Imaging Techniques in Biomedical Engineering

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CONTENTS

- Image Enhancement
- Image Segmentation
- Image classification

Image Enhancement

- The operation of processing an image so that the result is more suitable than the original image for a *specific* application.

- An digitally enhanced image can offer:
  1. Better contrast
  2. sharpness of detail and
  3. visibility of features

- Results can vary with each approach and image, so it can be beneficial to obtain several enhanced images with a variety of approaches.

Enhancement / Digital Subtraction Angiography

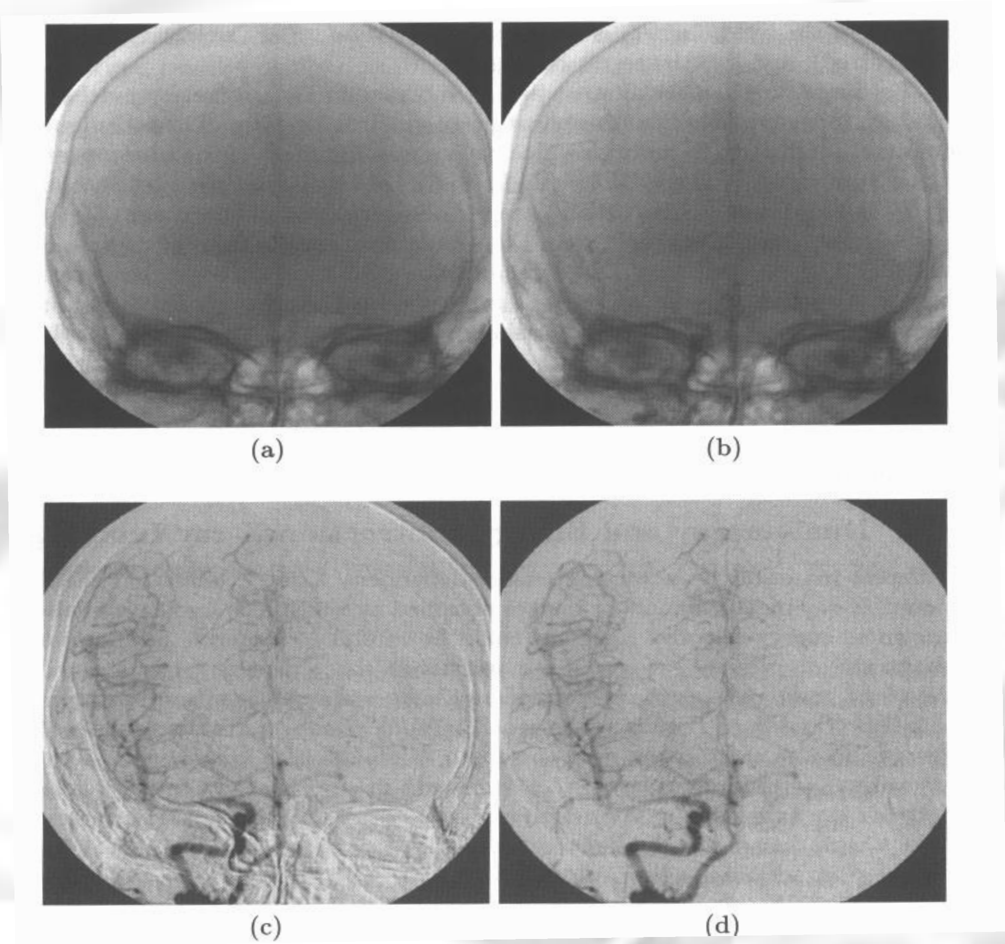
- Process:
- A dye is injected to increase the density of the blood.
- After a while a number of X-ray images is taken.
- Images that were taken before the injection of the dye are used as the mask or reference image.
- The mask is subtracted from the images that were taken with the dye to produce enhanced images.
- The mathematical procedure involved may be expressed simply as:

$$f = \alpha \cdot f_1 - \beta \cdot f_2$$

✓ Useful to detect sclerosis though it is sensitive to motion

❑ Enhancement / Digital Subtraction Angiography

- Images are obtained before (a,b) and after (c) the injection of the dye. The subtraction provides the enhanced image (d).



❑ Enhancement / Gray-scale Transforms

- Presence of different levels of density or intensity in the image, to improve the visibility of details.

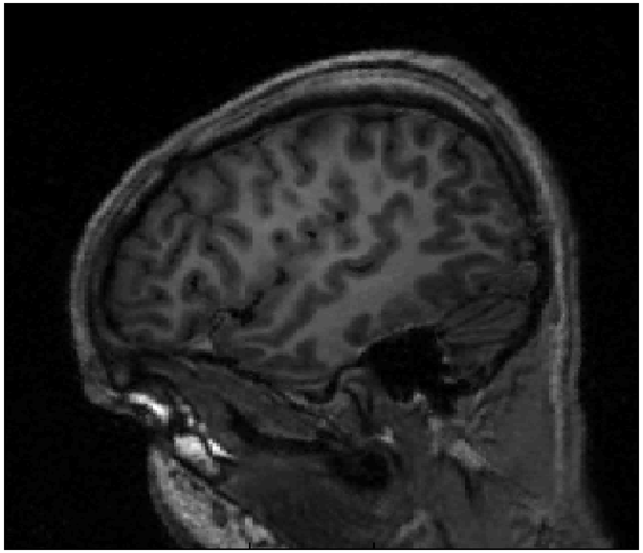
1. Gray-scale thresholding:

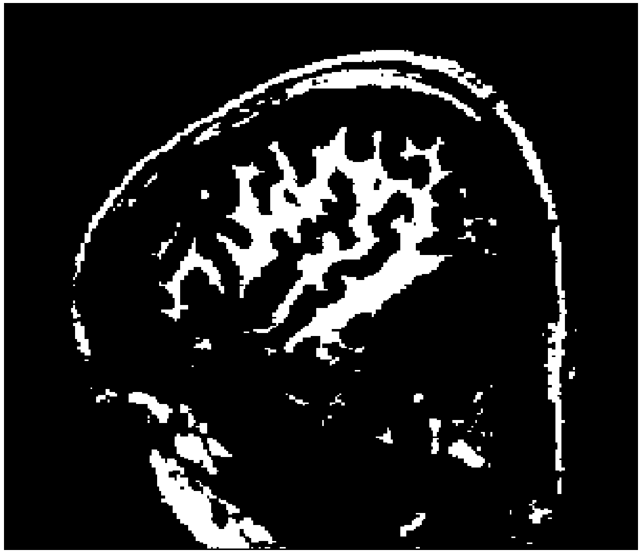
– Gray level object > *L* => new bi-level image.

Problem: Narrow range of gray levels.

Solution: Stretch the range of interest to the full range.

Original image **L = 30** **New Image**





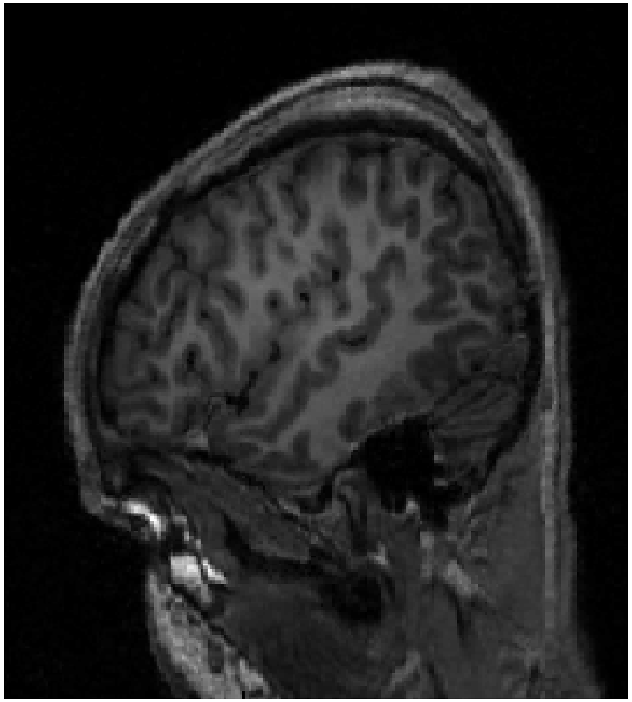
❑ Enhancement / Gray-scale Transforms

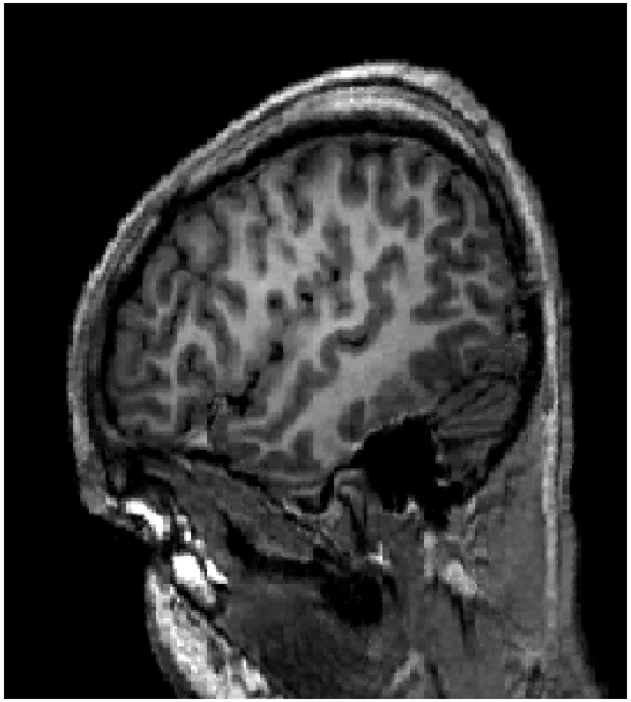
2. Gray-scale windowing:

- Linear transformation

$$g(m,n)=\begin{cases}0 \rightarrow f(m,n)\leq f_1\\ \dfrac{f(m,n)-f_1}{f_2-f_1} \rightarrow f_1 < f(m,n) < f_2\\ 1 \rightarrow f(m,n)\geq f_2\end{cases}$$

Original image **f1 = 5** **f2 = 60** **New image**





❑ Enhancement / Gray-scale Transforms

3. Gamma correction:

- Non-linear transformations

$$g(m,n) = [f(m,n)]^{\gamma}$$

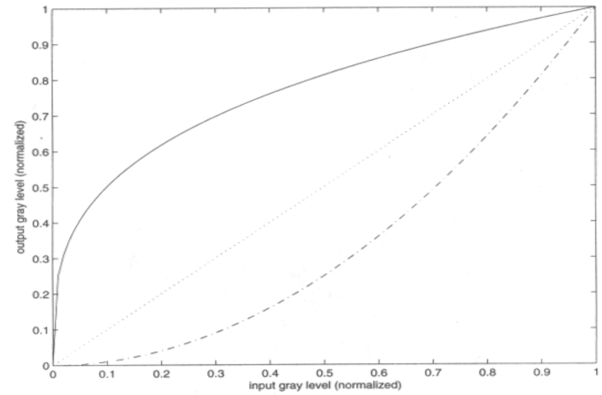
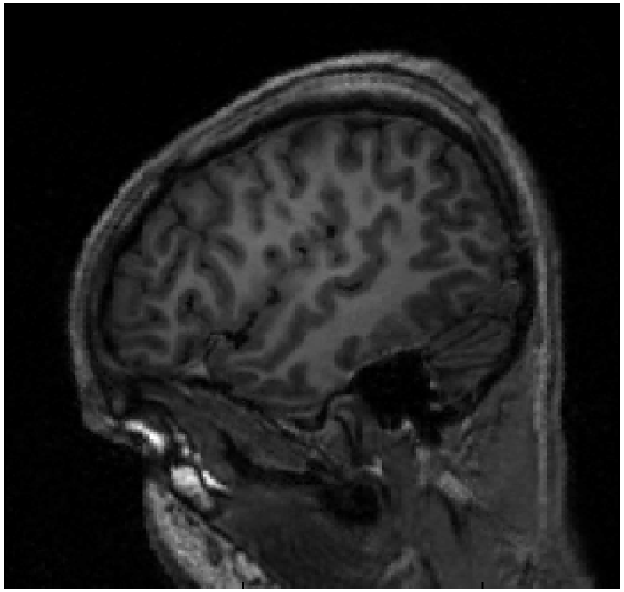
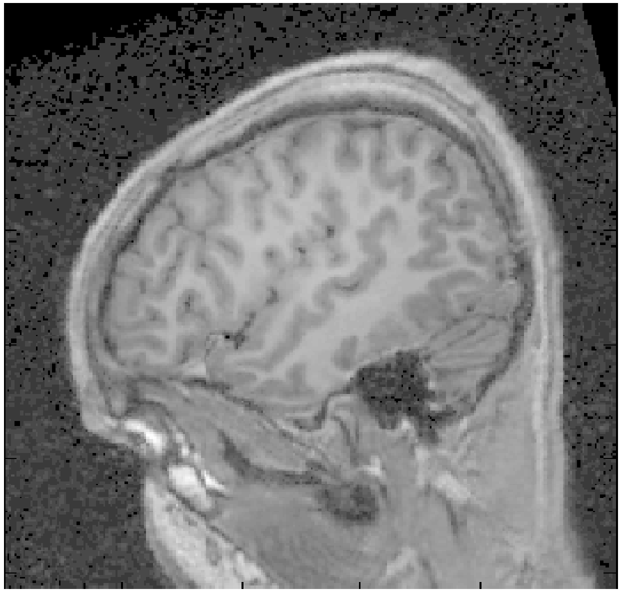


FIGURE 4.10
Gamma-correction transforms with $\gamma = 0.3$ (solid line), $\gamma = 1.0$ (dotted line), and $\gamma = 2.0$ (dash-dot line).

Original image **γ = 0.3** **New image**





Enhancement / Histogram Equalization

- Basic idea: find a map such that the histogram of the modified (equalized) image is uniform.

- Histogram

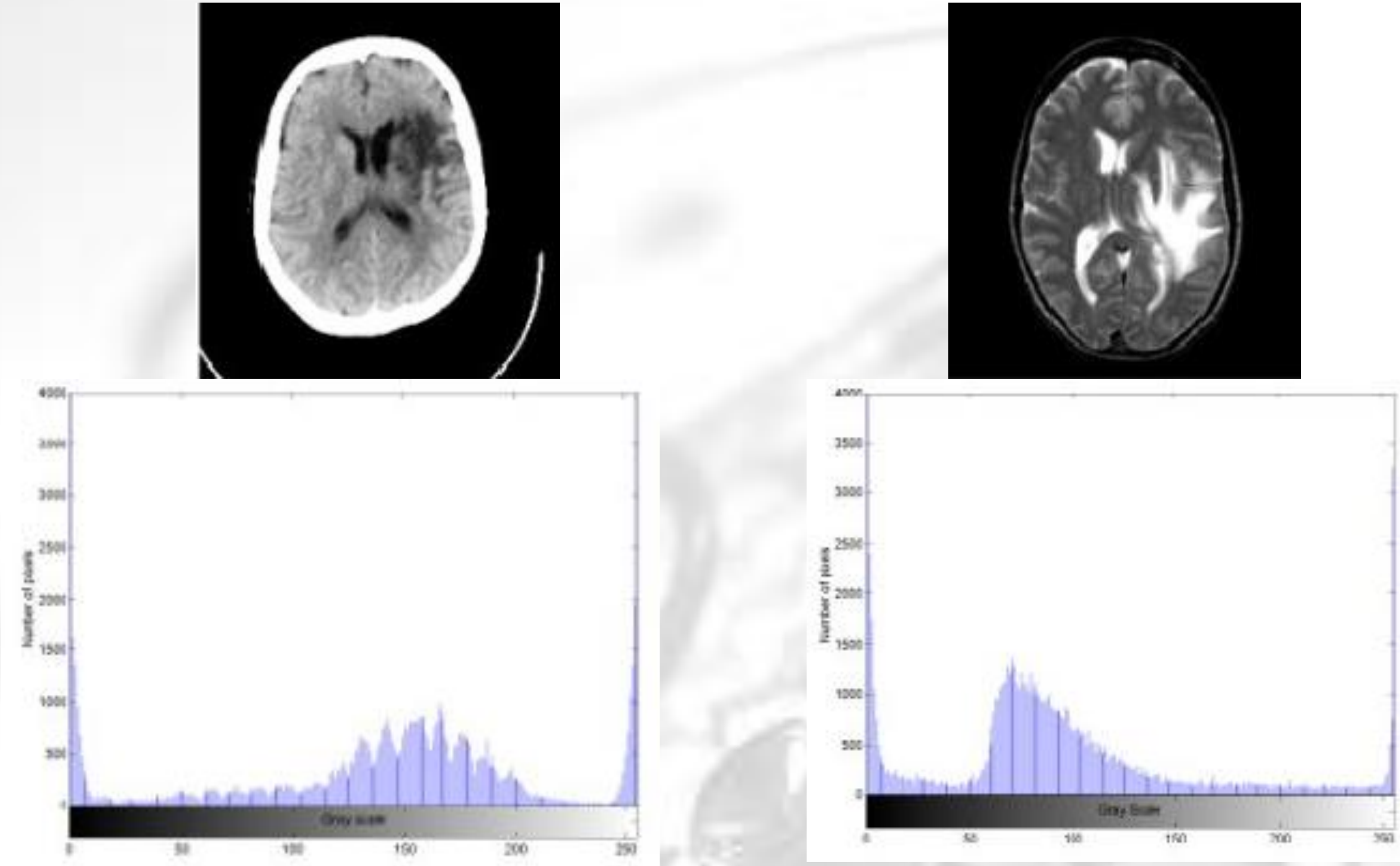
$$h(r_i) = n_i \qquad\qquad p(r_i) = \frac{n_i}{n}$$

$$i = 0,1,\ldots,L-1$$

- Histogram equalization

$$s_i = T(r_i) = \sum_{j=0}^{i} p_r(r_j) = \sum_{j=0}^{i} \frac{n_i}{n} \qquad i = 0,1,\ldots,L-1$$

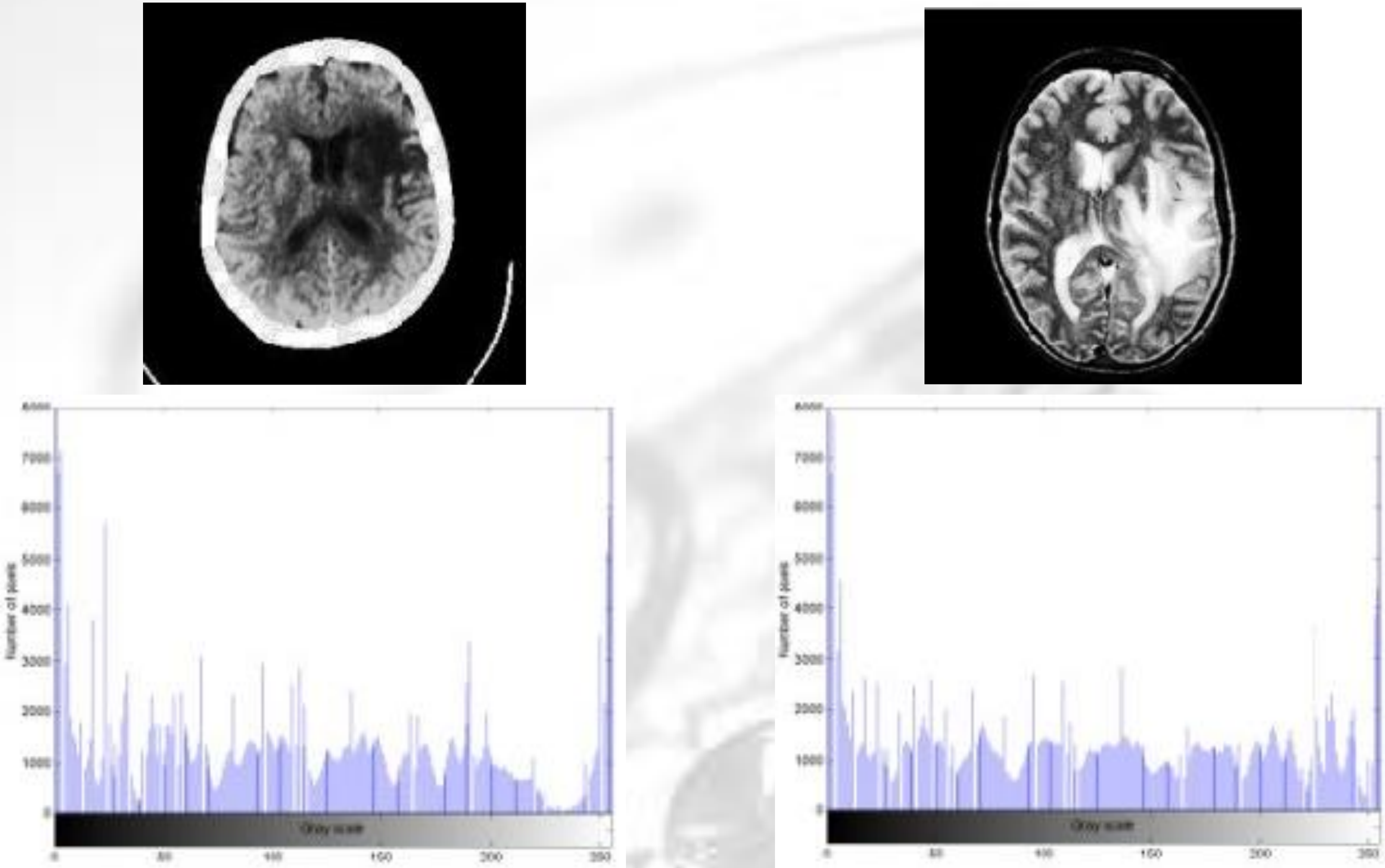
❑ Enhancement / Histogram Equalization



An X-ray CT image (top left) and T-2 weighted proton density image (top right) of human brain cross-sections with their respective histograms at the bottom. The MR image shows a brain lesion.

Medical Image Analysis, by Atam P. Dhawan, IEEE Press, 2003.

❑ Enhancement / Histogram Equalization



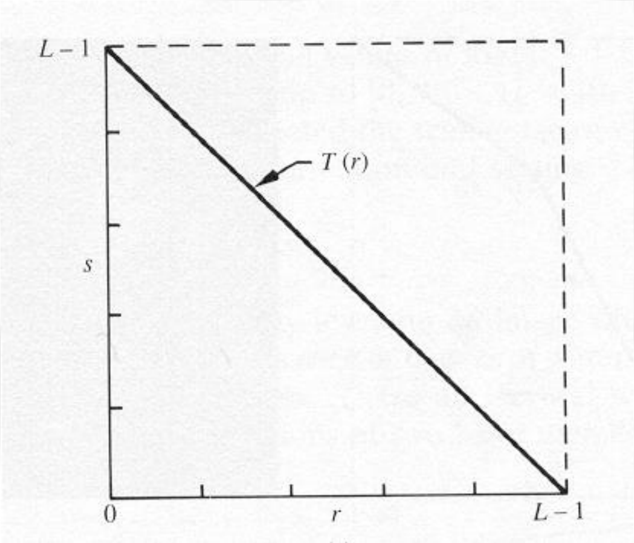
Histogram equalized images of the brain MR images shown previously and their histograms (bottom).

MEDICAL TECHNOLOGY & INTELLIGENT INFORMATION SYSTEMS

Medical Image Analysis, by Atam P. Dhawan, IEEE Press, 2003.

❑ Enhancement / Negative image

- Image negatives are obtained by mirror changing the RGB values of each image's pixel. A transformation function S = T(r) is shown in the figure:



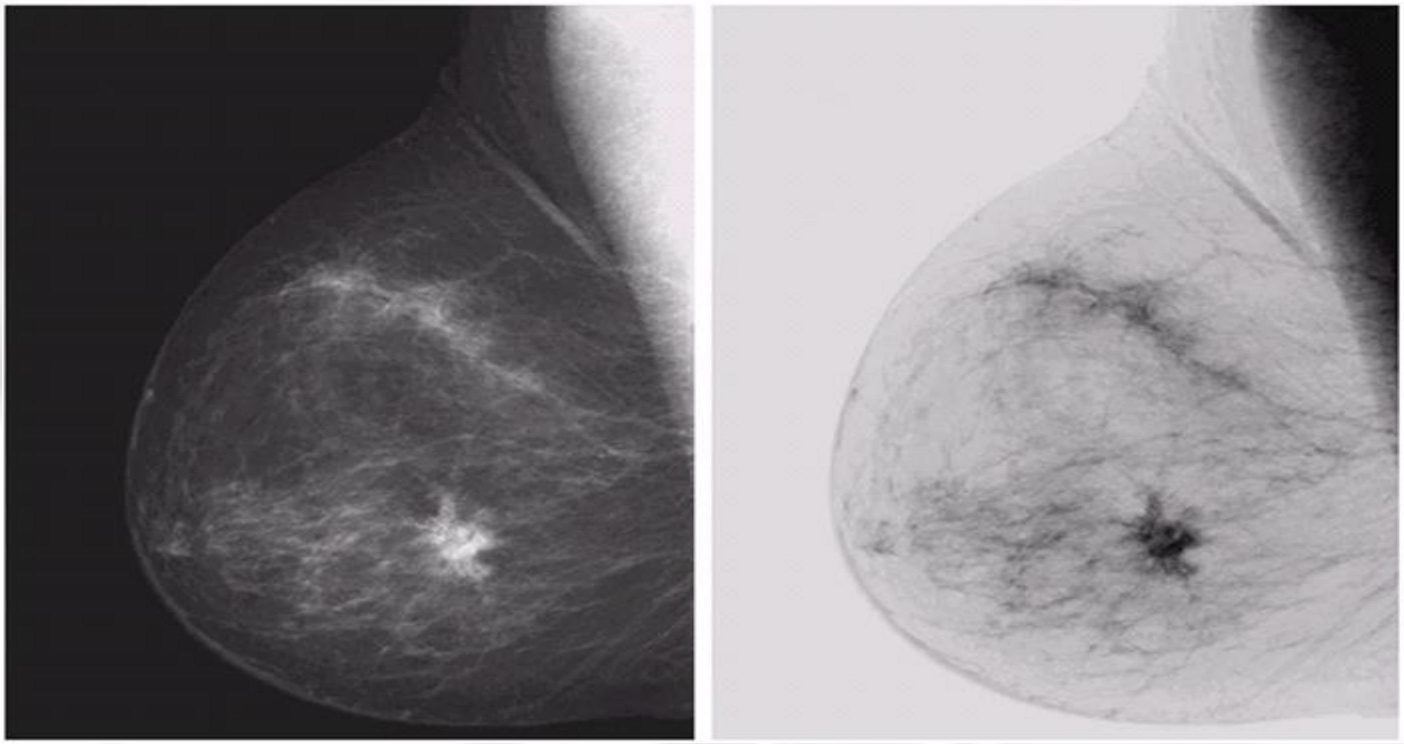
[0,L-1] the range of gray levels *S*= *L*-1-*r.*

- ✓ Function reverses the order from black to white so that the intensity of the output image decreases as the intensity of the input increases

http://www.becbapatla.ac.in/Fit/Fhtdocs/Subjects/326B/Lecture5.ppt

❑ Enhancement / Negative image

➢ The negative image of a mammogram:



http://www.becbapatla.ac.in/Fit/Fhtdocs/Subjects/326B/Lecture5.ppt

Enhancement / Homographic Filtering

- A schematic block diagram of homomorphic filtering:

$$f(x,y) \longrightarrow \boxed{\ln} \longrightarrow \boxed{\mathrm{FT}} \longrightarrow \boxed{H(u,v)} \longrightarrow \boxed{\mathrm{IFT}} \longrightarrow \boxed{\exp} \longrightarrow \hat{f}(x,y)$$

<u>Basic idea:</u>

$$f(x,y) = i(x,y)r(x,y)$$

Illumination (low freq.) — reflectance (high freq.)

$$\ln f(x,y) = \ln i(x,y) + \ln r(x,y)$$

$\boxed{\text{freq. domain enhancement}} \Rightarrow \boxed{\text{Inverse transformations}}$

Enhancement / Homographic Filtering

- An example:

- i(x,y) and r(x,y) components represent low- and high-frequency components, respectively.
- The circularly symmetric homomorphic filter function is:

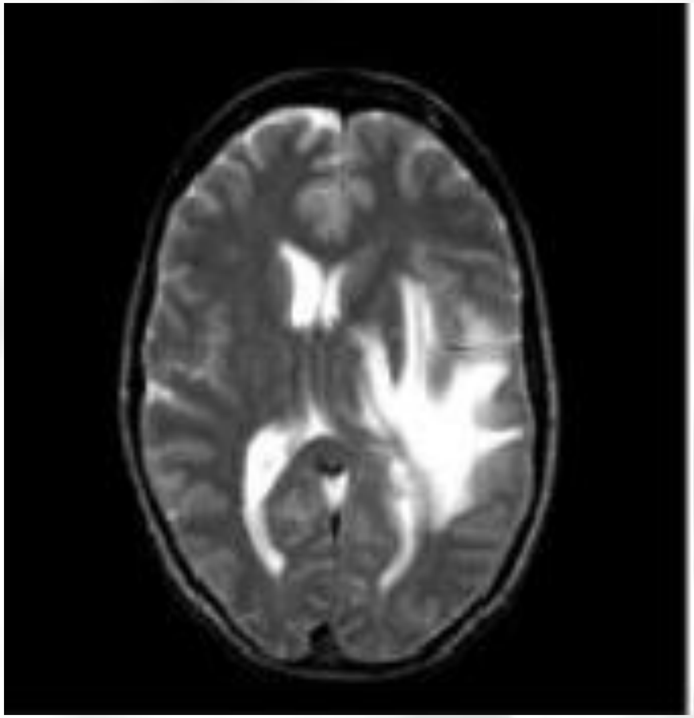
$$H(u,v) = (\gamma_H - \gamma_L)\left[1 - e^{c(D^2(u,v)/D^2)}\right] + \gamma_L$$

Shown in the figure:

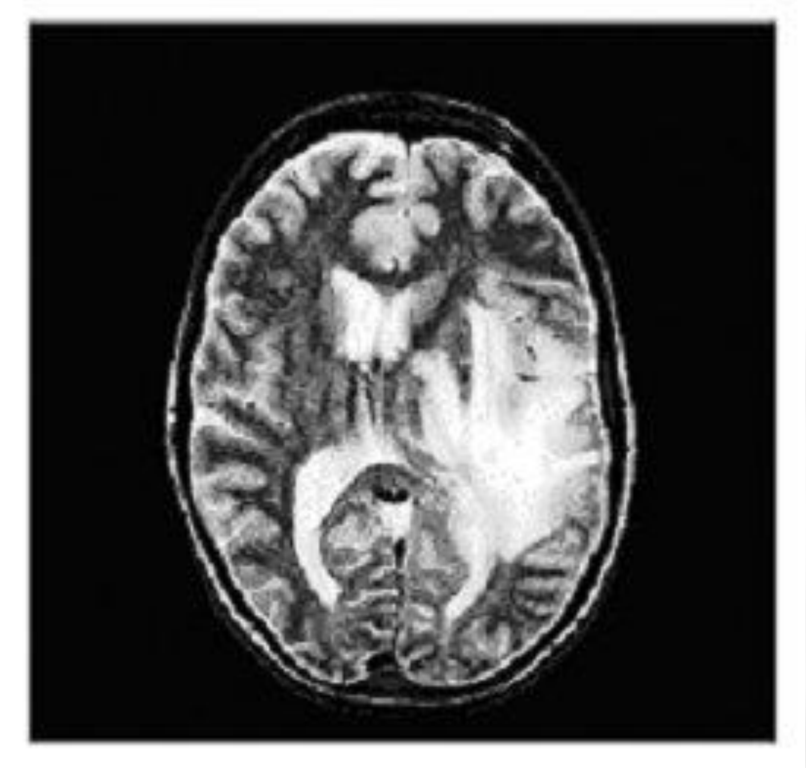
❑ Enhancement / Homographic Filtering

➢ An example:

The enhanced MR image obtained by Homomorphic filtering using the previous circularly symmetric function H(u,v).



Original



Enhanced

Image Segmentation

- Segmentation in the domain of medical imaging has some characteristics that make it easier and difficult at the same time.

- The imaging is narrowly focused on an anatomic region and its context well-defined, since the imaging modality, conditions and the organ identity is known. The pose variations are limited and there is prior knowledge of the Region of Interest.

- However, the medical images are very challenging due to their poor quality making the anatomical region segmentation from the background very difficult.

- The intensity variations alone are not sufficient to distinguish the foreground from the background, and additional cues are required to isolate ROIs.

❑ Image segmentation

➢ The segmentation task can be seen as a combination of two main processes:

1. *Modeling*: the generation of a representation over a selected feature space. This can be termed the modeling stage. The model components are often viewed as groups, or clusters in the high-dimensional space.

2. *Assignment*: the assignment of pixels to one of the model components or segments. In order to be directly relevant for a segmentation task, the clusters in the model should represent homogeneous regions of the image.

✓ In general, the better the image modeling, the better the segmentation produced.

❑ Image segmentation / Gaussian Mixture Models

- The feature space is generated from image pixels by a mixture of Gaussians. Each Gaussian can be assigned a semantic meaning, such as a tissue region.
- If such Gaussians could be automatically extra-cted, we can segment and track important image regions.
- Using a Maximum Likelihood (ML) formalism, we assume that the pixel intensities are independent samples from a mixture of probability distributions, called a finite mixture model, given by the probability density function

$$f(v_t|\Theta,\alpha) = \sum_{i=1}^{n} \alpha_i f_i(v_t|\theta_i)$$

where *υt* is the intensity of pixel *t*; *fi* is a component probability density function parameterized by *ϑi*, where *Θ* = [*ϑ*1 . . . *ϑn*] and the variables *αi* are mixing coefficients that weigh the contribution of each density function.

❑ Image segmentation / Gaussian Mixture Models

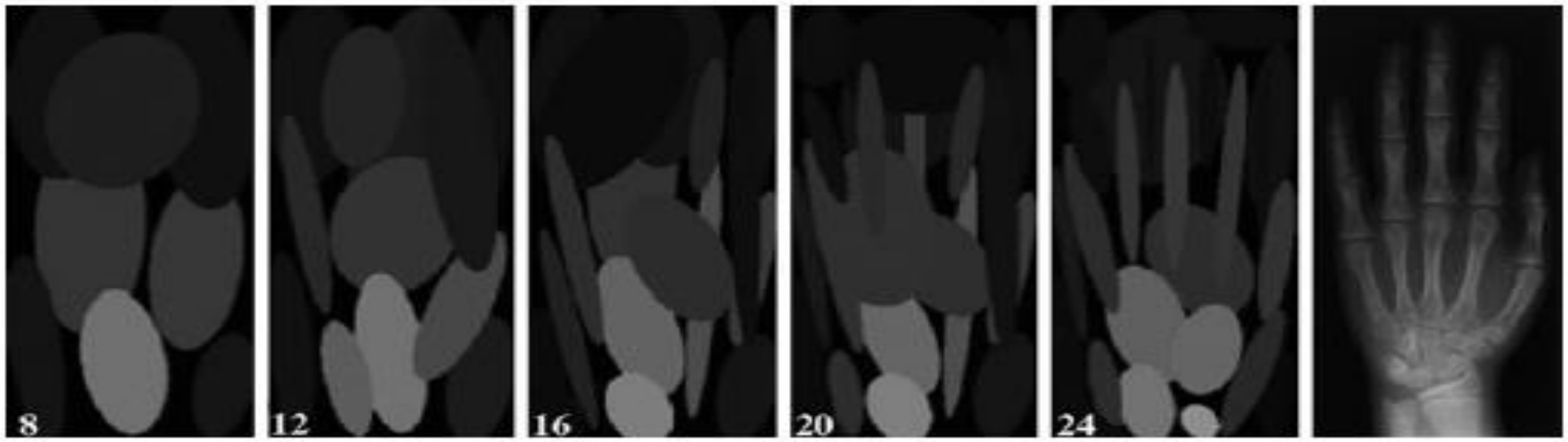
- In the representation phase, a transition is made from voxels to clusters (Gaussians) in feature space.
- The segmentation process forms a linkage back from the feature space to the raw input domain.
- A segmentation map can be generated by assigning each pixel to the most probable Gaussian cluster, i.e., to the component *i* of the model that maximizes the a posteriori probability:

$$\mathrm{Label}\{v_t\} = \arg\max_i \{\alpha_i f(v_t|\mu_i, \Sigma_i)\}$$

✓ To produce this visualization, the GMM models, formed from a 3D feature space of intensity and pixel coordinates (*I, x, y*), were projected onto the image plane (*x, y*).

❑ Image segmentation / Gaussian Mixture Models

- The GMM modeling of the feature space using an x-ray image is shown in the figure.



- ✓ The visual effect of varying the number *n* of Gaussians in the GMM is shown.
- ✓ A small *n* provides a very crude description. As we increase the number of Gaussians, finer detail can be seen in the blob representation.
- ✓ Larger *n* provides a more localized description, including finer detail such as the fingers.

❑ Image segmentation / Gaussian Mixture Models

- Delineation of gray matter, white matter, Cerebrospinal Fluid (CSF), lesions, diseased parts of white matter, in different anatomic and functional regions of the brain via multi-protocol MRI for studying the multiple sclerosis disease and in elderly subjects to study aging-related depression and dementia

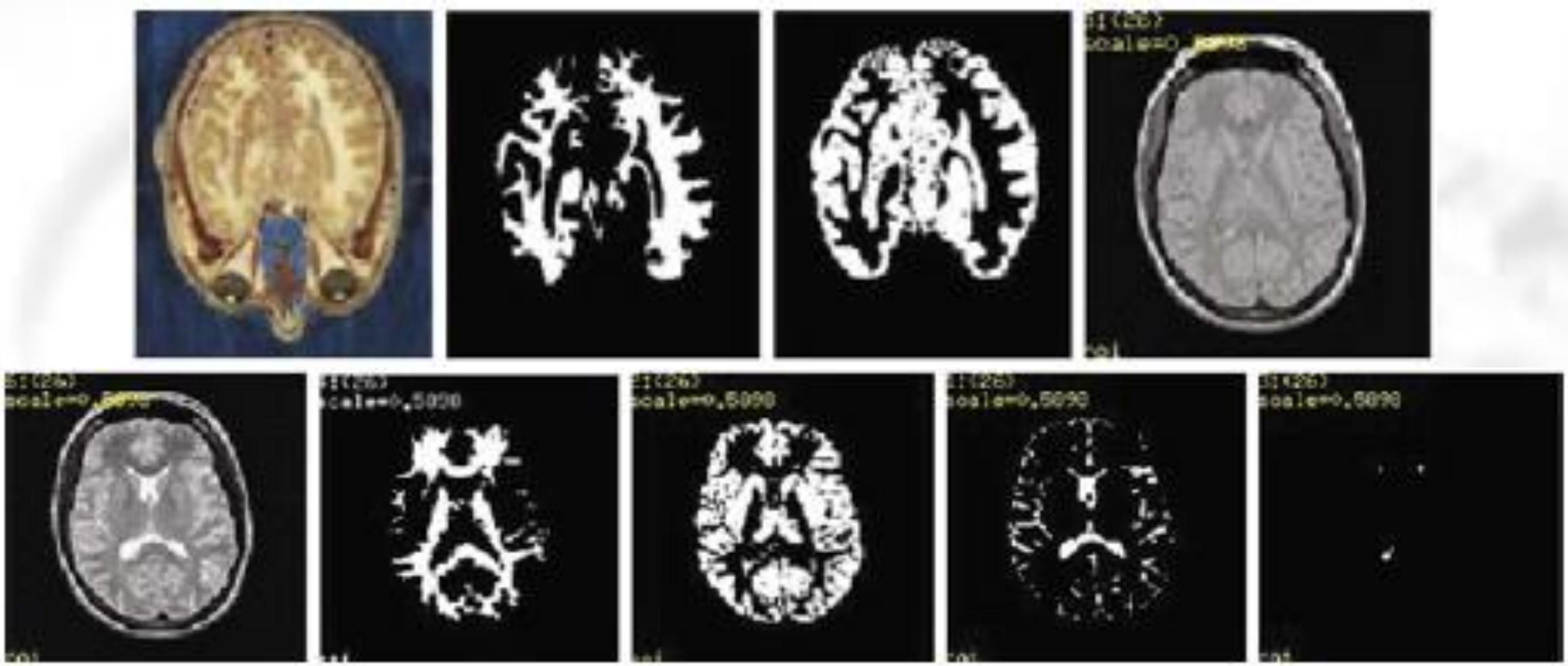
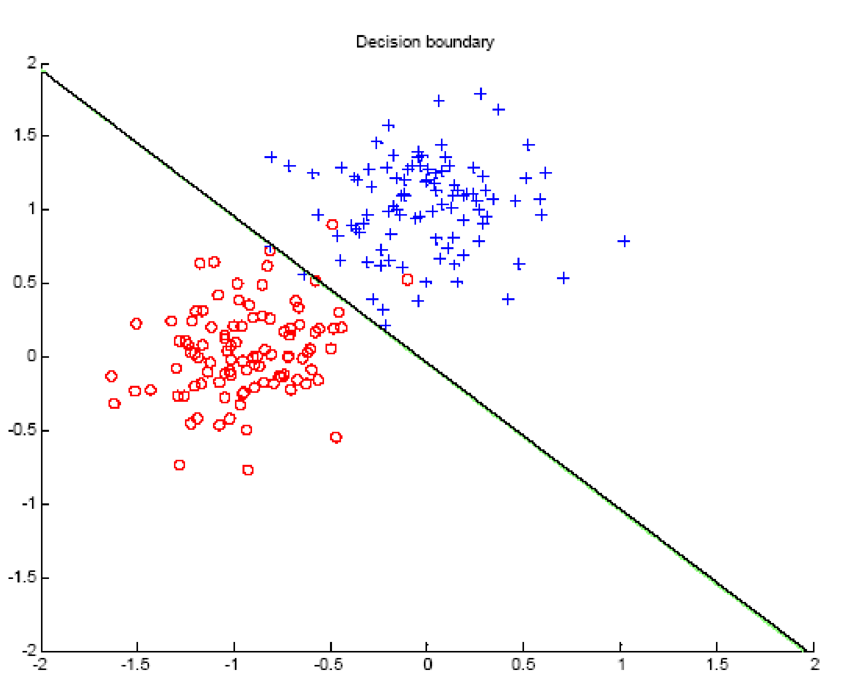


Image Classification

- Image classification is a procedure by which desired information is extracted from original image data through a designed algorithm.
- Four basic elements are involved in the definition of image classification:
  - original data.
  - classified data.
  - classification algorithm.
  - estimation criterion.
- The scale of image classification problem:
  - original input data: a 256 X 256 lattice grey image
  - classified image: a 256 X 256 lattice binary image
  - The number of possible output is power(2, 256*256). This is a very big number

Image Classification / Features

- A **feature** is a value describing something about image pixels: intensity, local gradient, distance from landmark, etc.)
- Multiple features put together form a **feature vector**, which defines a data point's location in n-dimensional **feature space.** A boundary is selected to discriminate the desired feature space:



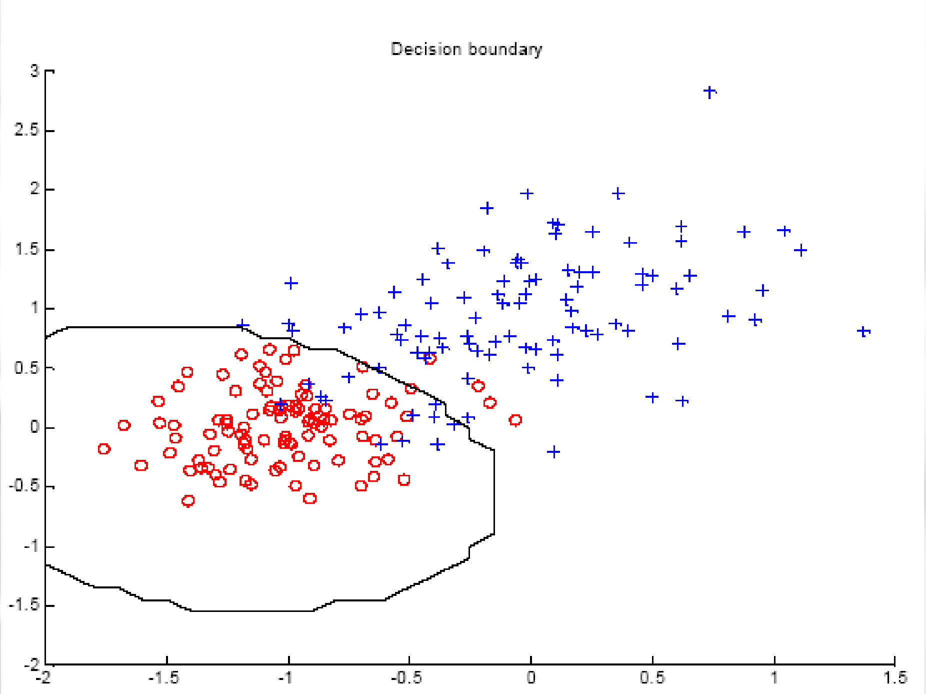


Image Classification / Features

- Feature Space:
  - The theoretical n-dimensional space occupied by n input raster objects (features).
  - Each feature represents one dimension, and its values represent positions along one of the orthogonal coordinate axes in feature space.
  - The set of feature values belonging to a data point define a vector in feature space.

- Statistical Notation:

Class probability distribution:

$$p(\mathbf{x},y) = p(\mathbf{x} \mid y)\, p(y)$$

$\mathbf{x}$: feature vector – $\{x_1,x_2,x_3\ldots,x_n\}$ / y: class

$p(\mathbf{x} \mid y)$: probabilty of $\mathbf{x}$ given y

$p(\mathbf{x},y)$: probability of both $\mathbf{x}$ and y

Image Classification / Binary model

- A binary classification example:

- Two class-conditional distributions:

$$p(\mathbf{x} \mid y = 0) \qquad p(\mathbf{x} \mid y = 1)$$

- Priors:

$$p(y = 0) + p(y = 1) = 1$$

Typical model:

$$p(\mathbf{x}, y) = p(\mathbf{x} \mid y)\, p(y)$$

$p(\mathbf{x} \mid y)$ = **Class-conditional distributions** (densities)

$p(y)$ = **Priors** of classes (probability of class y)

Model's output: $p(y \mid \mathbf{x})$ = **Posteriors** of classes

Image Classification / Binary model

- A binary classification example:

- The class distributions are modeled as multivariate Gaussians:

  $x \sim N(\mu_0, \Sigma_0)$ for $y = 0$
  $x \sim N(\mu_1, \Sigma_1)$ for $y = 1$

$$p(\mathbf{x} \mid \boldsymbol{\mu}, \boldsymbol{\Sigma}) = \frac{1}{(2\pi)^{d/2} |\boldsymbol{\Sigma}|^{1/2}} \exp\left[-\frac{1}{2} (\mathbf{x} - \boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1} (\mathbf{x} - \boldsymbol{\mu}) \right]$$

- ✓ Priors are based on training data, or a distribution can be chosen that is expected to fit the data well (e.g. Bernoulli distribution for a coin flip).

❑ Image Classification / Binary model

➢ A binary classification example:

Making a class decision:

- **Discriminant** functions ($g_n(\mathbf{x})$) must be defined.
- Basic choices:
  - Likelihood of data – choose the class (Gaussian) that best explains the input data (**x**):

$$\underbrace{p(\mathbf{x} \mid \mu_1, \Sigma_1)}_{g_1(\mathbf{x})} > \underbrace{p(\mathbf{x} \mid \mu_0, \Sigma_0)}_{g_0(\mathbf{x})} \quad \Rightarrow \quad \begin{array}{ll} \text{then} & y=1 \\ \text{else} & y=0 \end{array}$$

  - Posterior of class – choose the class with a better posterior probability:

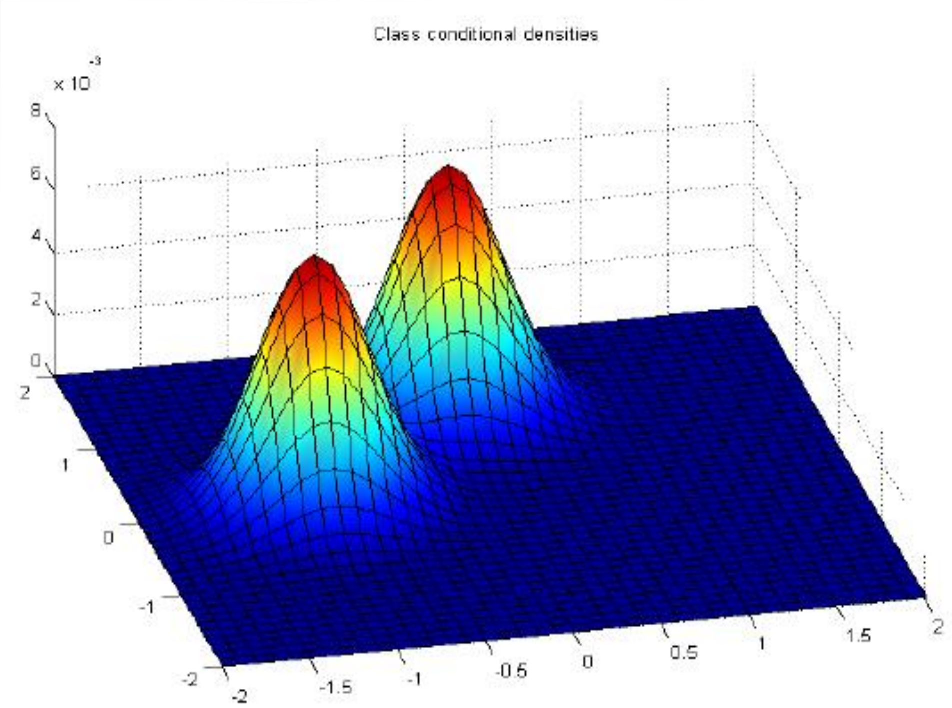
$$\underbrace{p(y=1 \mid \mathbf{x})}_{g_1(\mathbf{x})} > \underbrace{p(y=0 \mid \mathbf{x})}_{g_0(\mathbf{x})} \quad \Rightarrow \quad \begin{array}{ll} \text{then} & y=1 \\ \text{else} & y=0 \end{array}$$

❑ Image Classification / Binary model

➢ A binary classification example:

✓ When covariances are the same

$$\mathbf{x} \sim N(\boldsymbol{\mu}_0, \boldsymbol{\Sigma}),\ y = 0$$
$$\mathbf{x} \sim N(\boldsymbol{\mu}_1, \boldsymbol{\Sigma}),\ y = 1$$



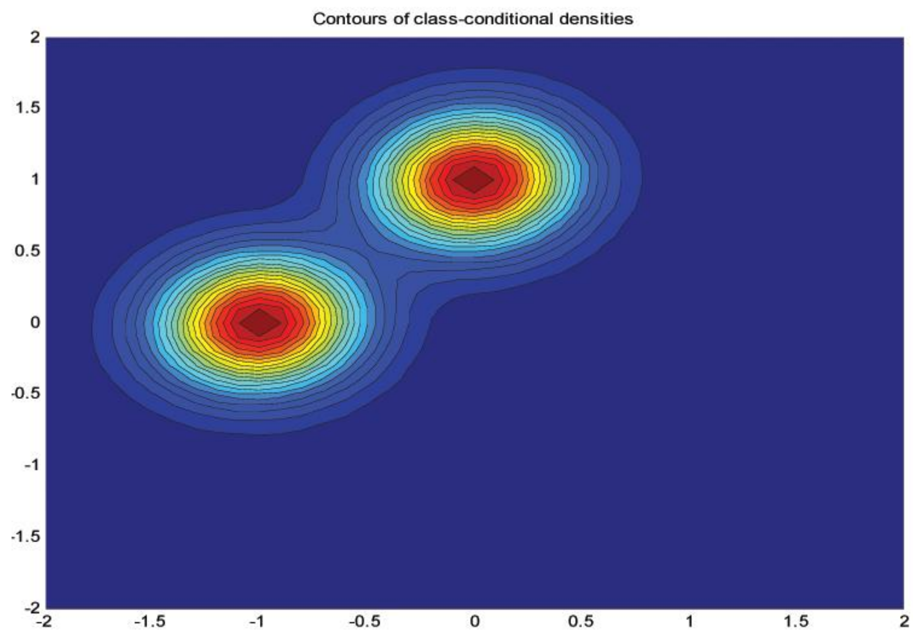
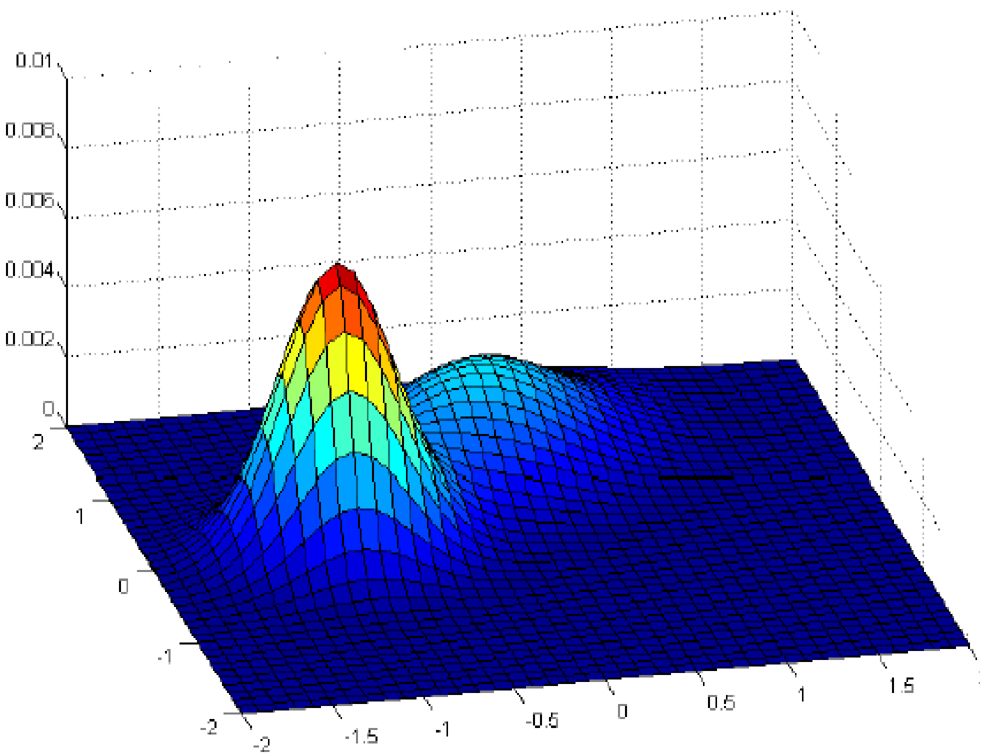


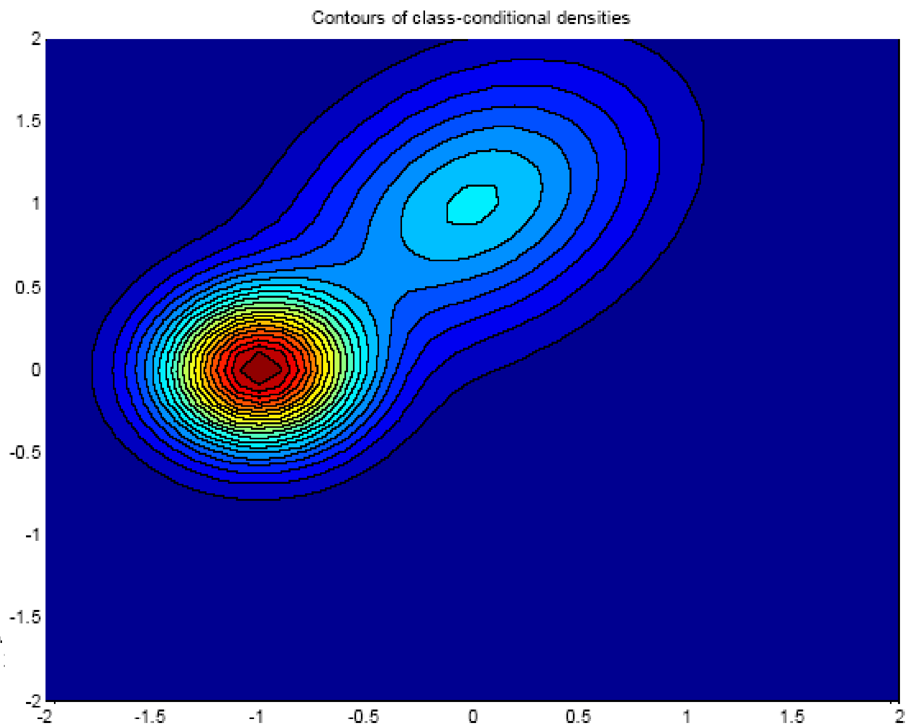
Image Classification / Binary model

- A binary classification example:

  - ✓ When covariances are different

$$\mathbf{x} \sim N(\boldsymbol{\mu}_0, \boldsymbol{\Sigma}),\ y = 0$$
$$\mathbf{x} \sim N(\boldsymbol{\mu}_1, \boldsymbol{\Sigma}),\ y = 1$$





Calculating Posteriors

- Use Bayes' Rule: $$P(A \mid B) = \frac{P(B \mid A)P(A)}{P(B)}$$
- In this case,

$$p(y=1 \mid \mathbf{x}) = \frac{p(\mathbf{x} \mid \mu_1, \mathbf{\Sigma}_1)\, p(y=1)}{p(\mathbf{x} \mid \mu_0, \mathbf{\Sigma}_0)\, p(y=0) + p(\mathbf{x} \mid \mu_1, \mathbf{\Sigma}_1)\, p(y=1)}$$

References

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- **Image Enhancement** - Antti Tuomas Jalava & Jaime Garrido Ceca.
- **Biological and medical physics, biomedical engineering -** Thomas M. Deserno, ISBN 978-3-642-15815-5, DOI 10.1007/978-3-642-15816-2.
- **Methods in Medical Image Analysis, Statistics of Pattern Recognition: Classification and Clustering -** Milos Hauskrecht, University of Pittsburgh Computer Science