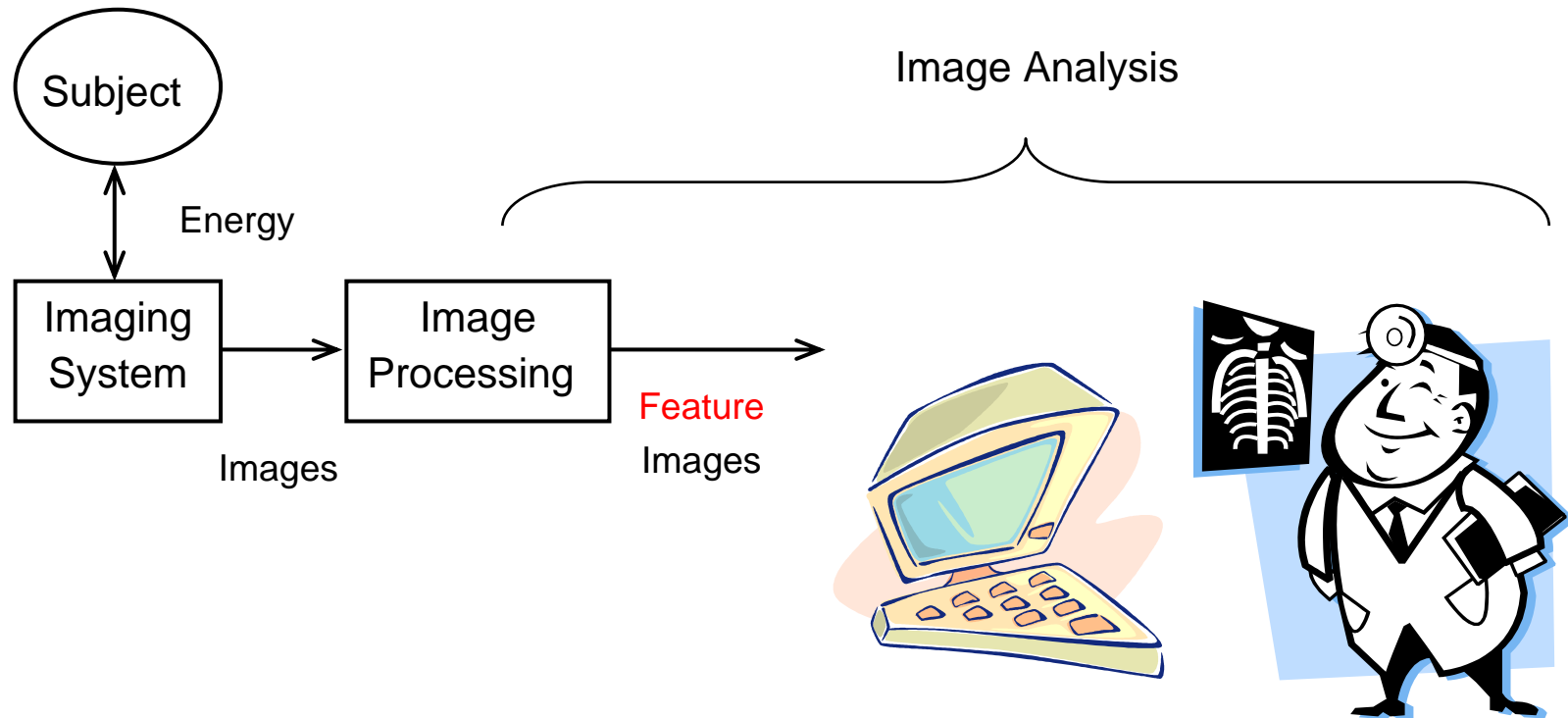


Introduction to Medical Image Processing

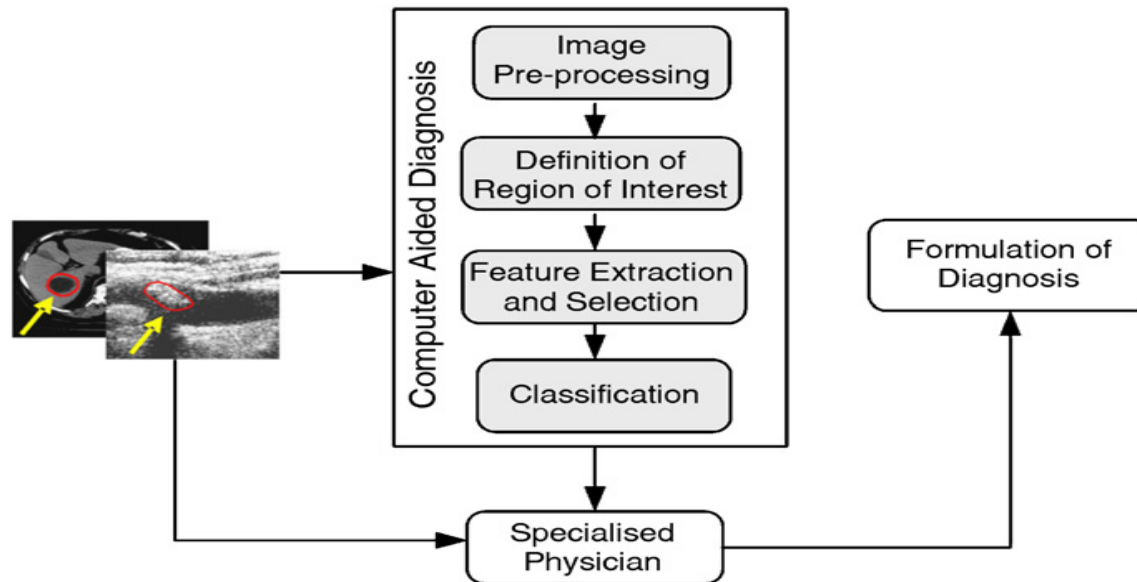
△ Essential environments of a medical imaging system



- Image processing may be a *post-imaging* or *pre-analysis* operator.
- Functions of Image processing and Image analysis may overlap each other.

Δ Goals of medical image analysis techniques:

- Quantification: Measuring the features on medical images, eg., helping radiologist obtain measurements from medical images (e.g., area or volume).
 - * To make the features measurable, it is necessary to extract objects from images by *segmentation*.
- Computer Aided Diagnosis (CAD): given measurements and features make a diagnosis. Help radiologists on their diagnosis procedure for accuracy and efficiency.



- Evaluation and validation techniques.

△ General image analysis (regardless of its application) encompasses:

- incorporation of prior knowledge
- classification of features
- matching of model to sub-images
- description of shape
- many other problems and approaches of AI...

△ About Digital Image Processing

- What is an Image?
 - Formal definition: A digital image is a multi-dimensional signal that is sampled in space and/or time and quantized in amplitude.
 - Looser definition: An image is a "picture."
The brightness values in the picture may represent distance, reflectivity, density, temperature, etc.
 - The image may be 2-D (planar), 3-D (volumetric), or N-D.

- Image elements: An image may be composed of:
 - 2-D: pixels = picture elements
 - 3-D: voxels = volume elements
 - 4-D and higher: hypervoxels = hypervolume elements

- What do images represent?

For medical images, pixels may represent parameters such as:

- X-ray attenuation (density)
- Water (proton) density
- Acoustic impedance (distribution)
- Optical reflectivity (or impedance)
- Electrical activity , etc. . . .

- How are images processed?

- Manual analysis: processed by human
- Semi-automatic analysis: human and computer work together to process image
- Automatic analysis: computer processes image, human reviews the results

- Purposes of image processing:
 - Preprocess image to reduce noise and blur (filtering)
 - Identify structures within the image (segmentation)
 - Extract “useful” information from the image (quantification)
 - Prepare the image for visualization (enhancement, reconstruction)
 - * Exact processing steps depend on the application.
- What we do to images:
 - Enhancement:
 - Noise reduction
 - Deblur
 - Improve contrast
 - Identify structures in image (segmentation):
 - Identify homogeneous regions in an image (label image pixels = segmentation)
 - Measure:

For example: Heart chamber volumes , Heart wall motion , Brain activity,
Fetus size/gender , Lesion size and extent , ...

- Visualize: For example: Surgical/Therapy planning , Image-guided surgery

Δ Processing verse Analysis

- Medical image processing

- Deals with the development of problem specific approaches to enhance the raw medical data for the purposes of *selective visualisation* as well as further analysis.

- Medical image analysis

- Concentrates on the development of techniques to supplement the usually *qualitative* and frequently *subjective* assessment of medical images by human experts.
- Provides *quantitative, objective* and *reproducible* information extracted from the medical images

Δ So many subjects:

57 chapters in *Handbook of Medical Image Processing and Analysis* ,
by Isaac Bankman (Ed.), Academic Press, 2009.

I Enhancement; Fundamental Enhancement Techniques; Adaptive Image Filtering; Enhancement by Multiscale Nonlinear Operators; Medical Image Enhancement with Hybrid Filters; **II Segmentation**; Overview and Fundamentals of Medical Image Segmentation; Image Segmentation by Fuzzy Clustering: Methods and Issues; Segmentation with Neural Networks; Deformable Models; Shape Information in Deformable Models; Gradient Vector Flow Deformable Models; Fully Automated Hybrid Segmentation of the Brain; Unsupervised Tissue Classification; Partial Volume Segmentation with Voxel Histograms; Higher Order Statistics for Tissue Segmentation; **III Quantification**; Two-dimensional Shape and Texture Quantification; Texture Analysis in Three Dimensions for Tissue Characterization; Computational Neuroanatomy Using Shape Transformations; Tumor Growth Modeling in Oncological Image Analysis; Arterial Tree Morphometry; Image-Based Computational Biomechanics of the Musculoskeletal System; Three-Dimensional Bone Angle Quantification; Database Selection and Feature Extraction for Neural Networks; Quantitative Image Analysis for Estimation of Breast Cancer Risk; Classification of Breast Lesions in Mammograms; Quantitative Analysis of Cardiac Function; Image Processing and Analysis in Tagged Cardiac MRI; Analysis of Cell Nuclear Features in Fluorescence Microscopy Images; Image Interpolation and Resampling; **IV Registration**; Physical Basis of Spatial Distortions in Magnetic Resonance Images; Physical and Biological Bases of Spatial Distortions in PET Images; Biological Underpinnings of Anatomic Consistency and Variability in the Human Brain; Spatial Transformation Models; Validation of Registration Accuracy; Landmark-based Registration Using Features Identified through Differential Geometry; Image Registration Using Chamfer Matching; Within-Modality Registration Using Intensity-Based Cost Functions; Across-Modality Registration Using Intensity-Based Cost Functions; Talairach Space as a Tool for Intersubject Standardization in the Brain; Warping Strategies for Intersubject Registration; Optimizing the Resampling of Registered Images; Clinical Applications of Image Registration; Registration for Image-Guided Surgery; Image Registration and the Construction of Multidimensional Brain Atlases; **V Visualization**; Visualization Pathways in Biomedicine; Three-Dimensional Visualization in Medicine and Biology; Volume Visualization in Medicine; Fast Isosurface Extraction Methods for Large Image Data Sets; Computer Processing Methods for Virtual Endoscopy; **VI Compression, Storage, and Communication**; Fundamentals and Standards of Compression and Communication; Medical Image Archive and Retrieval; Image Standardization in PACS; Imaging and Communication in Medical and Public Health Informatics; Dynamic Mammogram Retrieval from Web-Based Image Libraries; Quality Evaluation for Compressed Medical Images: Fundamentals; Quality Evaluation for Compressed Medical Images: Diagnostic Accuracy; Quality Evaluation for Compressed Medical Images: Statistical Issues; Three-Dimensional Image Compression with Wavelet Transforms.

△ Why Image Enhancement?

- Can't distinguish between tissues

The nature of the physiological system under investigation and the procedures used in imaging may diminish the contrast and the visibility of details.

- Data is too noisy for computer algorithm to perform well

Medical images are often deteriorated by noise due to various sources of interference and other phenomena that affect the measurement processes in imaging and data acquisition systems.

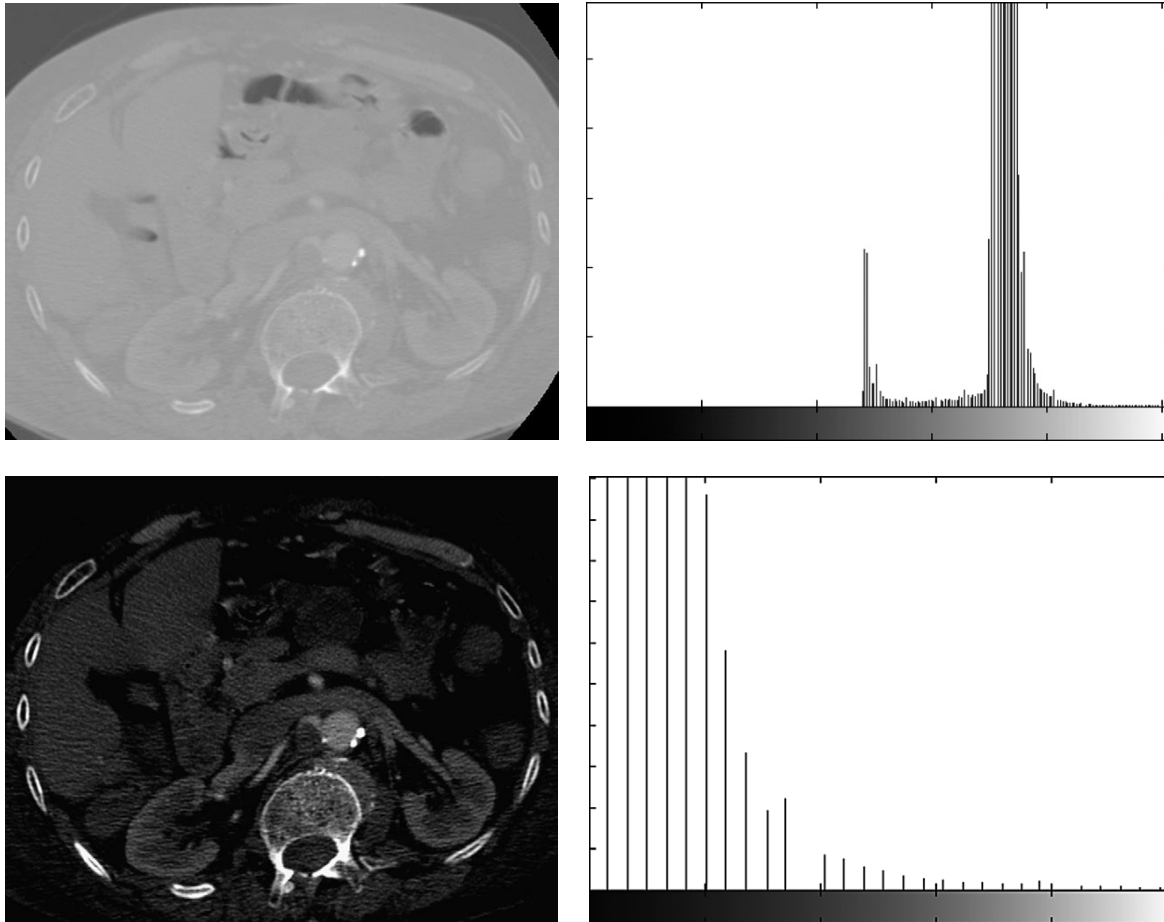
- Imaging artifacts interfere with visualization or computer processing

△ How to Enhance Image? By operations to

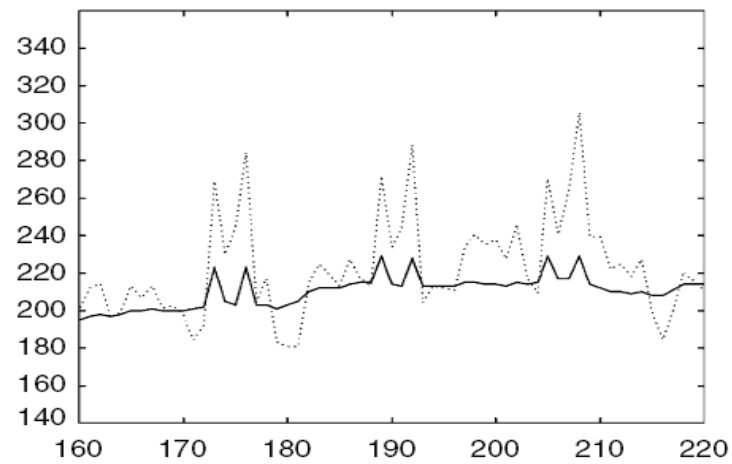
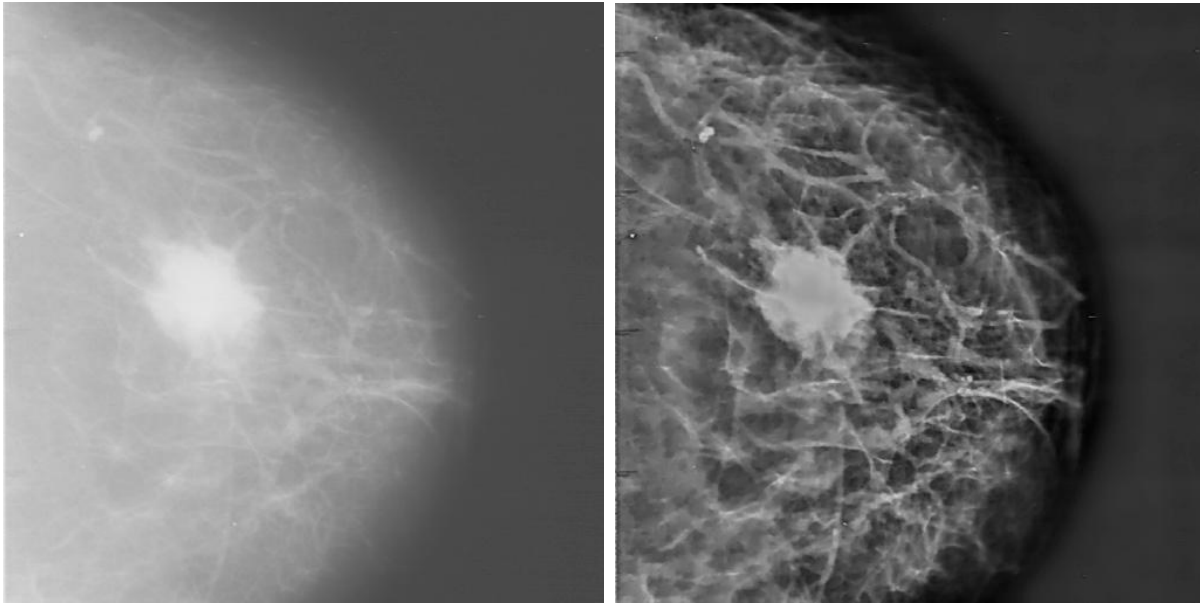
- Increase contrast
- Remove noise
- Emphasize edges: Edge boost, Unsharp masking.
- Modify shapes

- * Image enhancement techniques range from *linear* to *nonlinear*, from *fixed* to *adaptive*, and from *pixel-based* to *multiscale* methods, ...

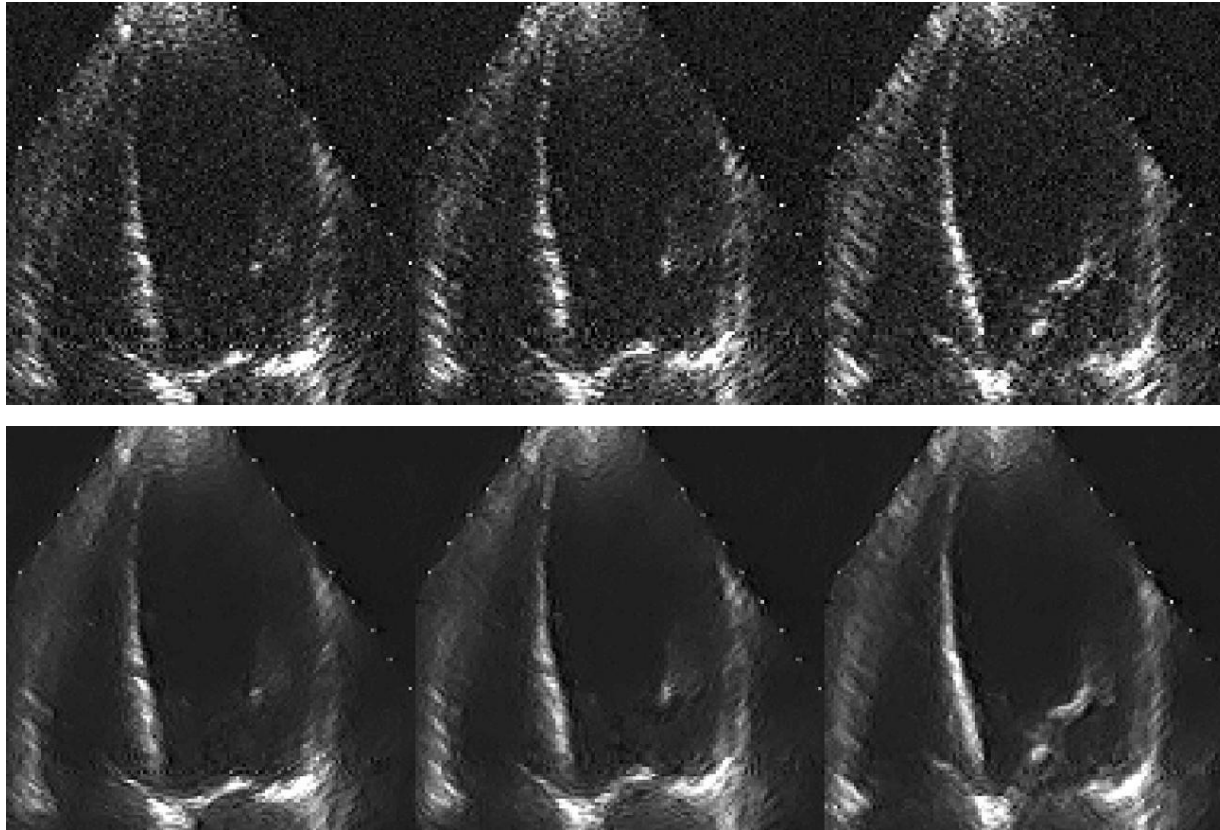
Δ Contrast Enhancement by Histogram Equalization



Δ Enhancement by adaptive wavelet shrinkage denoising
(only subimages with diagnostic information are reconstructed).



△ Enhancement by adaptive filtering: noise or speckle reduction.



- Adaptive image filtering needs some *a priori* information about the image.
(This is an image modeling problem)
- Geometric or statistical information are the primary information used.

Δ Medical Image Segmentation

- Segmentation, separation of structures of interest from the background and from each other, is an essential analysis function for which numerous algorithms have been developed in the field of image processing.
- The principal goal of the segmentation process is to partition an image into regions that are homogeneous with respect to one or more characteristics or features.
- Segmentation is an important tool in medical image processing, and it has been useful in many applications.

The applications include detection of the coronary border in angiograms, multiple sclerosis lesion quantification, surgery simulations, surgical planning, measurement of tumor volume and its response to therapy, functional mapping, automated classification of blood cells, study of brain development, detection of microcalcifications on mammograms, image registration, atlas-matching, heart image extraction from cardiac cineangiograms, detection of tumors, etc.

- In medical imaging, segmentation is important for feature extraction, image measurements, and image display.

In some applications it may be useful to classify image pixels into anatomical regions, such as bones, muscles, and blood vessels, while in others into pathological regions, such as cancer, tissue deformities, and multiple sclerosis lesions.

=> Segmentation can be thought as the preprocessor for further analysis.

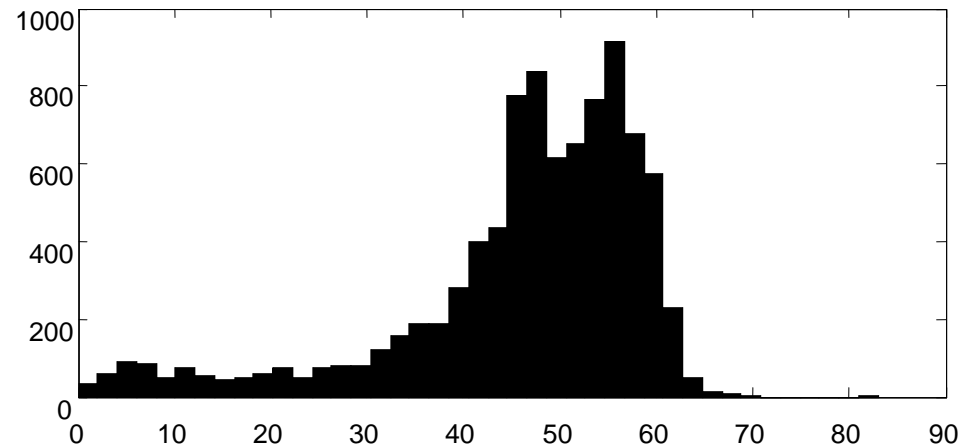
- A wide variety of segmentation techniques have been proposed.

However, there is no standard segmentation technique that can produce satisfactory results for all imaging applications.

- Segmentation techniques can be divided into classes in different ways.
e.g., based on the classification scheme:
 - *Manual, semiautomatic, and automatic*
 - *Pixel*-based (local methods) and *region*-based (global methods).
 - *Low-level* segmentation (thresholding, region growing, etc.), and *Model-based* segmentation (multispectral or feature map techniques, Markov random field, deformable models, etc.).
 - * Model-based techniques are suitable for segmentation of images that have artifacts, noise, and weak boundaries between structures.
 - * Deformable models: Snake model and Level Sets
 - *Classical* (thresholding, edge-based, and region-based techniques), *Statistical, Fuzzy, and Neural network* techniques.

△ Histogram analysis

- Histogram analysis is usually required before doing segmentation, it is a pixel-based technique.
- An example



The information from histogram

Number of modes

Mode to mode contrast

Spread of each mode
(seperability)



$x < 30$



$30 < x < 50$



$x > 50$

$x < 30$ contains mostly the bone

$30 < x < 50$ contains mostly the fluid region

$x > 50$ contains mostly the tissue region,

All of them are *noisy* and *partially correct*

=> Simple thresholding can not provide satisfactory segmentation

△ The general question is:

- How are the pixels grouped?
=> *Contour detection and linking* or *Region growing* approaches
- What is criterion of the homogeneity (or connectivity) for growing?
* Pixel connectivity can be deterministic or probabilistic.

△ Edge detection

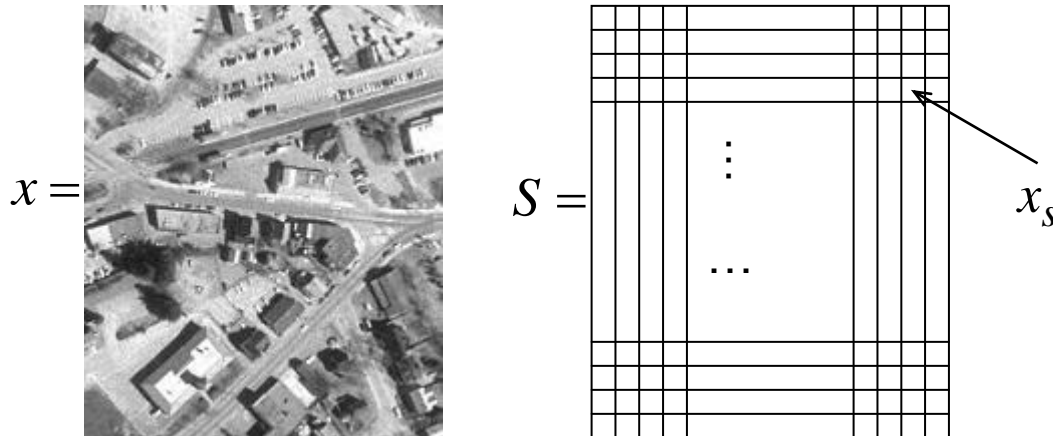
- Edges detected using Sobel's and Canny's detectors



- As the result of pixel-thresholding, detected edges are noisy and erroneous.
- Pre-processing for noise suppression or contour modeling are required.

△ Image Modeling by Random Process (Field)

- Images are in general treated as pieces of information, which are essentially random processes. Random process theory provides rich ways to handle the information carried in images
- When images are represented as random process, an image $x(i, j)$ is treated as a realization of the random process $X(i, j)$. Thus, an $(N \times N)$ image is considered as the outcomes of N^2 random number generators.
- The 2D index (i, j) is referred as site $s = (i, j)$, and collection of all sites $S = \{ s \}$ is named as a site system or lattice system in the “field of statistical mechanical system”.



Δ Definition of Neighborhood System

- Definitions

s - site or lattice point, $s \in S$

S - set of lattice points

X_s - the value of X at s

∂s - the neighboring points of s

- A neighborhood system ∂s must be symmetric

$$r \in \partial s \Rightarrow s \in \partial r \text{ also } s \notin \partial s$$

- Example of 8 point neighborhood

$X_{(0,0)}$	$X_{(0,1)}$	$X_{(0,2)}$	$X_{(0,3)}$	$X_{(0,4)}$
$X_{(1,0)}$	$X_{(1,1)}$	$X_{(1,2)}$	$X_{(1,3)}$	$X_{(1,4)}$
$X_{(2,0)}$	$X_{(2,1)}$	$X_{(2,2)}$	$X_{(2,3)}$	$X_{(2,4)}$
$X_{(3,0)}$	$X_{(3,1)}$	$X_{(3,2)}$	$X_{(3,3)}$	$X_{(3,4)}$
$X_{(4,0)}$	$X_{(4,1)}$	$X_{(4,2)}$	$X_{(4,3)}$	$X_{(4,4)}$



Neighbors of $X_{(2,2)}$

$$s = (2, 2)$$

$$\partial s = \{(1,1), (1,2), (1,3), (2,1), (2,3), (3,1), (3,2), (3,3)\}$$

Δ A simple Markov Random Field (MRF) model

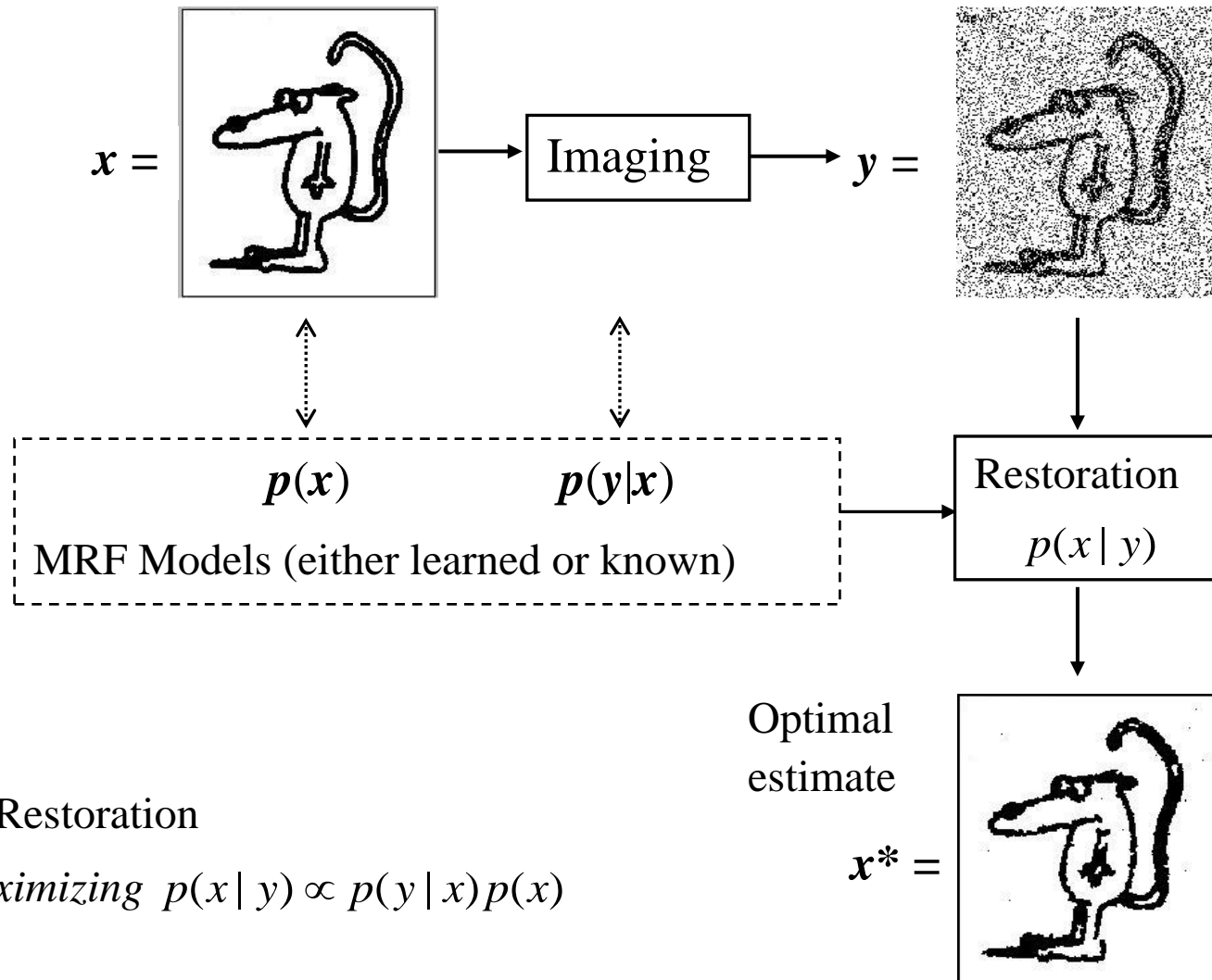
- Definition of MRF: A random field X on the lattice S with neighborhood system ∂s is said to be a *Markov random field*, if for all $s \in S$, $p(x_s | x_{i \neq s}) = p(x_s | x_{\partial s})$
- A very simple MRF model: the Ising model, it is described by the conditional probability model

$$p(x_s | x_{\partial s}) = \frac{\exp\left\{\sum_{s' \in \partial s} \beta x_s x_{s'}\right\}}{1 + \exp\left\{\sum_{s' \in \partial s} \beta x_{s'}\right\}}, \quad \text{with } X_s = \{0, 1\}$$

- For *small* β , the model represents *fine* texture images
For *large* β , the model represents *coarse* texture images



Δ Bayesian image restoration (or segmentation)



MAP Restoration

$$= \text{Maximizing } p(x|y) \propto p(y|x)p(x)$$

From Bayes theorem:

$$Posterior = \frac{Likelihood \bullet Prior}{Normalization Factor}$$

$$P(True Image \mid Observation) = \frac{P(Observation \mid True Image) \bullet P(True Image)}{P(Observation)}$$

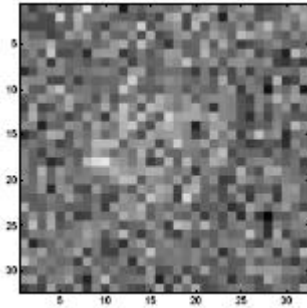
Prior: $P(True Image)$ = Probabilistic Model of *image*

Likelihood: $P(Observation \mid True Image)$ = Probabilistic Model of *Imaging Process*

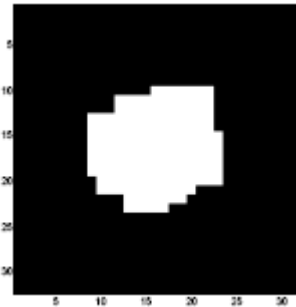
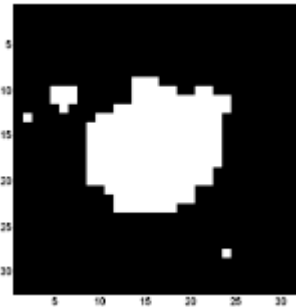
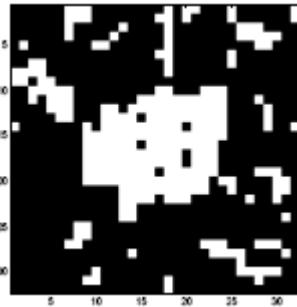
Both the prior and the likelihood allow the introduction of expert knowledge:

- The prior can express assumptions about what the “true scene” should be, e.g., piecewise smooth, which is essentially a Markovian assumption.
- The likelihood can incorporate knowledge about the degradation and distortions introduced in the imaging process. It gives the probability about what the observations should be *based on the “true scene”*, when degraded by additive or multiplicative noise, blurring, etc.

Δ Application-texture segmentation

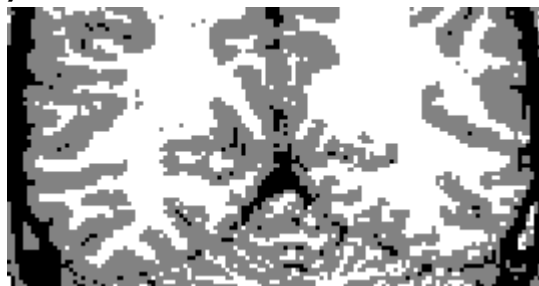


This image can be segmented to be any one of the followings
by using different value of β

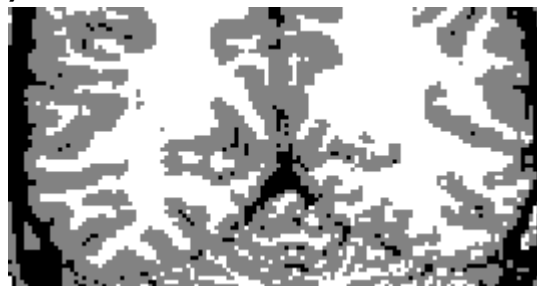


This image can be segmented as the followings
by using different value of β

$\beta = 0.1$



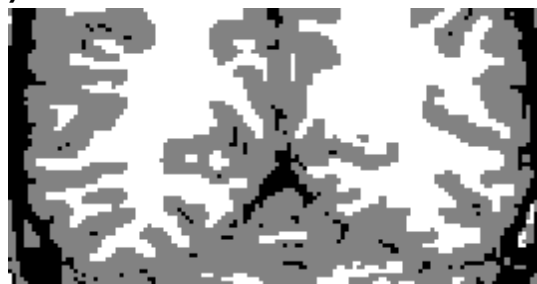
$\beta = 0.2$



$\beta = 0.5$



$\beta = 1.0$



$\beta = 2.0$



$\beta = 4.0$



* A three level MRF model is used.