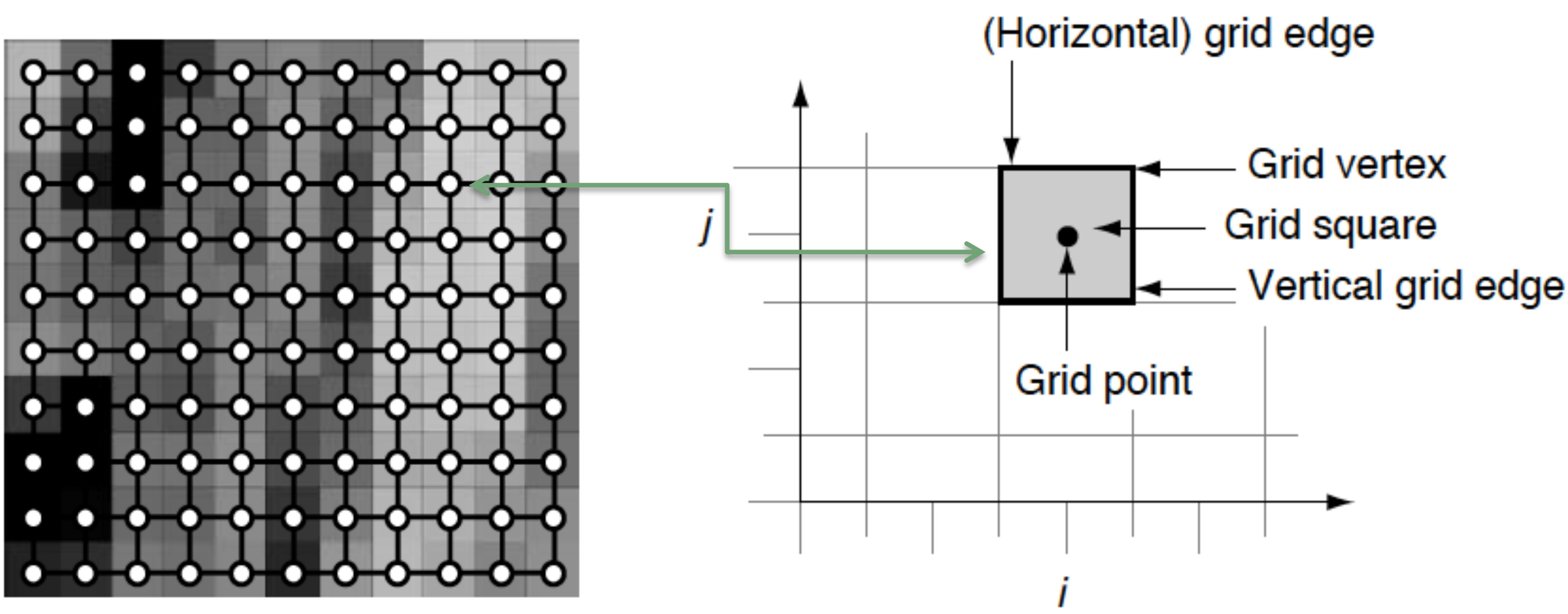


- Computers use discrete form of the images
- The process of transforming continuous space into discrete space is called digitization



REMARKS

- **Definition:** A (2D) image *P* is a function defined on a (finite) rectangular subset *G* of a regular planar orthogonal array. G is called (2D) grid, and an element of G is called pixel. P assigns a value of *P(p)* to each $p \in G$



Histogram

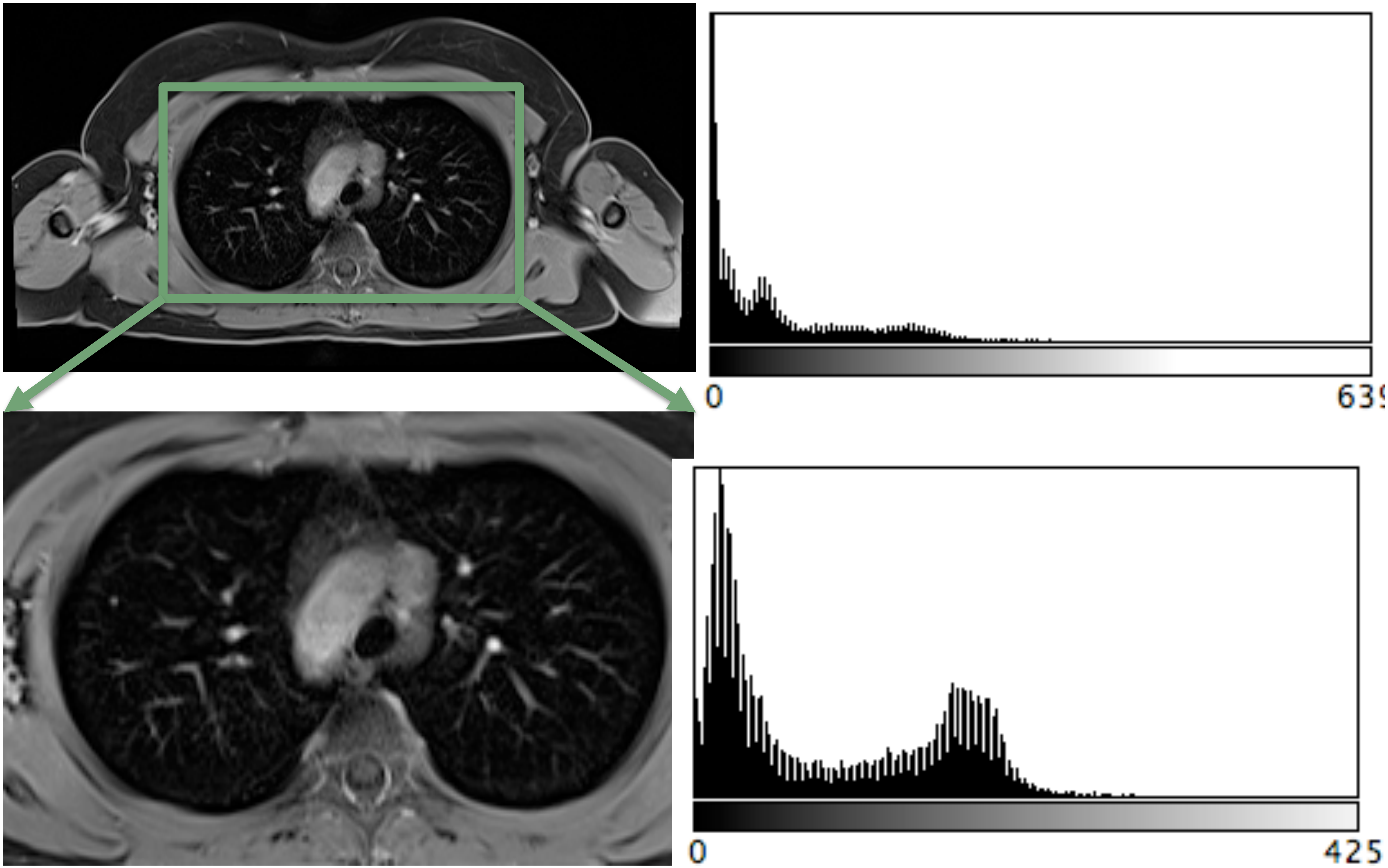
- Histogram of an image provides the frequency of the brightness (intensity) value in the image.
- Provides a natural bridge between images and a probabilistic description.
  - Ex. Probability of pixel (x,y) that has a brightness (intensity) value z

Pseudo-Code for Histogram

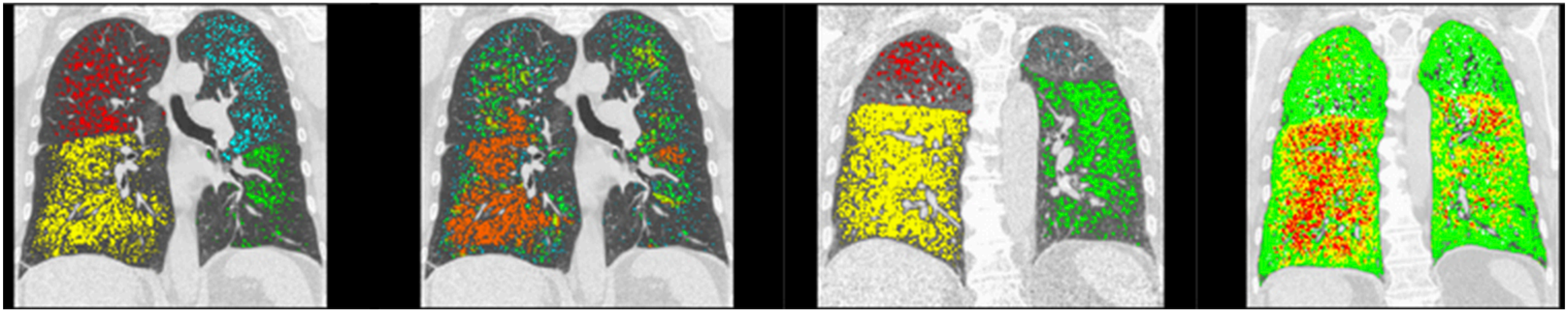
1. Create an array ***h*** with zero in its elements
2. For all pixel locations *(x,y)* of the image *A*, increment ***h****(A(x,y))* by 1

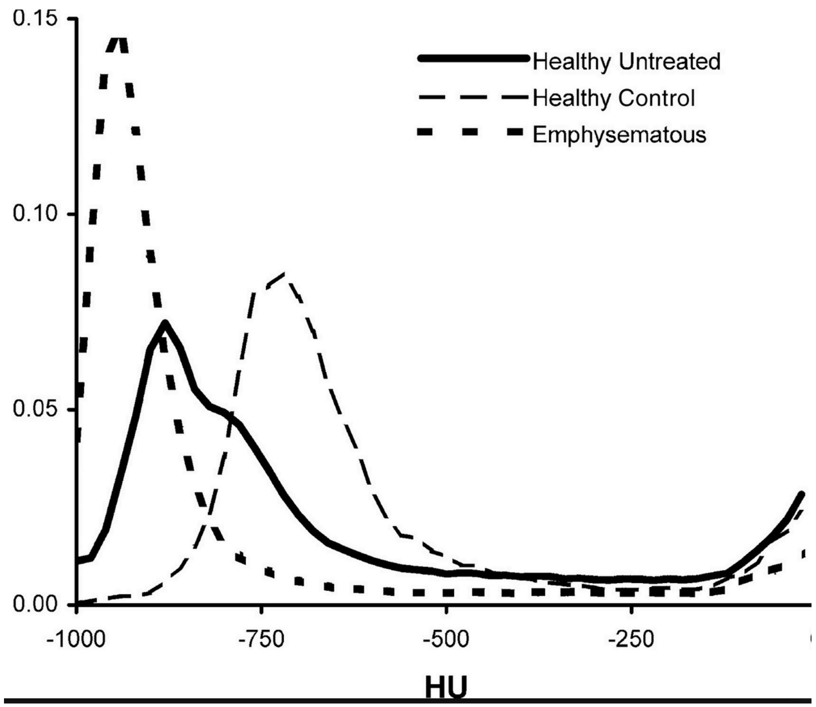
$$h(i) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} \delta(f(m,n) - i), \quad i = 0, 1, \ldots, P-1,$$

$$\delta(w) = \begin{cases} 1 & w = 0, \\ 0 & \text{otherwise.} \end{cases}$$


0
0
425

Ex: Histogram based analysis of Lung CT (credit: ***imbio***)





- **Spatial resolution**
  - determines the smallest structure that can be represented in a digital image.
- **Contrast resolution**
  - Local change in brightness and defined as the ratio between average brightness of an object and background
  - is an indirect measure of the perceptibility of structures. The number of intensity levels has an influence on the likelihood with which two neighboring structures with similar but not equal appearance will be represented by different intensities.

$$Contrast_{global} = \frac{I_{max} - I_{min}}{I_{max} + I_{min}}$$

Another method for measuring contrast

- **RMS (root mean square) contrast:**

$$Contrast_{RMS} = \sqrt{\frac{1}{MN-1}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(I(i,j) - avg(I))^2}$$

The measure takes all pixels into account instead of just the pixels with maximum and minimum intensity values (M and N are size of the image, avg means mean operation over the entire image I).

Image Artifacts

- **Noise**
  - MRI (ex: Gaussian,)
  - PET / SPECT (ex: Poisson, mixed Poisson-Gaussian)
  - CT (ex: Gaussian)
  - DTI, DWI, ...
- **Intensity inhomogeneity**
  - MRI
- **Intensity Non-Standardness**
  - MRI
- **Partial Volume**
  - MRI, PET,…

Image Artifacts

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- **Partial Volume**
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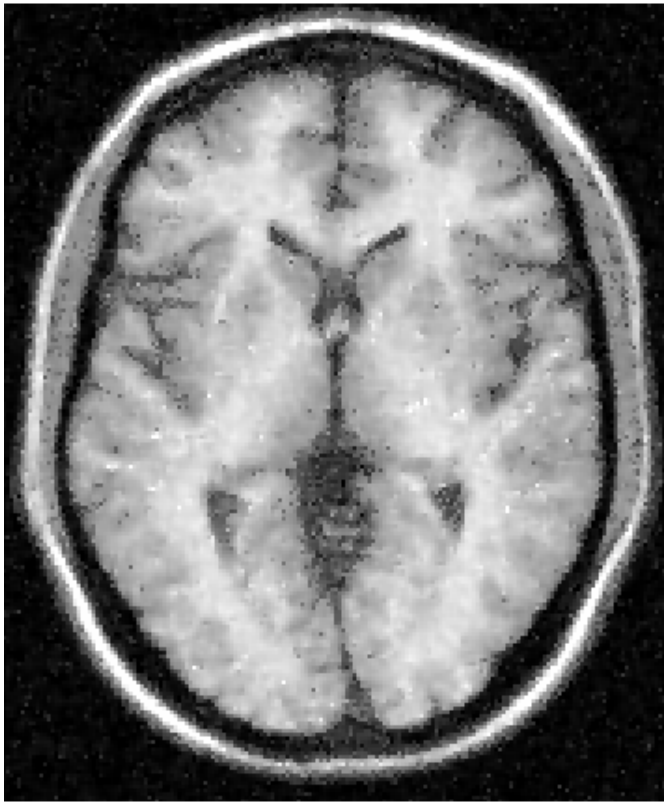
Noise

Noise is corrupting the image information, and it is unwanted.

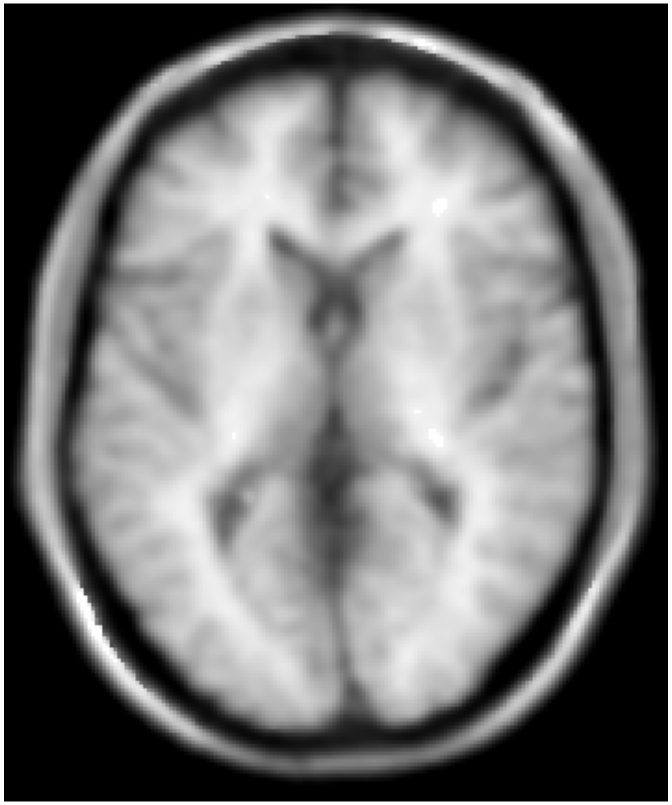
- **Signal independent noise**
  - $g = f + n$
    - *Gaussian*
- **Signal dependent noise**
  - $g = f*n$
    - *Poisson*

- *Often, medical images are considered to have Gaussian noise, however PET/SPECT images have mixed Poisson/Gaussian, and MRI have Rician type noise.*

Noise Suppression



Higher noise, higher contrast



Lower noise, lower contrast

For best results, we need lower noise and higher contrast.

Linear Filtering

- From linear system theory, we know that an image I(i,j) can be written as follows (convolution)

$$I(i,j) = \sum_{k,l} I(k,l)\delta(i-k, j-l)$$

Linear Filtering

- From linear system theory, we know that an image I(i,j) can be written as follows (convolution)

$$I(i,j) = \sum_{k,l} I(k,l)\delta(i-k, j-l)$$

- Practically, for a linear-shift invariant kernel *f*, convolution operation can be written as cross-correlation

$$f * I(i,j) = \sum_{k,l} f(k,l) I(i-k, j-l) = \sum_{k,l} h(k,l) I(i+k, j+l) = h.I(i,j)$$

$$h(i,j) = f(-i,-j)$$

Convolution Operation

$$f*h=\sum_k\sum_l f(k,l)\,h(-k,-l)$$

$f = \text{Image}$

$h = \text{Kernel}$

h

h_1	h_2	h_3
h_4	h_5	h_6
h_7	h_8	h_9

$X-flip$

h_7	h_8	h_9
h_4	h_5	h_6
h_1	h_2	h_3

$Y-flip$

f

f_1	f_2	f_3
f_4	f_5	f_6
f_7	f_8	f_9

$*$

h_9	h_8	h_7
h_6	h_5	h_4
h_3	h_2	h_1

$$\begin{aligned} f*h = {} & f_1h_9+f_2h_8+f_3h_7 \\ & +f_4h_6+f_5h_5+f_6h_4 \\ & +f_7h_3+f_8h_2+f_9h_1 \end{aligned}$$

Correlation Operation

$$f \otimes h = \sum_k \sum_l f(k,l)h(k,l)$$

f = Image

h = Kernel

$$f \otimes h: \quad \begin{array}{c} f \\ \begin{array}{|c|c|c|} \hline f_1 & f_2 & f_3 \\ \hline f_4 & f_5 & f_6 \\ \hline f_7 & f_8 & f_9 \\ \hline \end{array} \end{array} \otimes \begin{array}{c} h \\ \begin{array}{|c|c|c|} \hline h_1 & h_2 & h_3 \\ \hline h_4 & h_5 & h_6 \\ \hline h_7 & h_8 & h_9 \\ \hline \end{array} \end{array} \longrightarrow$$

$$\begin{aligned} f \otimes h = {} & f_1h_1 + f_2h_2 + f_3h_3 \\ & + f_4h_4 + f_5h_5 + f_6h_6 \\ & + f_7h_7 + f_8h_8 + f_9h_9 \end{aligned}$$

Correlation and Convolution

- Convolution is a filtering operation, expresses the amount of overlap of one function as it is shifted over another function

- Correlation compares the similarity of two sets of data (relatedness of the signals!)

Noise suppression: Image Filtering

- Enhance or restore data by removing noise <u>without significantly blurring</u> the structures in the images.

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Noise suppression: Image Filtering

- Enhance or restore data by removing noise <u>without significantly blurring</u> the structures in the images.
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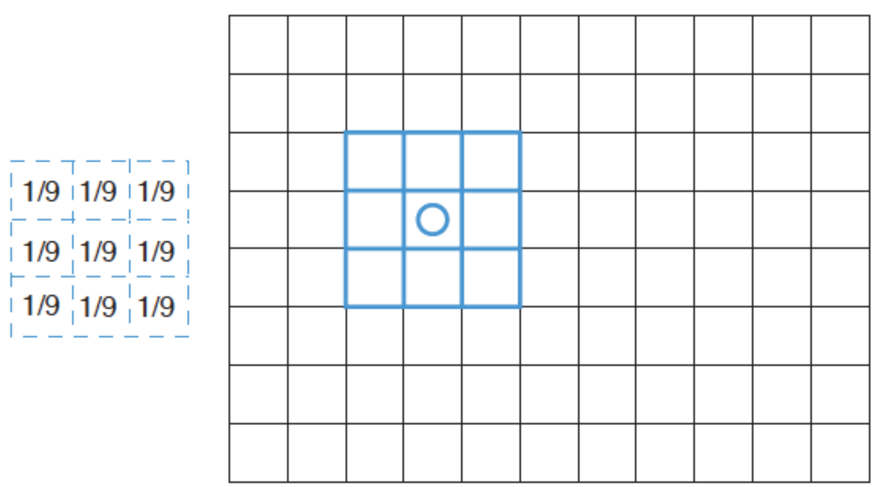
- Box (averaging/smoothing) Filtering:

$$S = (C, f) \longrightarrow S_F = (C, f_F)$$



Noise suppression: Image Filtering

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$$S = (C, f) \longrightarrow S_F = (C, f_F)$$

$$f_F(\nu) = \sum_{\nu_i \in N(\nu)} w_i f(\nu_i)$$

Noise suppression: Image Filtering

Gaussian

0.01	0.08	0.01
0.08	0.64	0.08
0.01	0.08	0.01

- Gaussian Filtering:

$$S = (C, f) \longrightarrow S_F = (C, f_F)$$

$$f_F(\nu) = \sum_{\nu_i \in N(\nu)} w_i f(\nu_i)$$

  – f_F is a Gaussian weighted average of f in a neighborhood of N of voxel v

Remark: Why Gaussian Assumption?

- Most common natural model
- Smooth function, it has infinite number of derivatives
- It is Symmetric
- Fourier Transform of Gaussian is Gaussian.
- Convolution of a Gaussian with itself is a Gaussian.
- Gaussian is separable; 2D convolution can be performed by two 1-D convolutions
- There are cells in eye that perform Gaussian filtering.

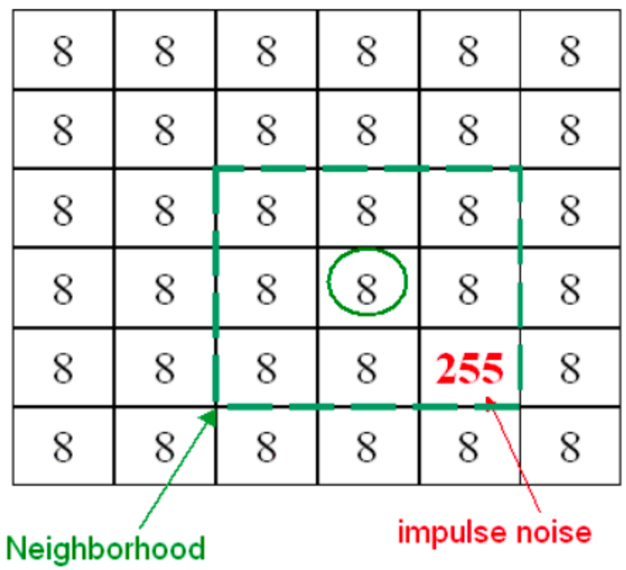
Noise suppression: Image Filtering

- Enhance or restore data by removing noise without significantly blurring the structures in the images.
- Literature is vast! We will cover only a few of them.
- Median Filtering:

$$S = (C, f) \longrightarrow S_F = (C, f_F)$$

  – f_F is median intensity in a neighborhood of voxel v.

Median Filtering (Details)



[8 8 8 8 8 8 8 8 255]

median

Filtering Operation (Spatial Domain)

Example: **Box Filtering (smoothing)**

What does it do?

- Replaces each pixel with an average of its neighborhood

- Achieve smoothing effect (remove sharp features)

$$g[\cdot,\cdot]$$

$$\frac{1}{9}\begin{bmatrix}1 & 1 & 1\\ 1 & 1 & 1\\ 1 & 1 & 1\end{bmatrix}$$

Filtering Operation (Spatial Domain)

$$g[\cdot\,,\cdot\,]\ \frac{1}{9}\begin{bmatrix}1&1&1\\1&1&1\\1&1&1\end{bmatrix}$$

$f[.,.]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$h[.,.]$

$$h[m,n]=\sum_{k,l} g[k,l]\, f[m+k,n+l]$$

Credit: S. Seitz

Filtering Operation (Spatial Domain)

$$g[\cdot\,,\cdot\,]\ \frac{1}{9}\begin{bmatrix}1 & 1 & 1\\ 1 & 1 & 1\\ 1 & 1 & 1\end{bmatrix}$$

$f[.,.]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$h[.,.]$

	0	10							

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0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$h[.,.]$

	0	10	20						

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$f[.,.]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$h[.,.]$

	0	10	20	30					

$$h[m,n]=\sum_{k,l} g[k,l]\,f[m+k,n+l]$$

Credit: S. Seitz

Filtering Operation (Spatial Domain)

$$g[\cdot\,,\cdot\,]\ \frac{1}{9}$$

1	1	1
1	1	1
1	1	1

$$f[.,.]$$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$$h[.,.]$$

	0	10	20	30	30				

$$h[m,n] = \sum_{k,l} g[k,l]\, f[m+k, n+l]$$

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0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$h[.,.]$

	0	10	20	30	30				
				?					

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1	1	1
1	1	1

$f[.,.]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$h[.,.]$

	0	10	20	30	30				
						?			
				50					

$$h[m,n]=\sum_{k,l} g[k,l]\, f[m+k,n+l]$$

Credit: S. Seitz

$$g[\cdot,\cdot] \quad \frac{1}{9}\begin{bmatrix}1&1&1\\1&1&1\\1&1&1\end{bmatrix}$$

Filtering Operation (Spatial Domain)

$f[.,.]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

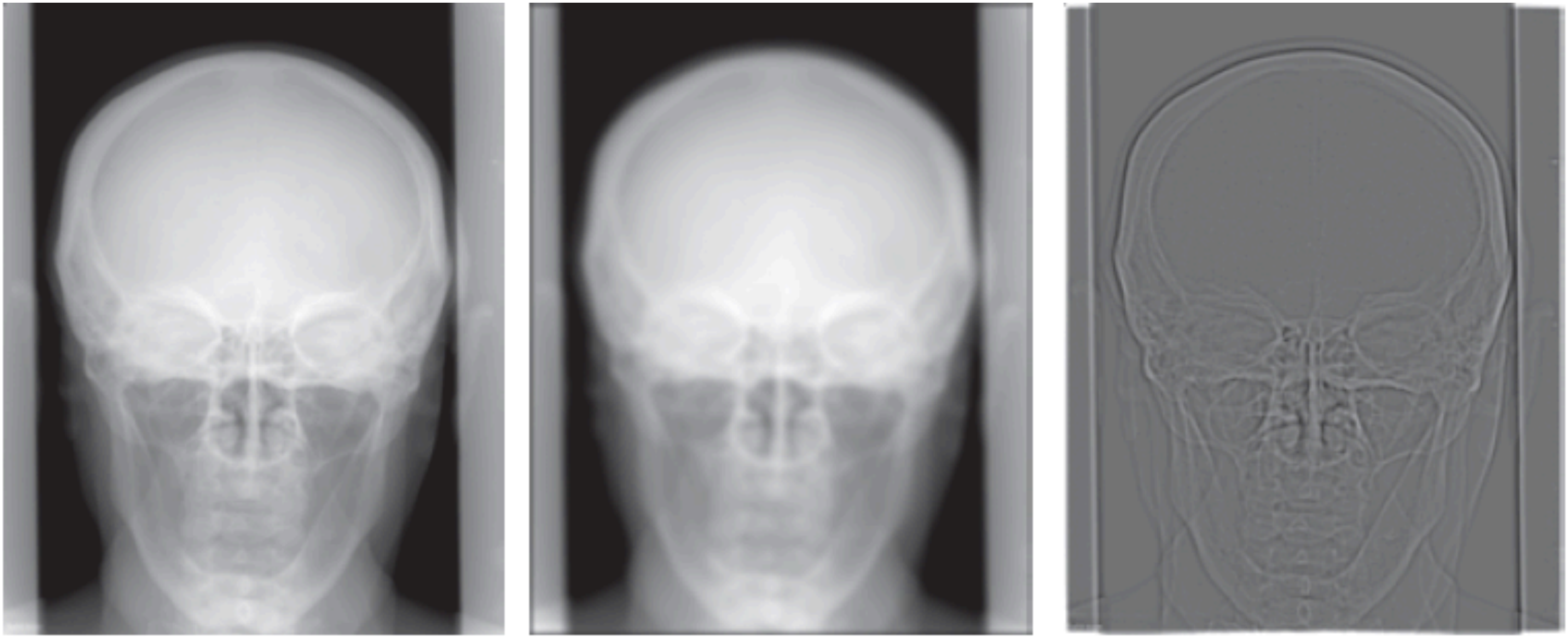
$h[.,.]$

	0	10	20	30	30	30	20	10	
	0	20	40	60	60	60	40	20	
	0	30	60	90	90	90	60	30	
	0	30	50	80	80	90	60	30	
	0	30	50	80	80	90	60	30	
	0	20	30	50	50	60	40	20	
	10	20	30	30	30	30	20	10	
	10	10	10	0	0	0	0	0	

$$h[m,n]=\sum_{k,l} g[k,l]\, f[m+k,n+l]$$

Credit: S. Seitz

Filtering X-ray

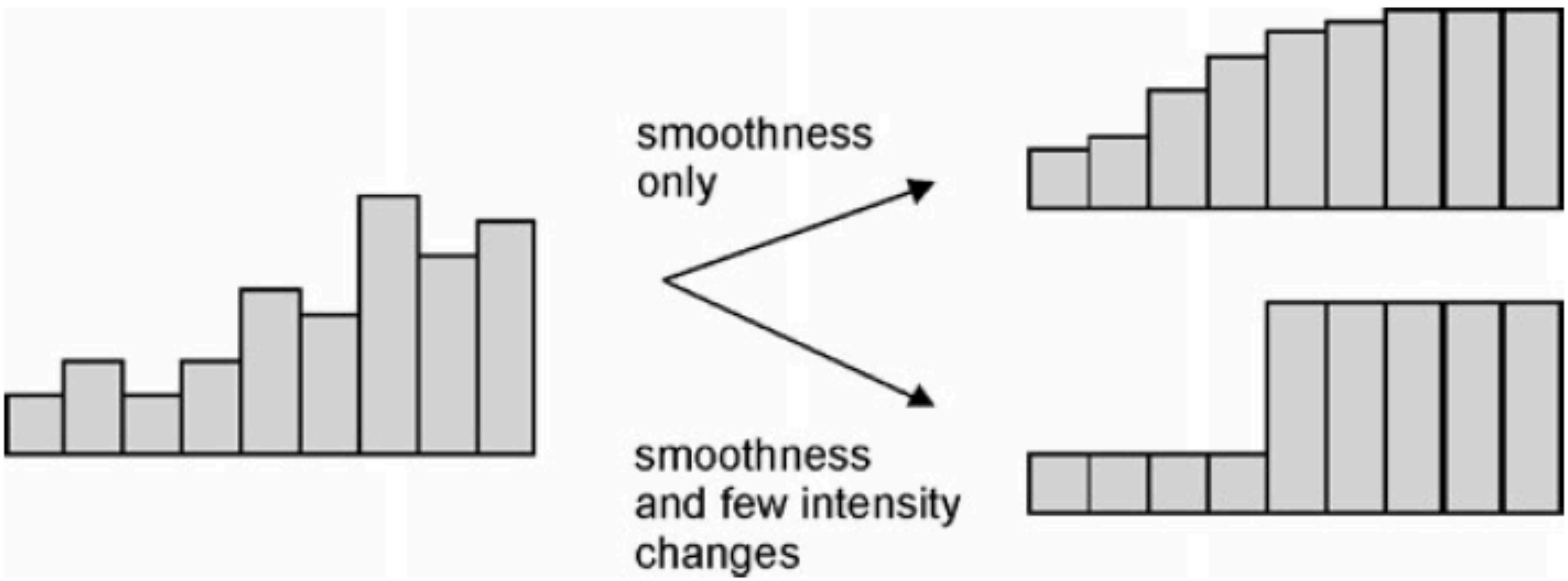


(a) (b) (c)

a. Radiography of the skull, b. low-pass filter with a Gaussian filter (std=15, 20 x 20), c. high-pass Filter obtained from subtracting b from a.

Unsharp Masking

Lower Noise, Higher Contrast



histogram histogram

Unsharp Masking

- Not only noise removal, but edge enhancement is necessary!

$$I = g * I + (I - g * I)$$

Unsharp Masking

- Not only noise removal, but edge enhancement is necessary!

$$I = \underbrace{g * I}_{\substack{\text{Smoothed image} \\ \text{(low pass)}}} + \underbrace{(I - g * I)}_{\substack{\text{Edge enhanced image} \\ \text{(high pass)}}}$$

Unsharp Masking

- Not only noise removal, but edge enhancement is necessary!

$$I = \underbrace{g * I}_{\substack{\text{Smoothed image} \\ \text{(low pass)}}} + \underbrace{(I - g * I)}_{\substack{\text{Edge enhanced image} \\ \text{(high pass)}}}$$

$$I' = g * I + (1 + \alpha)(I - g * I)$$

$$\alpha > 0$$

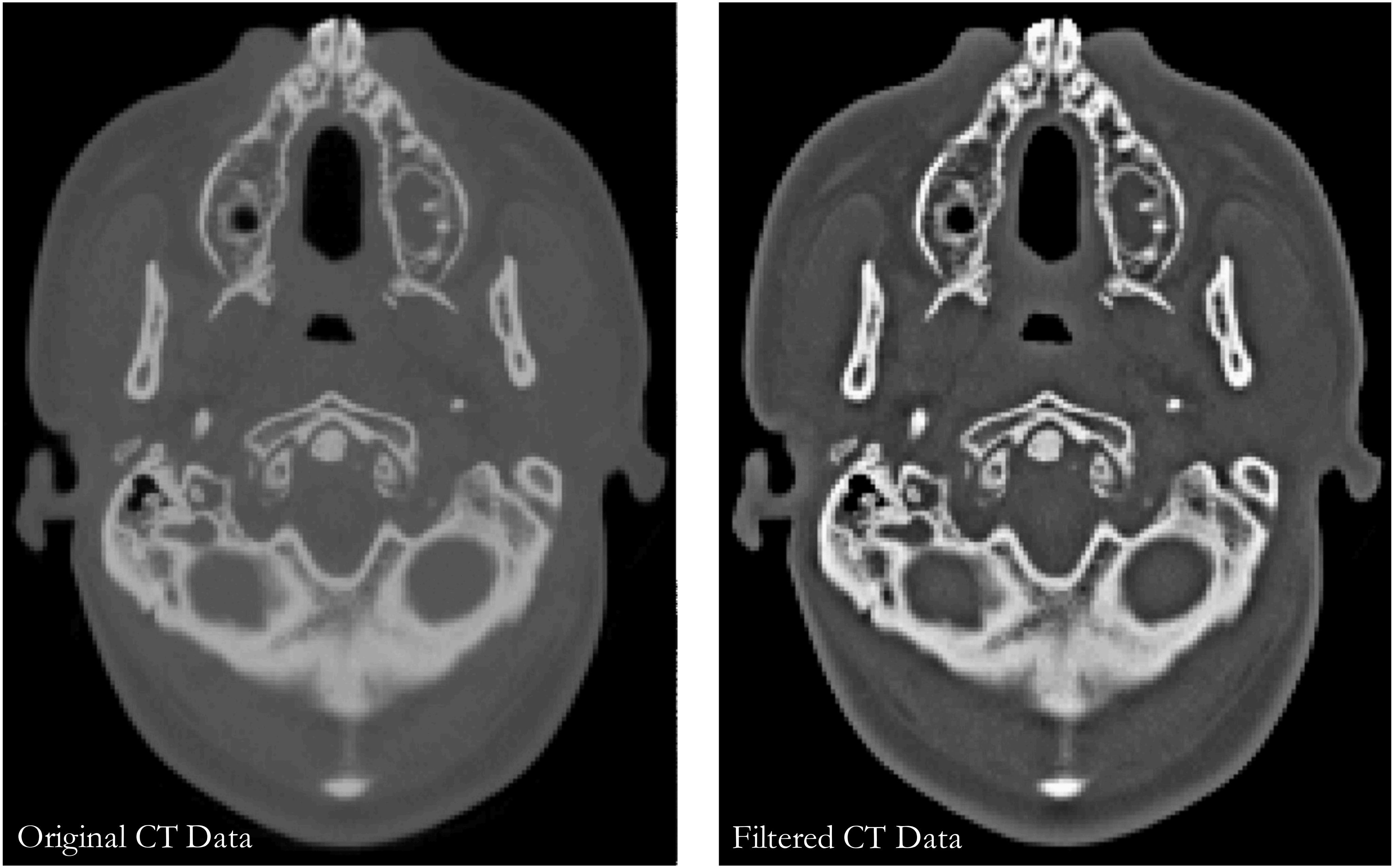
Reminder: Edges are located in high frequency of the images!

Hand X-ray Unsharp Masking (alpha=0.5)

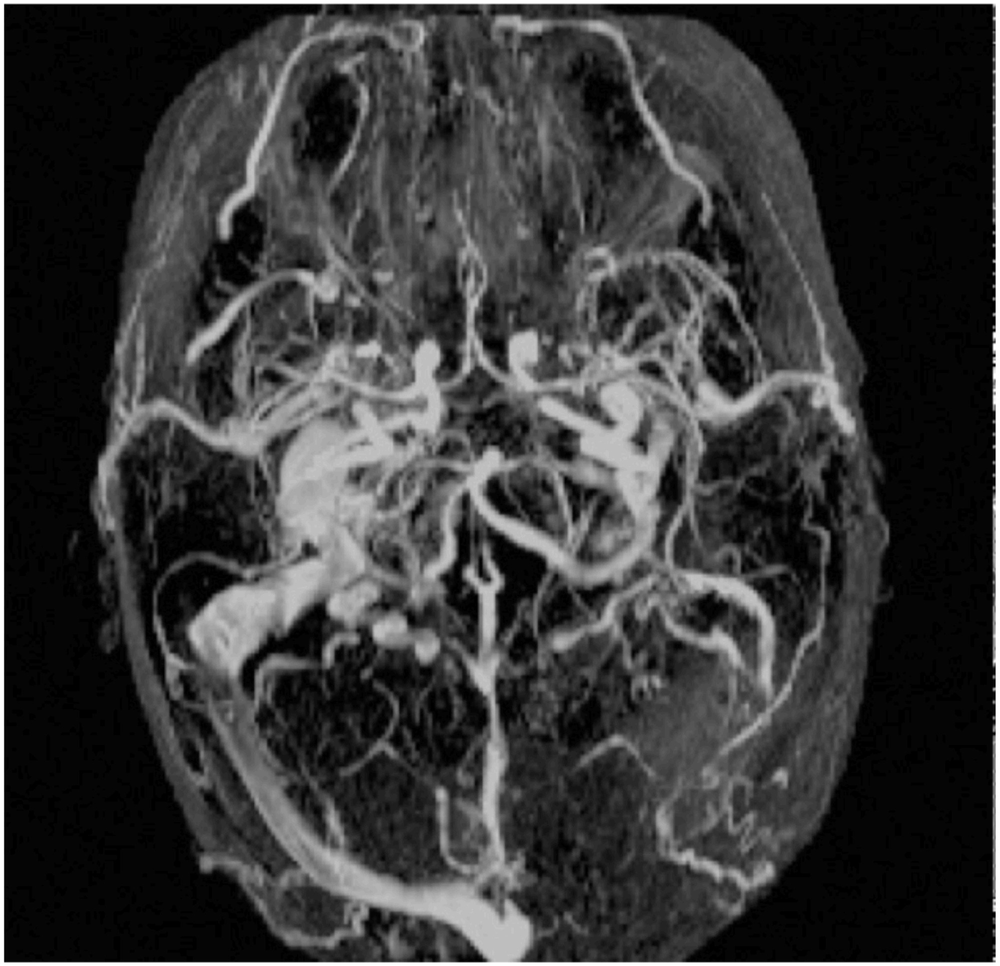
Original Image

Enhanced Image

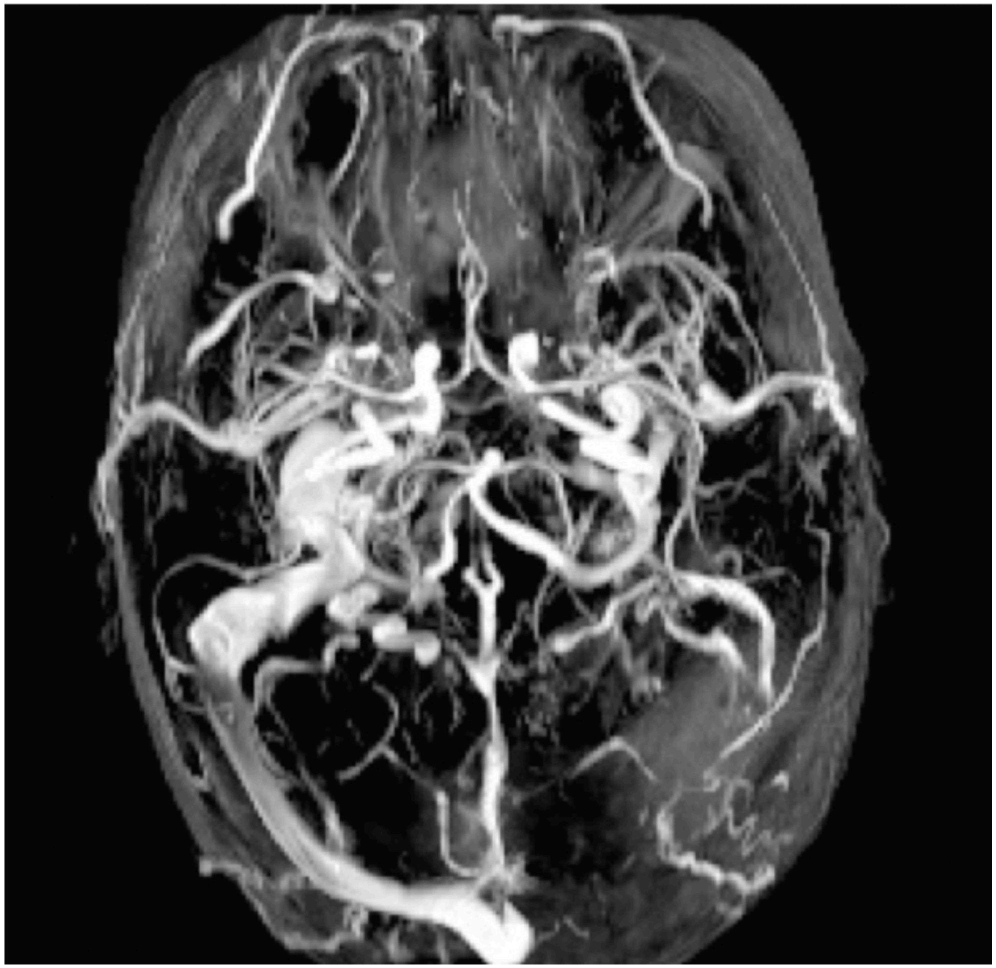
Unsharp Masking: Example CT (head, axial)



Adaptive Filtering: Example head MRA

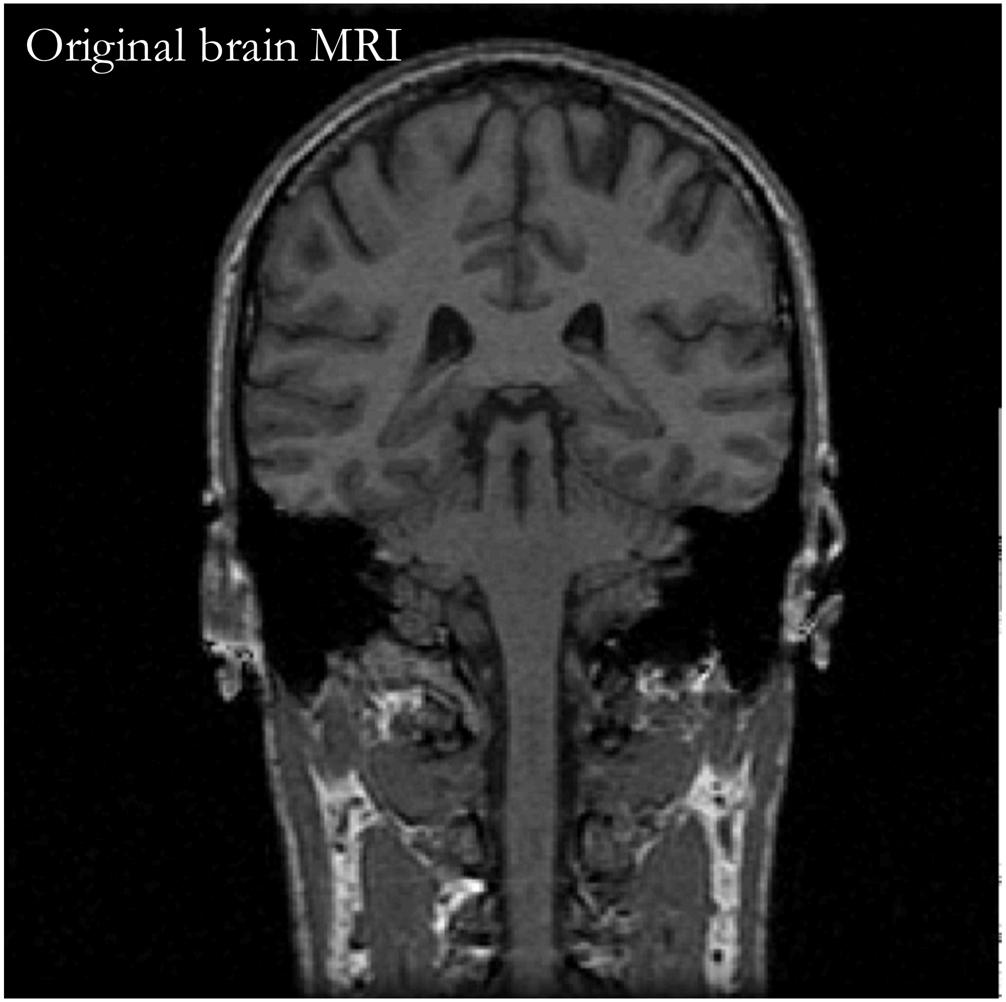


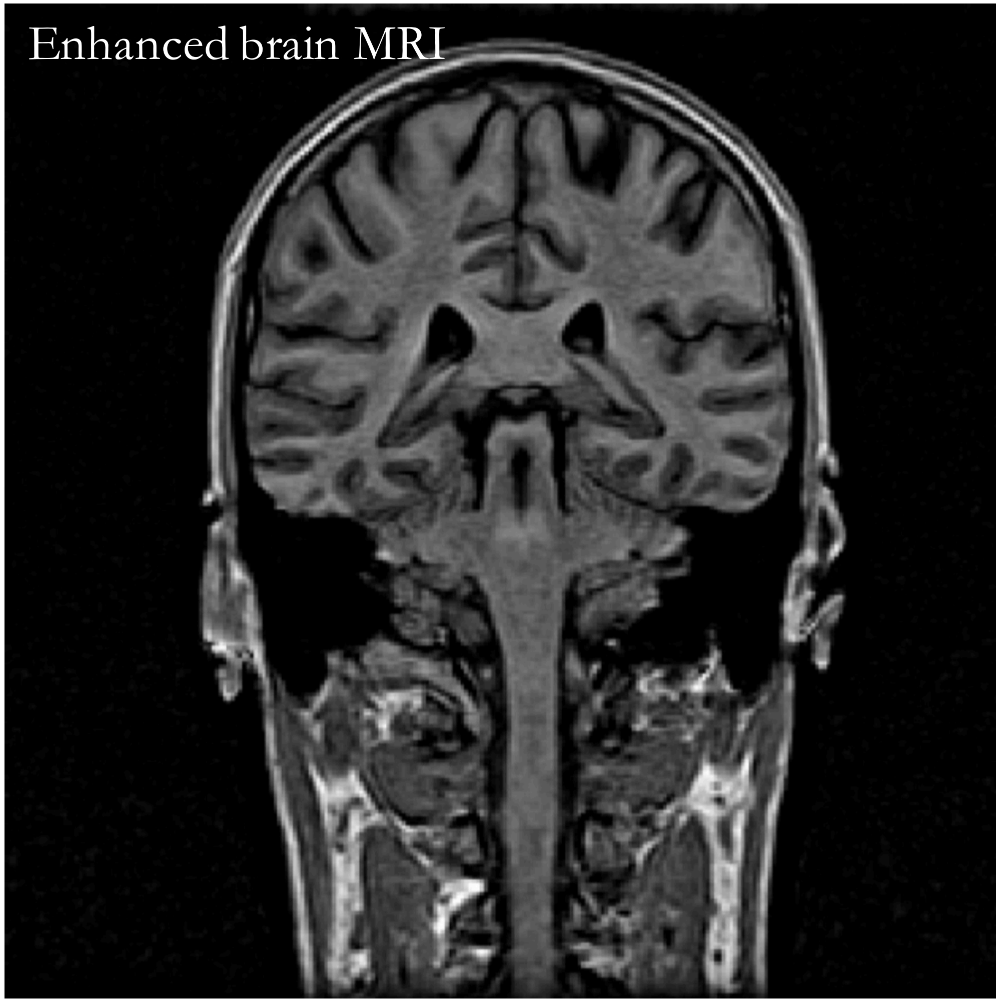
MIP of MRA data before filtering



MIP of MRA data after filtering

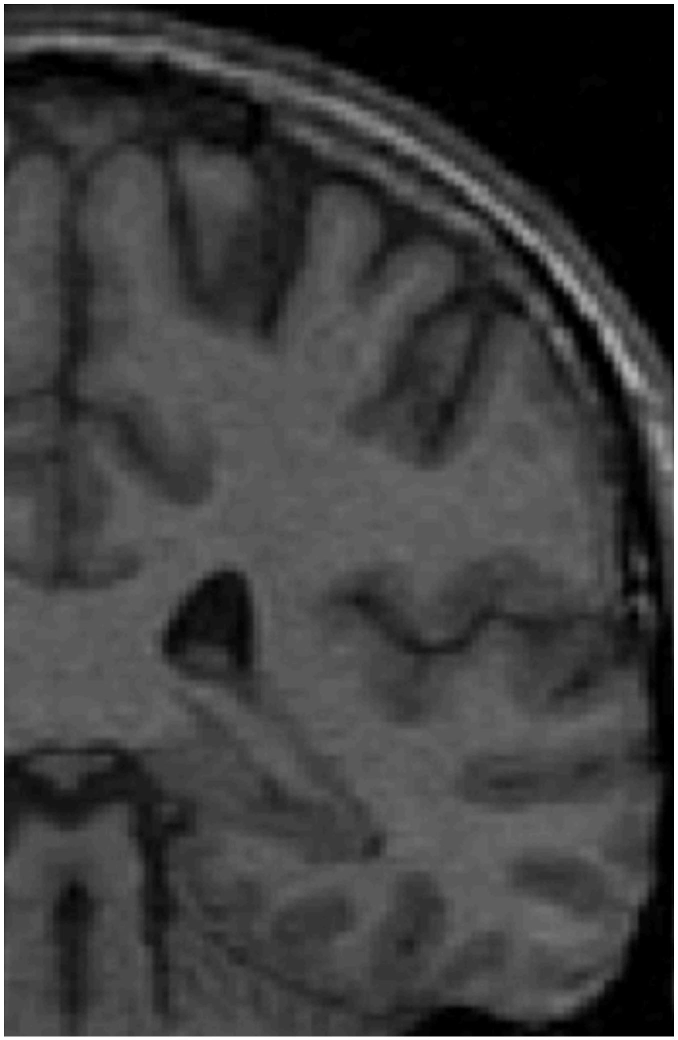
Adaptive Filtering: Example brain MRI

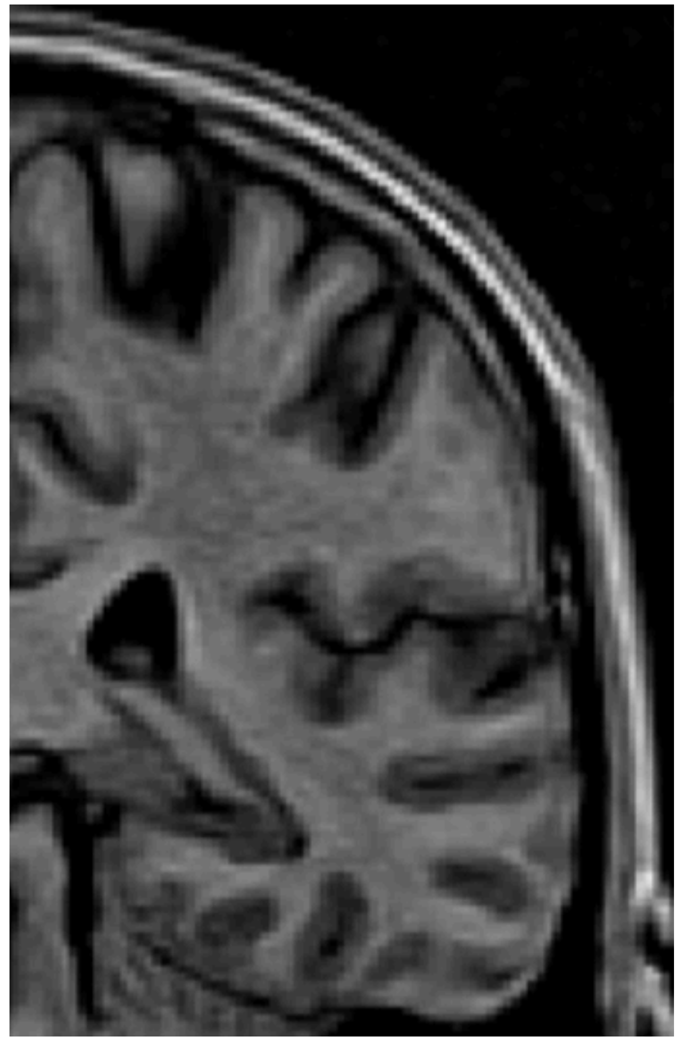




Note the improved contrast between brain and CSF (cerebrospinal fluid)

Adaptive Filtering: Example brain MRI (zoomed)

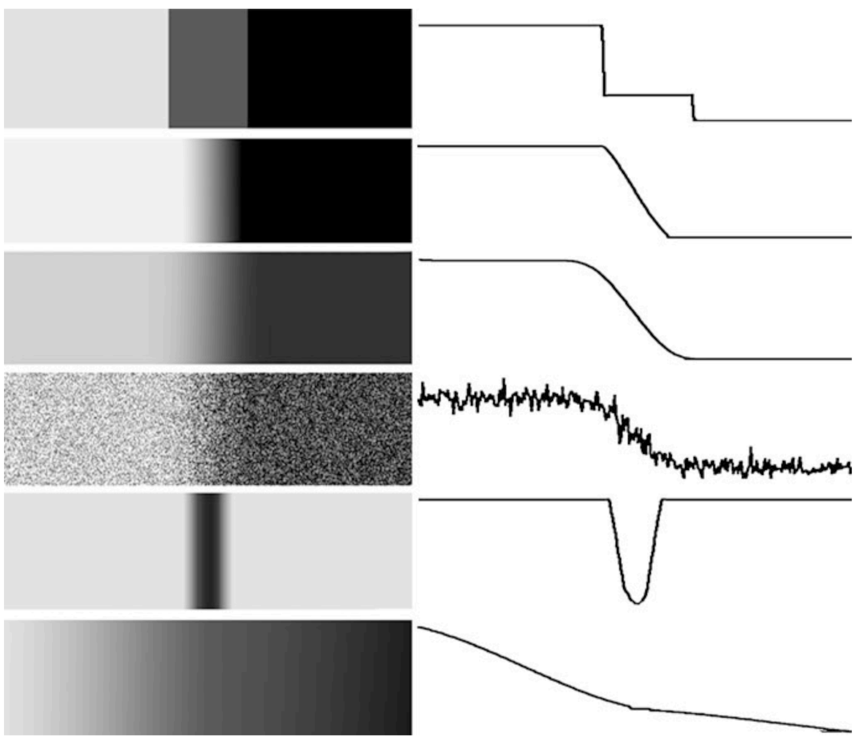




Note the improved contrast between brain and CSF (cerebrospinal fluid)

Edges

- Discontinuities in images are features that are often useful for initializing an image analysis procedure.
- Edges are important information for understanding an image; by moving "non-edge" data we also simplify the data.



Edges → rate of change

Rate of change → differentiation

Differentiation → difference in digital domain

Edges

- Discontinuities in images are features that are often useful for initializing an image analysis procedure.
- Edges are important information for understanding an image; by moving "non-edge" data we also simplify the data.

- Goal: Identify sudden changes (discontinuities) in an image
  - Most semantic and shape information from the image can be encoded in the edges
  - More compact than pixels
  - Marks the border of an object

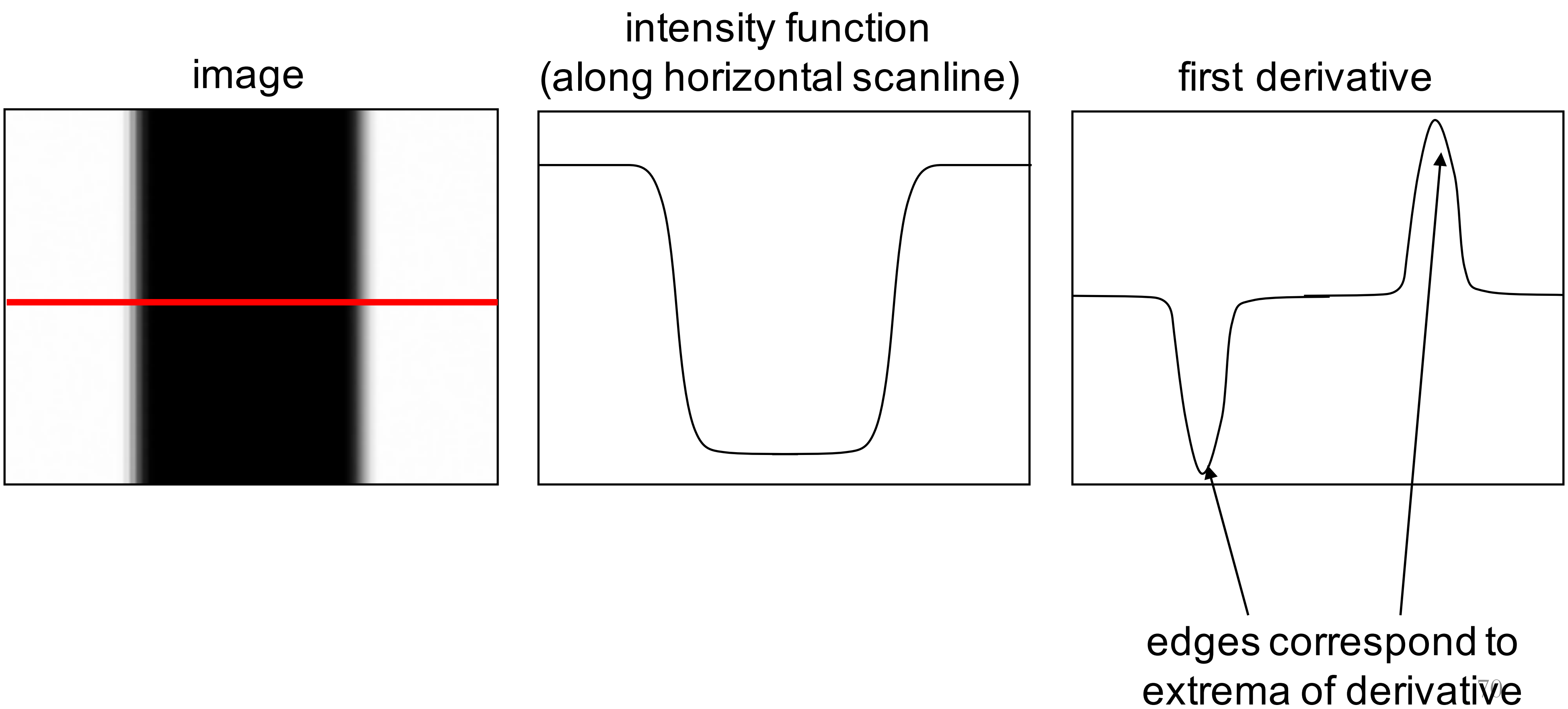
Edges ➔ rate of change

Rate of change ➔ differentiation

Differentiation ➔ difference in digital domain

Characterizing Edges

- An edge is a place of rapid change in the image intensity function



Derivative of Images

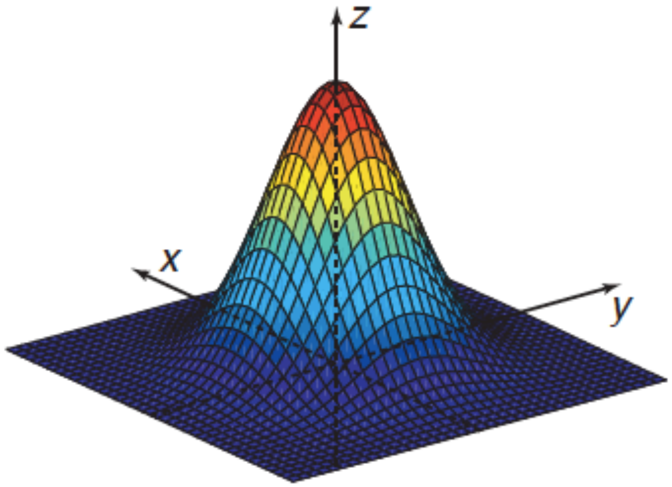
Derivative masks

$$f_x \Rightarrow \frac{1}{3}\begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} \qquad f_y \Rightarrow \frac{1}{3}\begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}$$

$$I = \begin{bmatrix} 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \\ 10 & 10 & 20 & 20 & 20 \end{bmatrix} \qquad I_x = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & \boxed{10} & \boxed{10} & 0 & 0 \\ 0 & 10 & 10 & 0 & 0 \\ 0 & 10 & 10 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

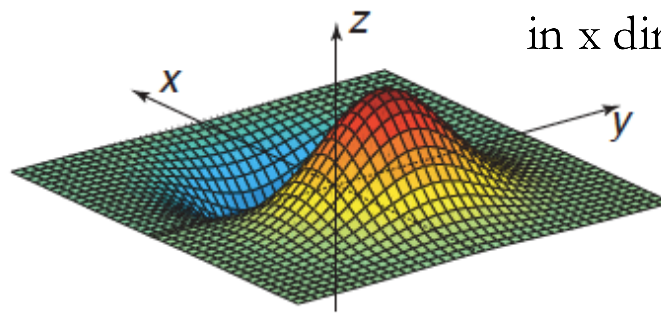
Laplacian: Difference of Gaussians

Gaussian



(a)

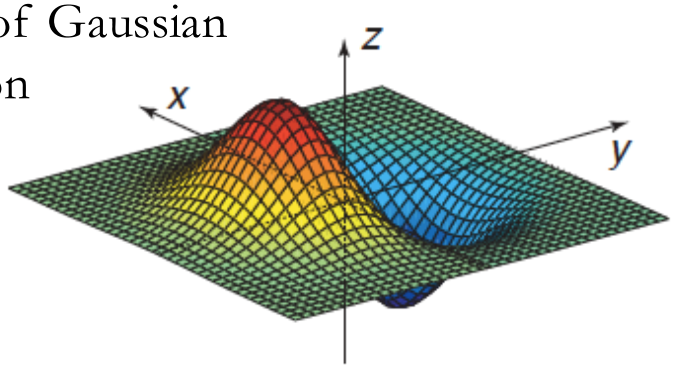
Derivative of Gaussian
in x direction
(gradient)



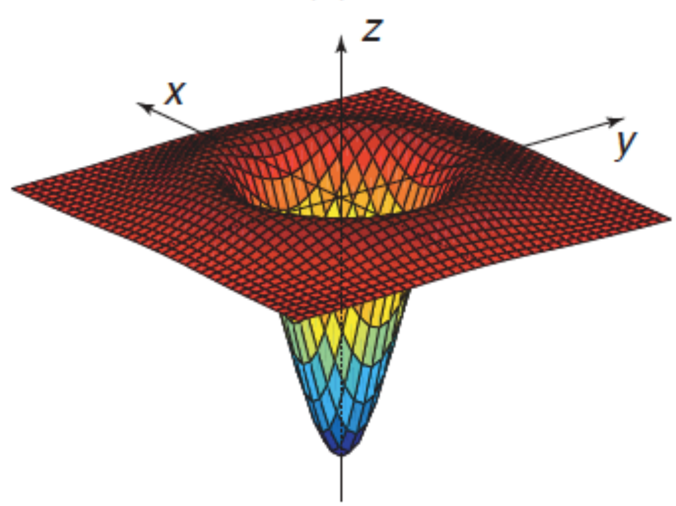
(b)

Derivative of Gaussian
in y direction

(gradient)



(c)



(d)

Laplacian of
Gaussian

Difference of Gaussians ~ Laplacian

Gaussian

0.01	0.08	0.01
0.08	0.64	0.08
0.01	0.08	0.01

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

0.05	0	−0.05
0.34	0	−0.34
0.05	0	−0.05

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

0.05	0.34	0.05
0	0	0
−0.05	−0.34	−0.05

∇^2

0.3	0.7	0.3
0.7	−4	0.7
0.3	0.7	0.3

How to measure for evaluating noise removal algorithms?

- Simultaneously suppressing noise and retaining high contrast is difficult … trade-off game. Filter Operating Characteristic (FOC) curve captures this trade-off.

Residual Noise RN: Standard deviation of intensity within pbject region

Relative Contrast RC:

$$RC = \frac{|\mu_O - \mu_B|}{\sqrt{\sigma_O \sigma_B}}$$

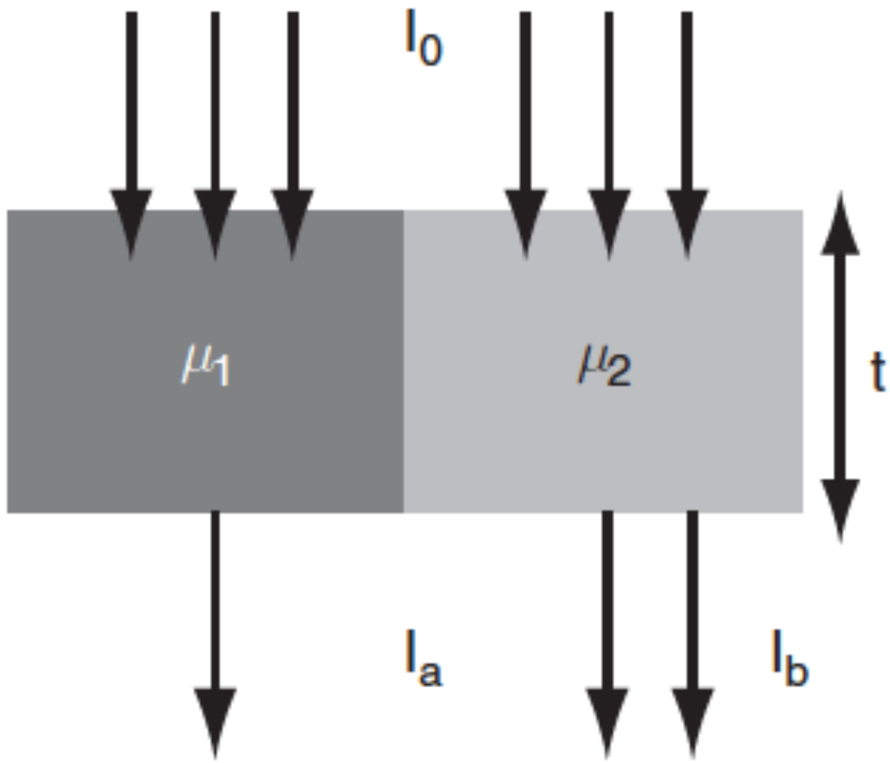
- μ_O, μ_B - object & background mean;
- σ_O, σ_B - object & background std.
- FOC is a curve of 1-RC vs 1-RN.

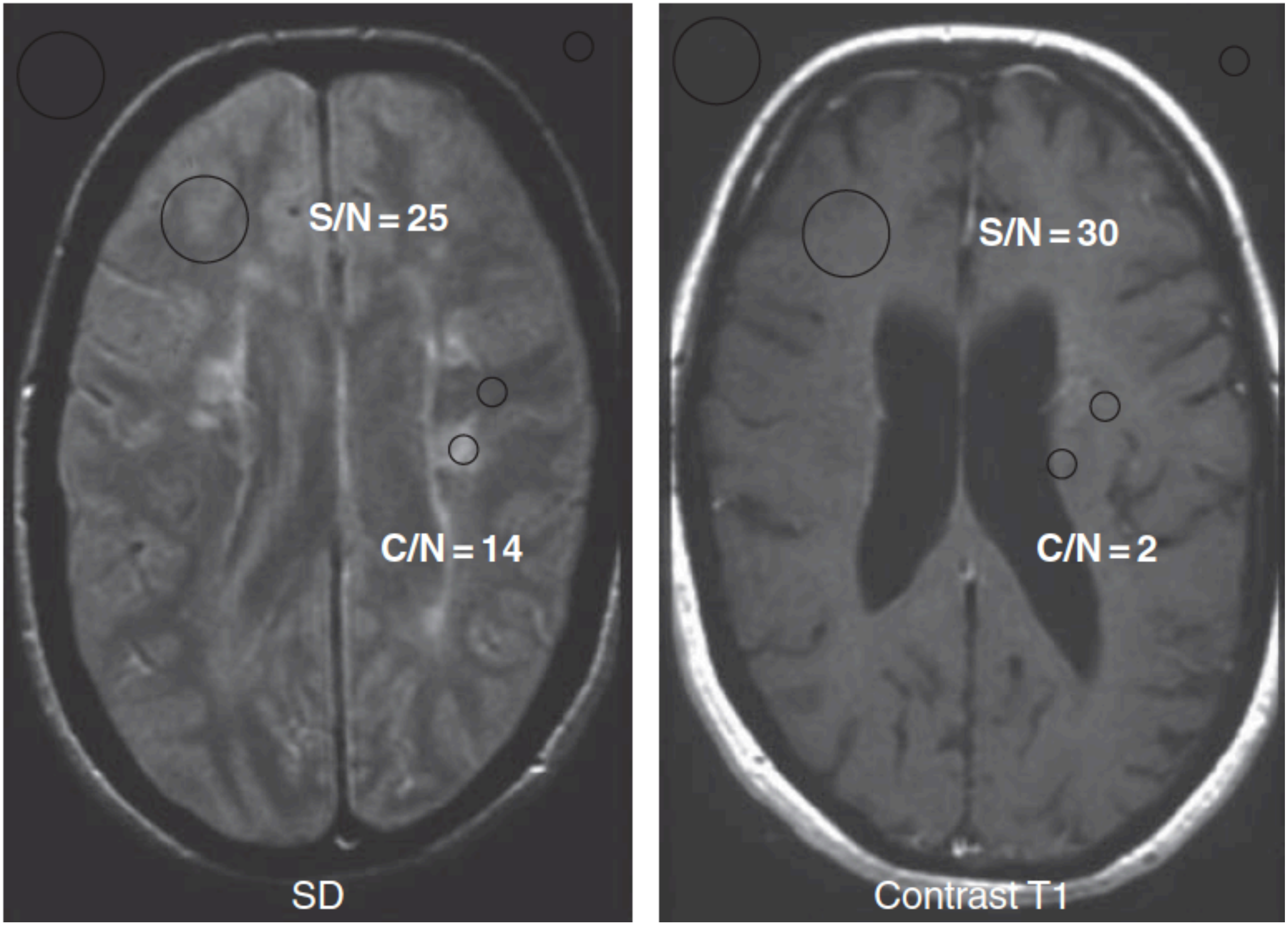
How to measure for evaluating noise removal algorithms?

- SNR (signal-to-noise ratio): basic measure of image quality
- SNR in an image is simply determined by averaging signal intensity within similar-sized regions of interest (ROIs) inside and outside the sample (background).

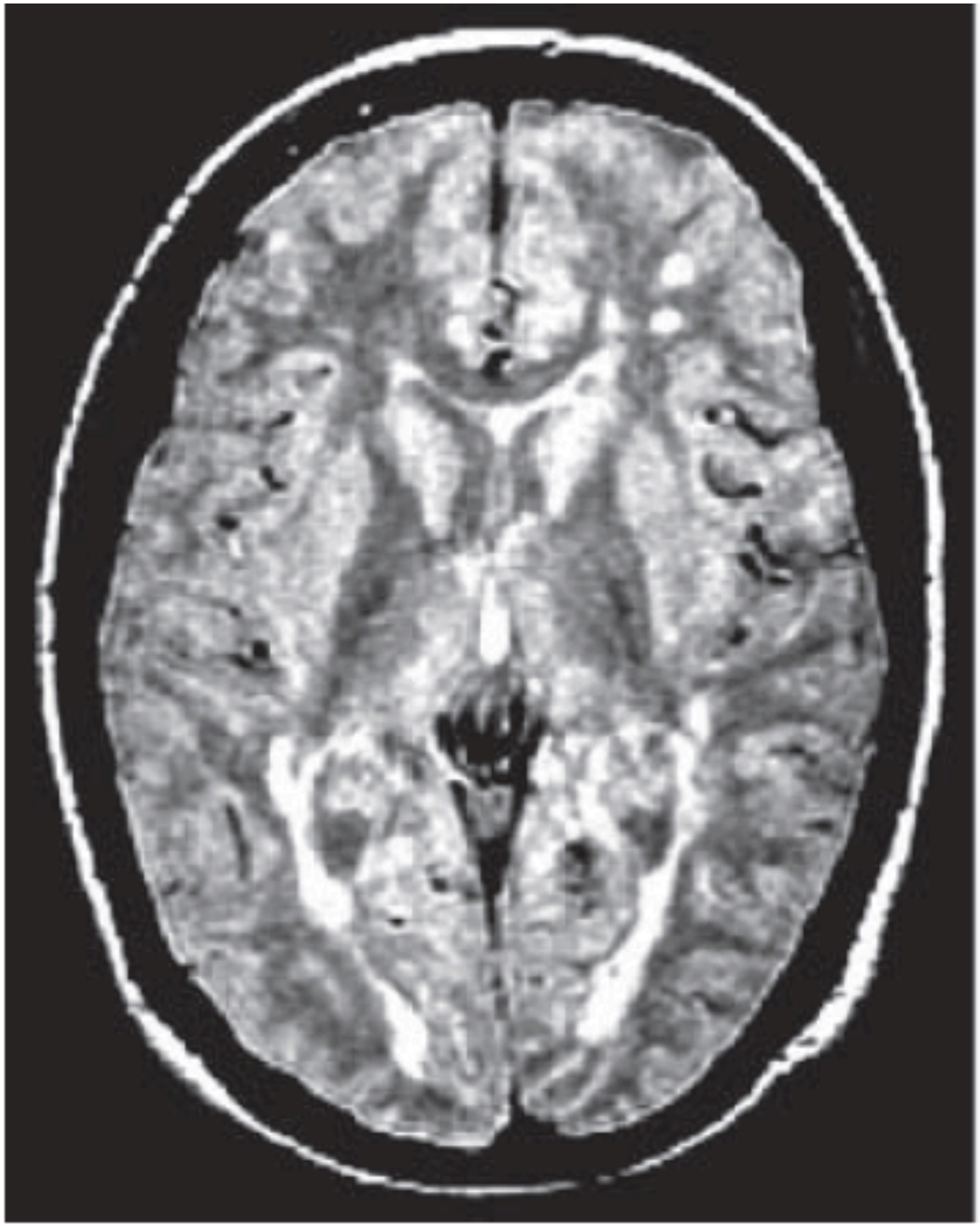
- CNR (contrast-to-noise ratio):

  (S1-S2)/N
- CNR in an image is determined by averaging signal intensity in similar-sized ROIs placed within two objects in the sample and another ROI outside the sample

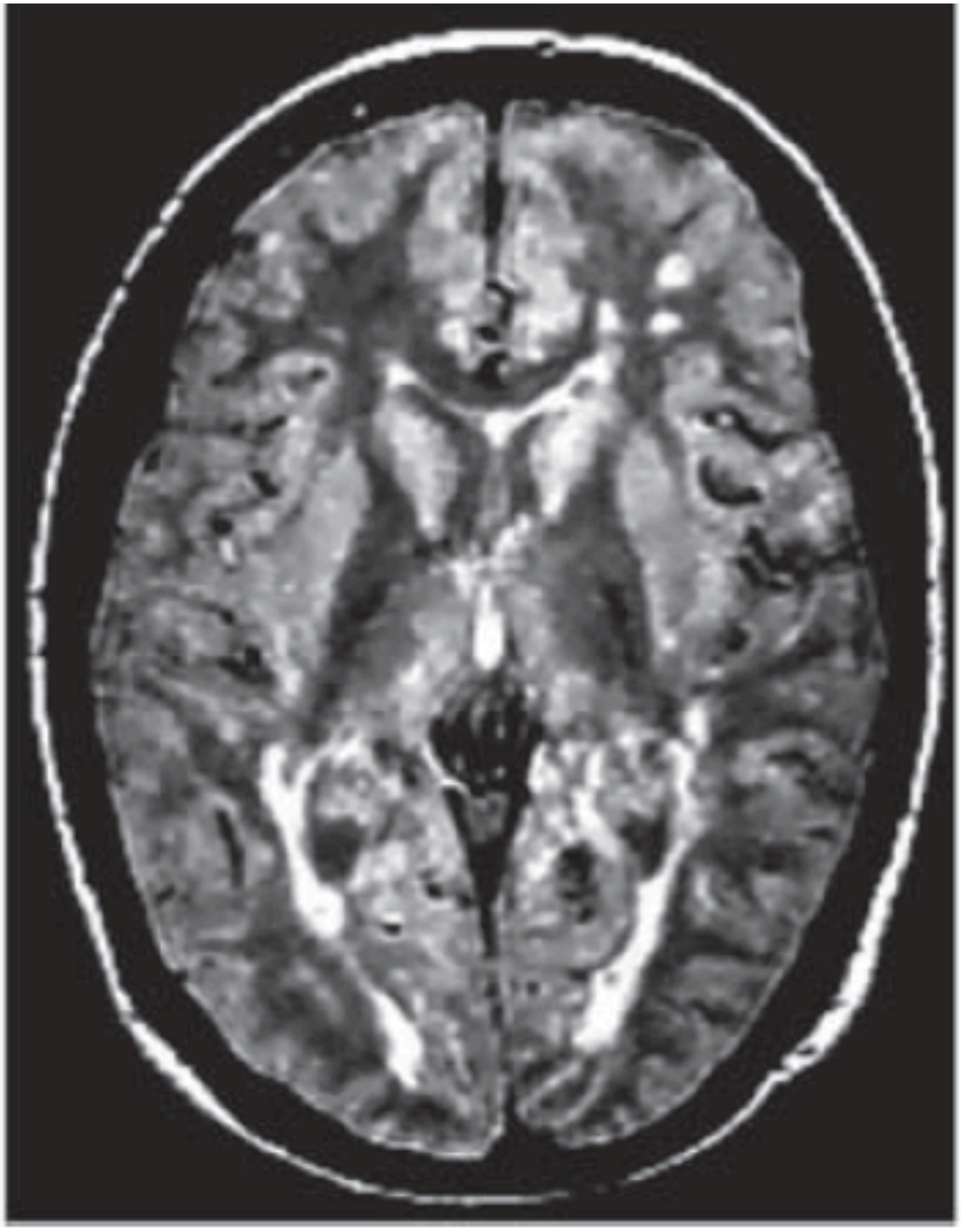




SNR (S/N) (of normal brain) and CNR (C/N) of multiple sclerosis plaques to normal brain on spin-density and T_1 magnetic resonance images.



Original



Noise Suppression

Summary

- CAVA: computer aided visualization and analysis
- CAD: computer aided diagnosis
- Coordinate Systems
- Pre-Processing Images
  - Gaussian Smoothing, Median Filtering, Unsharp Masking
  - Edge Enhancement
  - Evaluation for image quality metric (contrast and noise)

References and Slide Credits

- Jayaram K. Udupa, MIPG of University of Pennsylvania, PA.
- P. Suetens, Fundamentals of Medical Imaging, Cambridge Univ. Press.
- N. Bryan, Intro. to the science of medical imaging, Cambridge Univ. Press.
- CAP 5415 Computer Vision (Fall 2016) Lecture Presentations

- Next Lecture (Preprocessing of Medical Images II)
  - Diffusion based Smoothing in Medical Scans
  - Intensity inhomogeneity Correction in MRI
  - Intensity Standardization in MRI
  - Noise Removal in PET/SPECT Images