Texture Descriptors

Texture is usually defined as the smoothness or roughness of a surface.

There are two types of texture: random and regular:

- Random texture cannot be exactly described by words or equations; it must be described statistically. The surface of a pile of dirt or rocks of many sizes would be random. It is analyzed by statistical methods

- Regular texture can be described by words or equations or repeating pattern primitives. Clothes are frequently made with regularly repeating patterns. It is is analyzed by structural or spectral (Fourier) methods.

Random Texture Descriptors

The statistical moments computed from an image histogram:

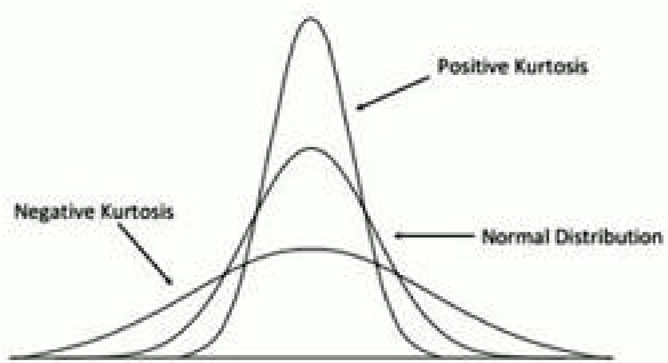
$$\mu_n(z) = \sum_{i=0}^{K-1} (z_i - m)^n p(z_i)$$

z = intensity
p(z) = PDF or histogram of z

where

$$m = \sum_{i=0}^{K-1} z_i p(z_i)$$

Example: The 2nd moment = variance σ^2 → measure "smoothness"
The 3rd moment → measure "skewness"
The 4th moment → measure "Kurtosis" (flatness)



Random Texture Descriptors

- The measure relative smoothness R:

$$R = 1 - \frac{1}{1 + \sigma^2(z)}$$

- The uniformity:

$$U = \sum_{i=0}^{L-1} p^2(z_i)$$

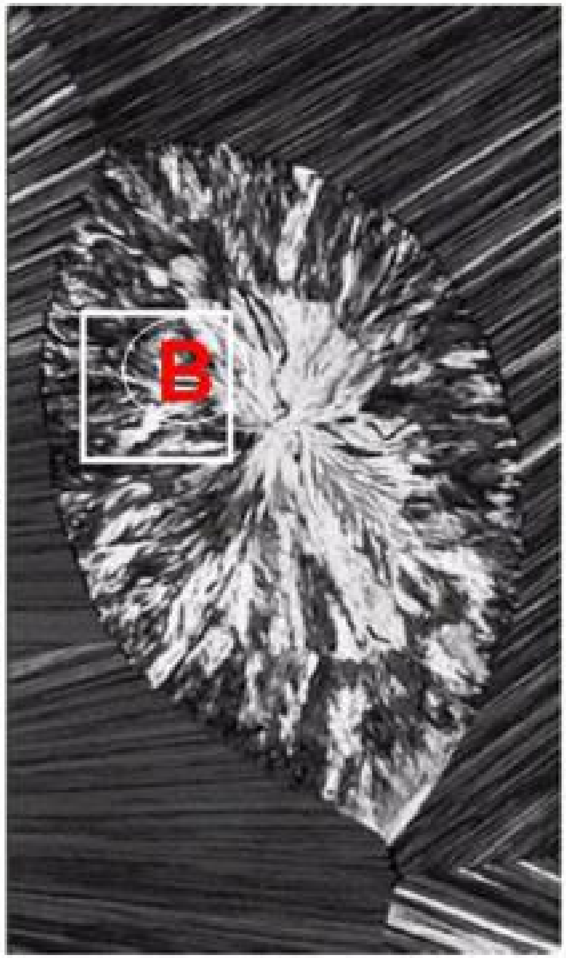
- The average entropy:

$$e = -\sum_{i=0}^{L-1} p(z_i) \log_2 p(z_i)$$

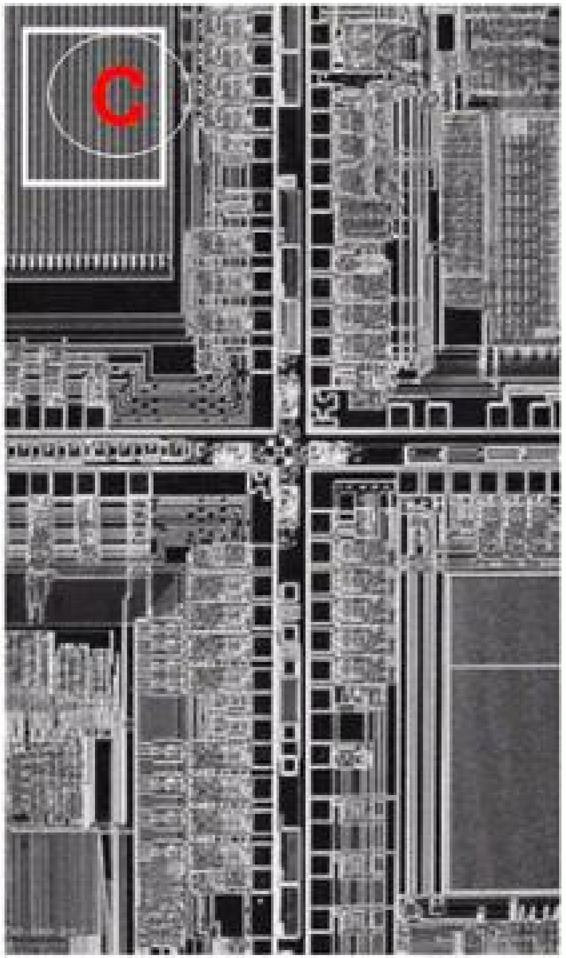
Random Texture Descriptors

Examples: optical microscope images:

Superconductor
(smooth texture)



Cholesterol
(coarse texture)

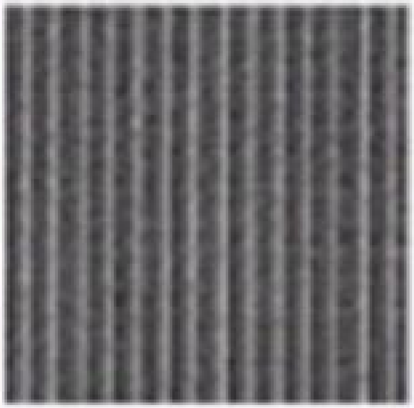


Microprocessor
(regular texture)

Statistical Approaches

A Smooth

B Coarse



C Regular

Texture	Mean	Standard deviation	R (normalized)	Third moment	Uniformity	Entropy
Smooth	82.64	11.79	0.002	−0.105	0.026	5.434
Coarse	143.56	74.63	0.079	−0.151	0.005	7.783
Regular	99.72	33.73	0.017	0.750	0.013	6.674

Regular Texture Descriptor

Structural concepts:

- Suppose that we have a rule of the form $S \rightarrow aS$, which indicates that the symbol S may be rewritten as aS.

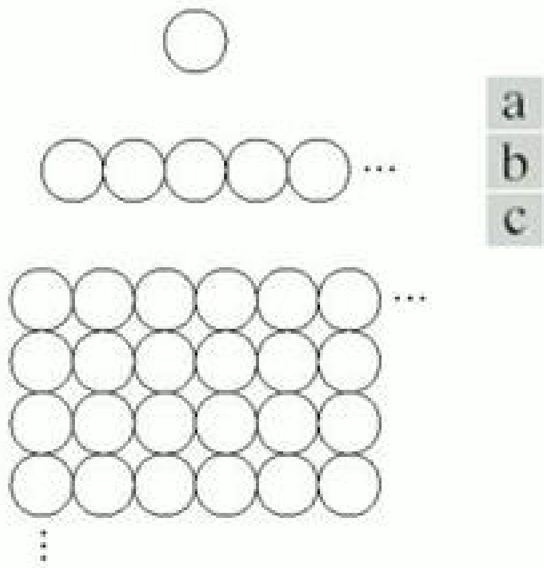


FIGURE 11.23 (a) Texture primitive. (b) Pattern generated by the rule $S \rightarrow aS$. (c) 2-D texture pattern generated by this and other rules.

If '*a*' represents a circle and the meaning of "circle to the right" is assigned to a string of the form *aaaa*....

Patterns and features

One of the most interesting aspects of the world is that it can be considered to be made up of patterns.

Norbert Wiener

A pattern is arrangement of descriptors

Pattern classes:

A pattern class is a family of patterns that share some common properties

Pattern recognition:

To assign patterns to their respective classes

Patterns and features

A pattern is a set of consistent, characteristic form, style of an object-

- Signature
- Color
- Shape
- Entropy

Pattern recognition is a study of how machines can:

- Observe its environments
- Learn to distinguish patterns of interest
- Make sound decisions and reasonable assignments of patterns to possible classes.

Patterns and features

Three common pattern arrangements used in practices are

- Vectors
- Strings
- Trees

Vector Pattern - Iris flowers

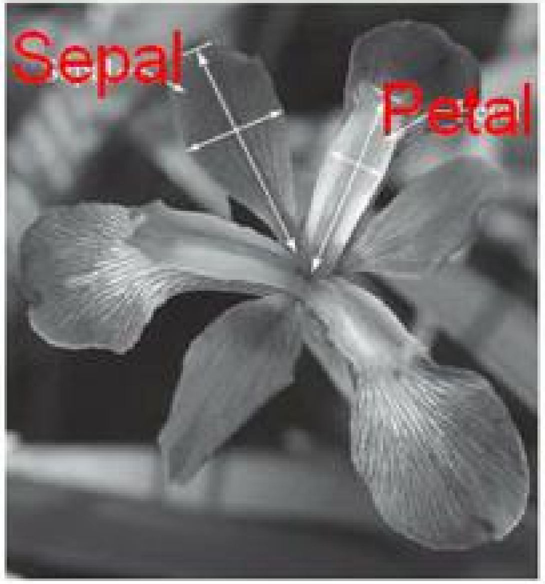
The Problem of Species in the Northern Blue Flags, Iris versicolor L. and Iris virginica L.

Author: Edgar Anderson

Source: Annals of the Missouri Botanical Garden, Vol. 15, No. 3, Sep1928, pp. 241-332

Three types of Iris Flowers

Vector Pattern - Iris flowers



$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}$$

x_1 = Petal width
x_2 = Petal length
x_3 = Sepal width
x_4 = Sepal length

Three types of Iris Flowers

Vector Pattern - Iris flowers

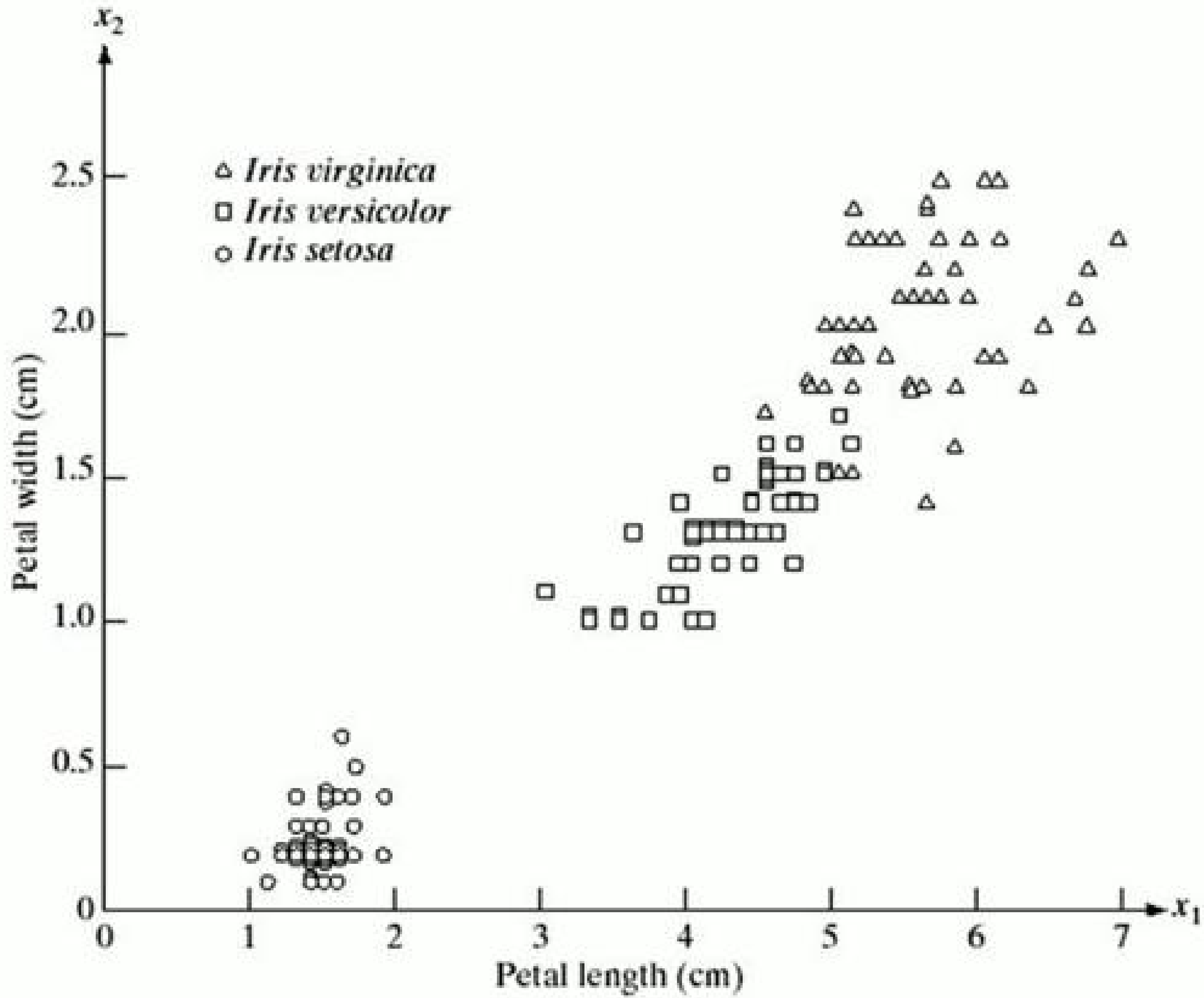


FIGURE 12.1 Three types of iris flowers described by two measurements.

Pattern Vector Different types of noisy shapes.

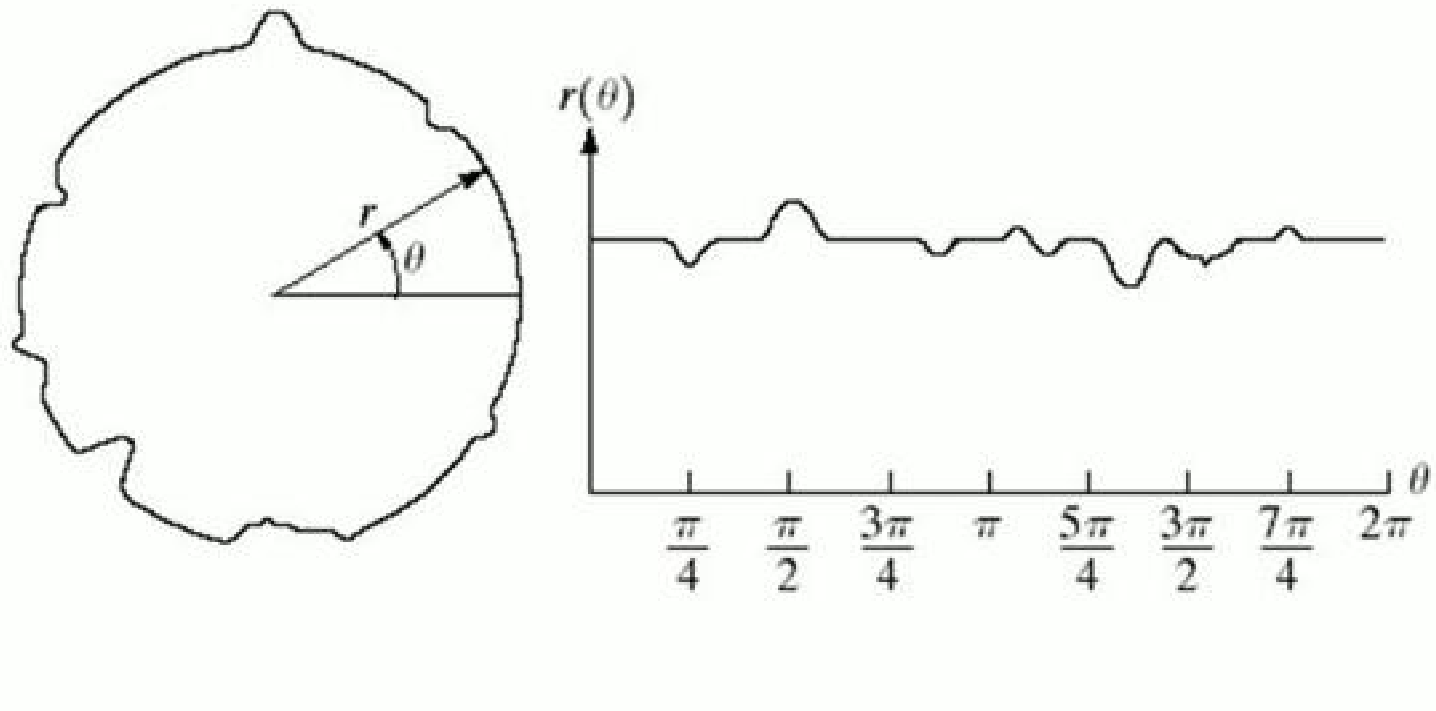
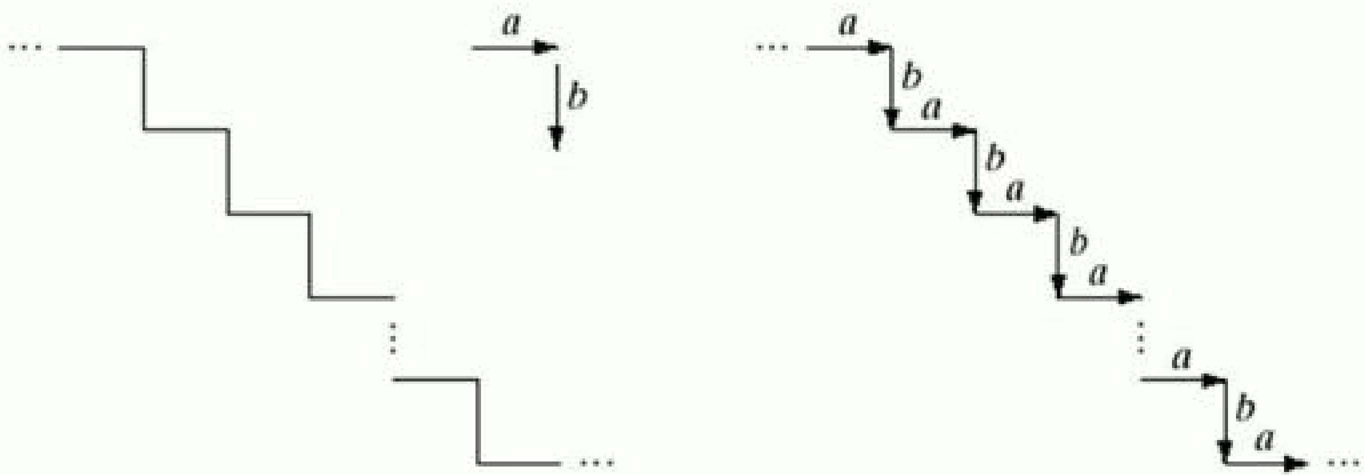


FIGURE 12.2 A noisy object and its corresponding signature.

String descriptions adequately generate patterns of objects and other entities whose structure is based on relatively simple connectivity of primitives, usually associated with boundary shape.



a b

FIGURE 12.3 (a) Staircase structure. (b) Structure coded in terms of the primitives *a* and *b* to yield the string description ...*ababab* ....

Satellite Image of downtown area and surrounding residential area.

Tree descriptions is more powerful than string ones. Most hierarchical ordering schemes lead to tree structure.

Example – Satellite Image of downtown area and surrounding residential area.

FIGURE 12.4 Satellite image of a heavily built downtown area (Washington, D.C.) and surrounding residential areas. (Courtesy of NASA.)

Tree Pattern

Satellite Image of downtown area and surrounding residential area.

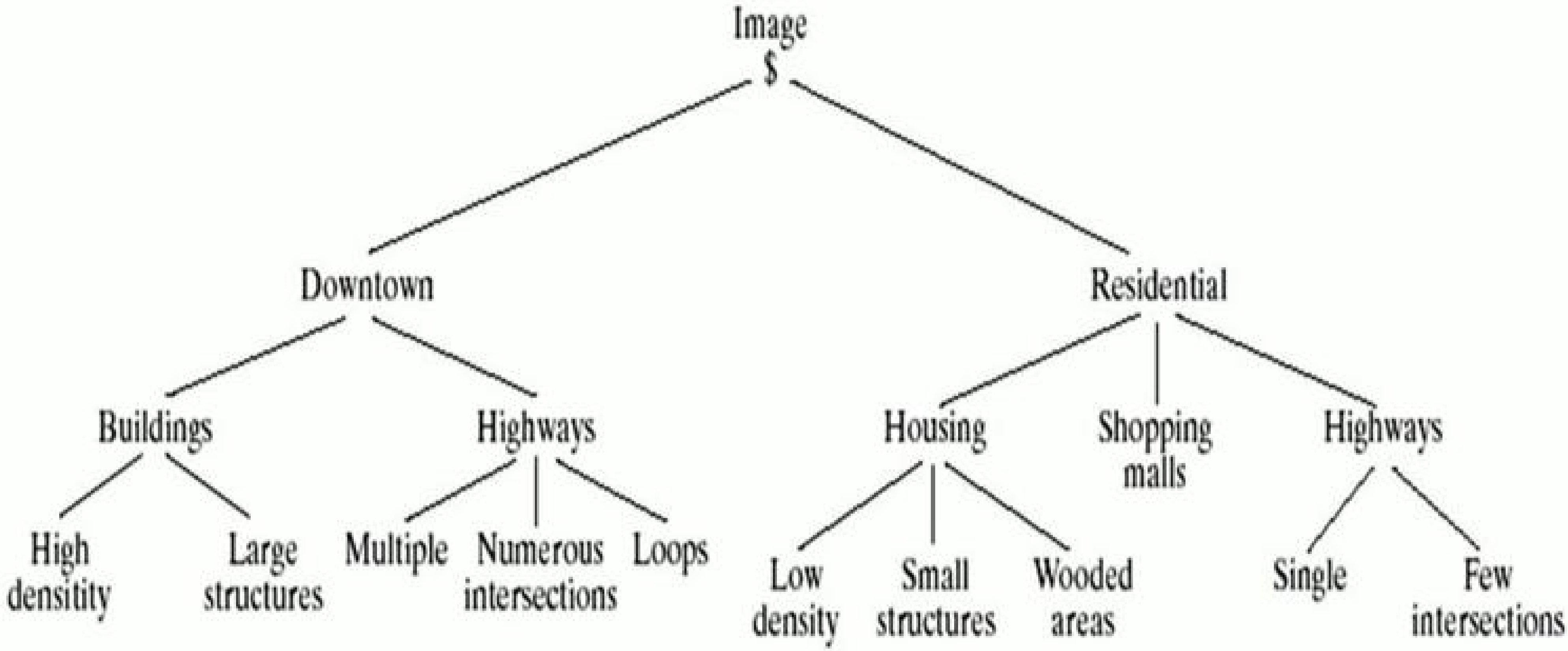


FIGURE 12.5 A tree description of the image in Fig. 12.4.

Application: Face

An Efficient Facial Image Indexing Network are required to reduce authentication and verification process.

Social media flooded with images and needed to establish identity of the persons.

Collection of facial images is large - Challenges increased with in efficiency.

Size of the database increases, identification demanding comparison with all the stored images becomes very compute intensive.

To address this challenge, specialized techniques needed that aims to reduce search space for the comparison.

Application: Face

Model regularized to produce short 10-dimensional feature vector such that the embedding space of same subjects are close, while those belonging to different subjects lie far.

Clustering is applied to get representatives of index entries for the index table.

When a probe image is presented to the system, its feature vector is computed.

The most similar index corresponding to the part of the face is computed and the samples lying in that cluster are retrieved for comparison with the probe image.

Identification with indexing is found to be seven times more efficient as compared to normal method

Recognition Based on Decision

Decision-theoretic approaches to recognition are based on the use decision functions.

- Let $\mathbf{x} = (x_1, x_2, \ldots, x_n)^T$ represent an *n*-dimensional pattern vector. For *W* pattern classes $\omega_1, \omega_2, \ldots, \omega_W$, we want to find *W* decision functions $d_1(\mathbf{x}), d_2(\mathbf{x}), \ldots, d_W(\mathbf{x})$ with the property that, if a pattern **x** belongs to class ω_i, then

$$d_i(\mathbf{x}) > d_j(\mathbf{x}) \qquad j = 1,2,\ldots,W;\ j \neq i$$

- The decision boundary separating class ω_i and ω_j is given by

$$d_i(\mathbf{x}) = d_j(\mathbf{x}) \quad \text{or} \quad d_i(\mathbf{x}) - d_j(\mathbf{x}) = 0$$

Minimum-Distance Classifier

Recognition Based on Decision

The minimum-distance classifier is also referred to as the *nearest-neighbor classifier.*

$$\mathbf{m}_j = \frac{1}{n_j} \sum_{x \in c_j} \mathbf{x} \qquad j = 1, 2, \ldots, N_c$$

selecting the smallest distance is equivalent to evaluating the functions

$$d_j(\mathbf{x}) = \mathbf{m}_j^T \mathbf{x} - \frac{1}{2} \mathbf{m}_j^T \mathbf{m}_j \qquad j = 1, 2, \ldots, N_c$$

a minimum-distance classifier follow directly from this equation- $d_{ij}(\mathbf{x}) = d_i(\mathbf{x}) - d_j(\mathbf{x})$

$$= (\mathbf{m}_i - \mathbf{m}_j)^T \mathbf{x} - \tfrac{1}{2}(\mathbf{m}_i - \mathbf{m}_j)^T(\mathbf{m}_i + \mathbf{m}_j) = 0$$

Example 13.1

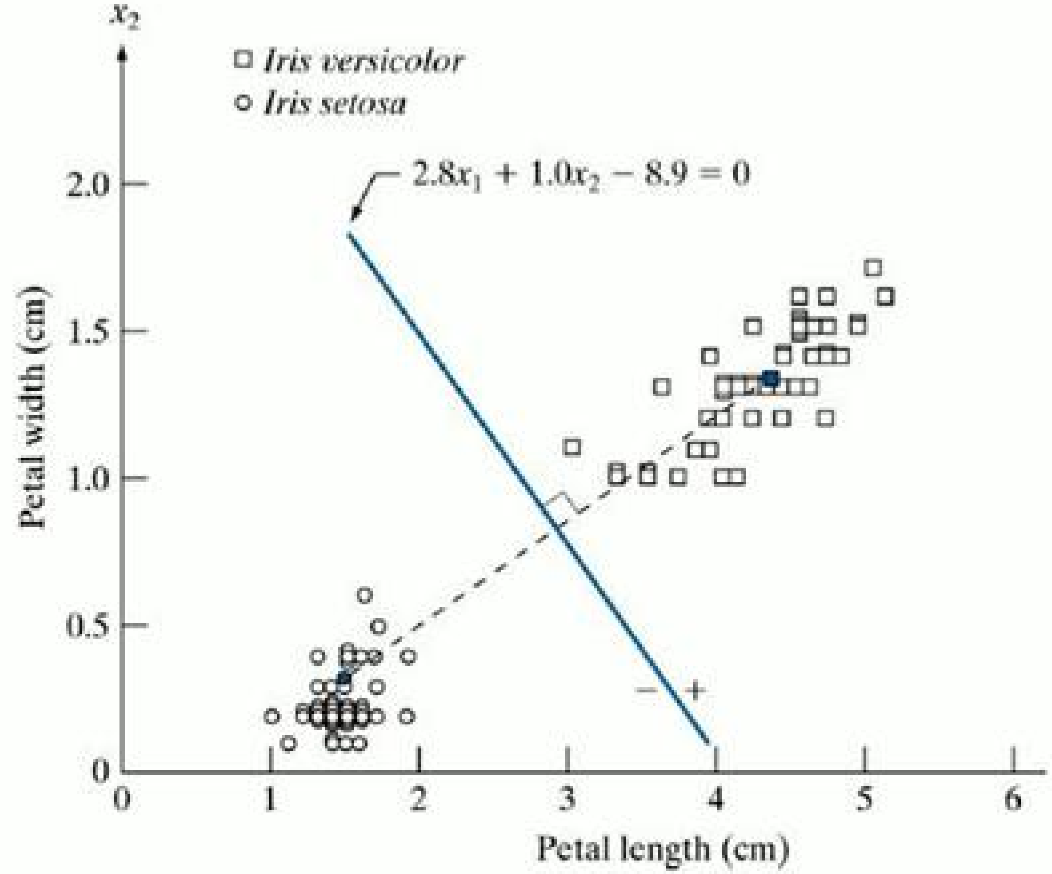
The Iris versicolor and setosa data as classes respectively. The means of the two classes

$m_1 = (4.3, 1.3)^T$ and $m_2 = (1.5, 0.3)^T$

$$d_1(\mathbf{x}) = \mathbf{m}_1^T\mathbf{x} - \tfrac{1}{2}\mathbf{m}_1^T\mathbf{m}_1$$
$$= 4.3x_1 + 1.3x_2 - 10.1$$

$$d_2(\mathbf{x}) = \mathbf{m}_2^T\mathbf{x} - \tfrac{1}{2}\mathbf{m}_2^T\mathbf{m}_2$$
$$= 1.5x_1 + 0.3x_2 - 1.17$$

$$d_{12}(\mathbf{x}) = d_1(\mathbf{x}) - d_2(\mathbf{x})$$
$$= 2.8x_1 + 1.0x_2 - 8.9 = 0$$



The Iris versicolor and setosa data as classes respectively. The means of the two classes

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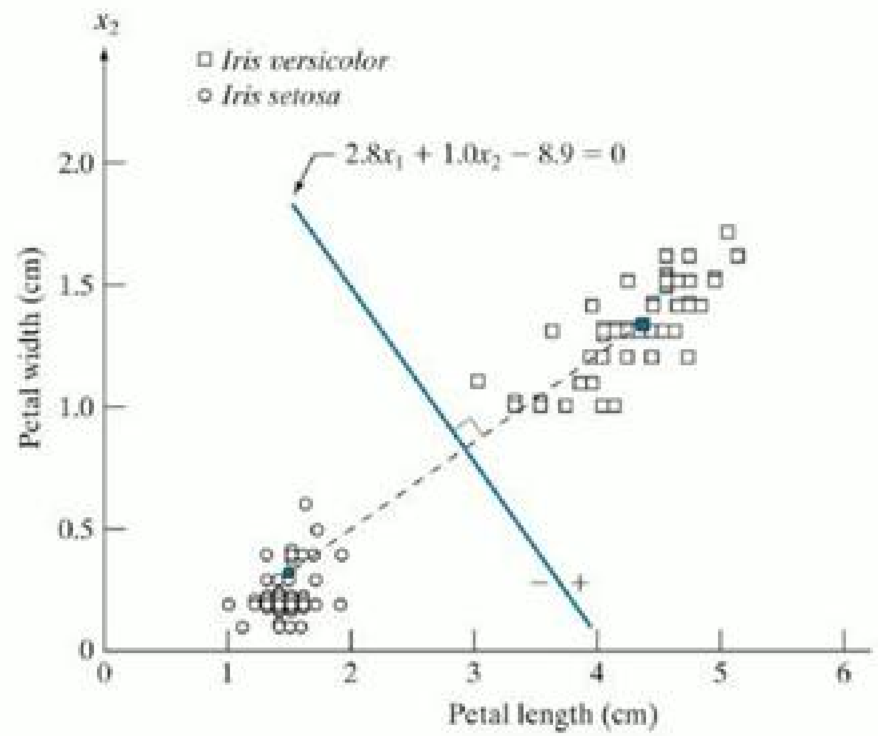
$$d_{ij}(\mathbf{x}) = d_i(\mathbf{x}) - d_j(\mathbf{x})$$
$$= (\mathbf{m}_i - \mathbf{m}_j)^T\mathbf{x} - \tfrac{1}{2}(\mathbf{m}_i - \mathbf{m}_j)^T(\mathbf{m}_i + \mathbf{m}_j)$$

$$d_{12}(\mathbf{x}) = d_1(\mathbf{x}) - d_2(\mathbf{x})$$
$$= 2.8x_1 + 1.0x_2 - 8.9 = 0$$



Theoretic Methods Matching

- Minimum distance classifier – decision boundary

$$d_{12}(\mathbf{x}) = d_1(\mathbf{x}) - d_2(\mathbf{x})$$
$$= 2.8x_1 + 1.0x_2 - 8.9 = 0$$

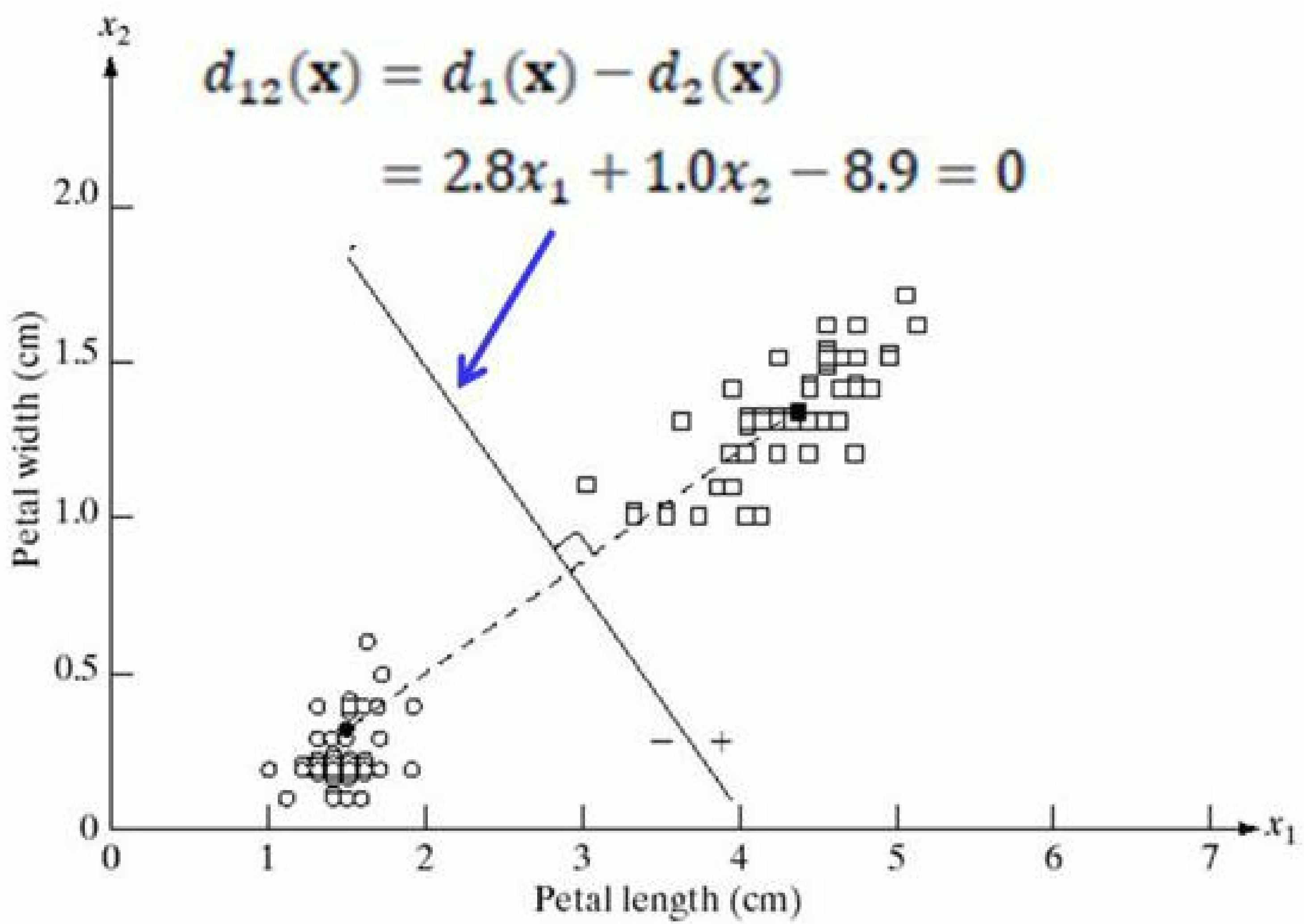


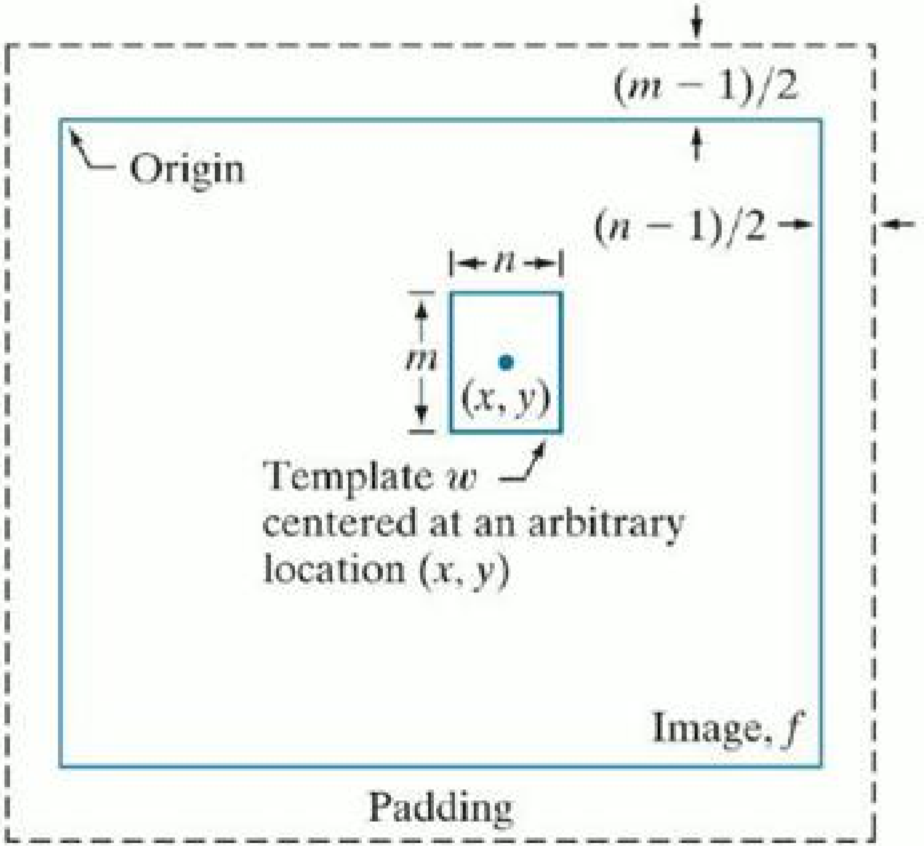
FIGURE 12.6 Decision boundary of minimum distance classifier for the classes of *Iris versicolor* and *Iris setosa*. The dark dot and square are the means.

Theoretic Methods Matching by Correlation

- The correlation of a kernel *w(x,y) with an image f(x,y)* is -

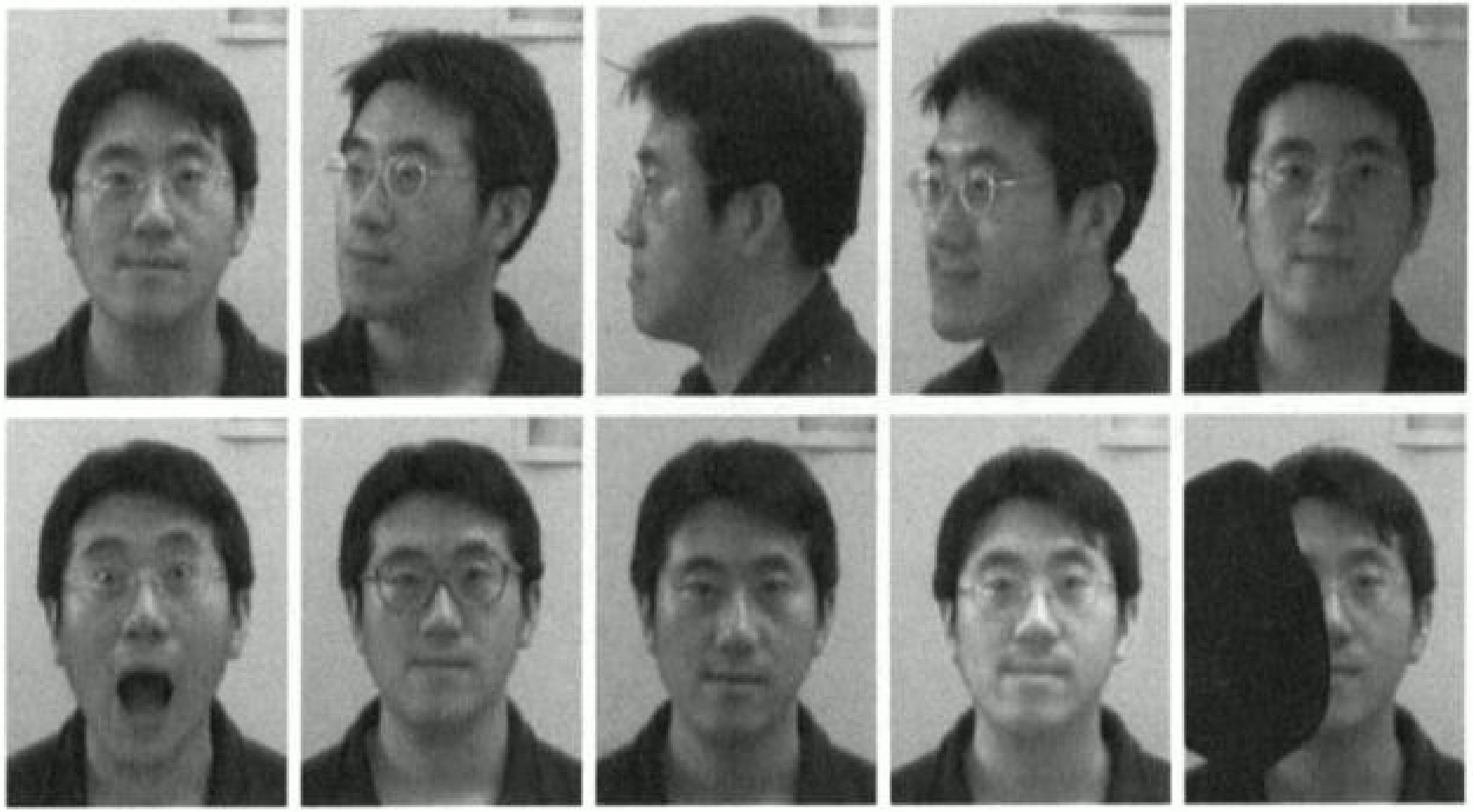
$$c(x,y) = \sum_s \sum_t f(s,t)\,w(x+s,y+t)$$

$$\text{for } x = 0,1,2,\ldots,M-1, \quad y = 0,1,2,\ldots,N-1$$



$$\gamma(x,y) = \frac{\sum_s \sum_t [w(s,t)-\bar{w}][f(x+s,y+t)-\bar{f}_{xy}]}{\left\{\sum_s \sum_t [w(s,t)-\bar{w}]^2 \sum_s \sum_t [f(x+s,y+t)-\bar{f}_{xy}]^2\right\}^{\frac{1}{2}}}$$

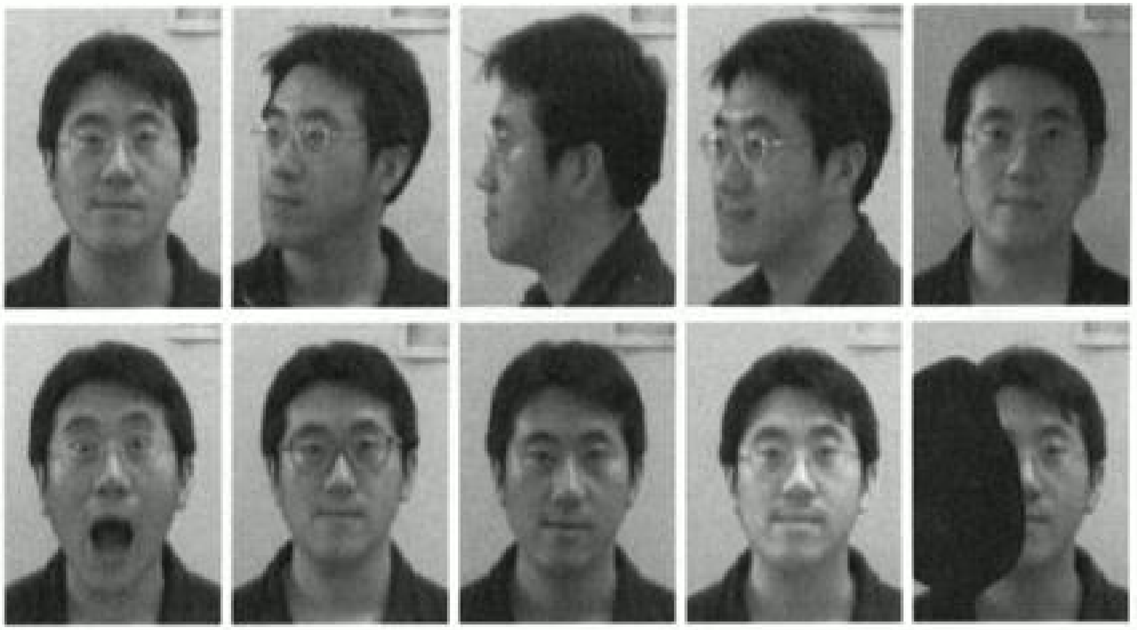
Principal Components Analysis



Sample unconstrained face images of the same person with variations in pose, illumination, expression, alignment and Occlusion.

Principal Components Analysis

Since images are array of data points with each point representing unique attribute, PCA can be used for reducing the image data (extracting features) to smaller dimension to represent the image qualities and remaining variability as possible.



Principal Components Analysis

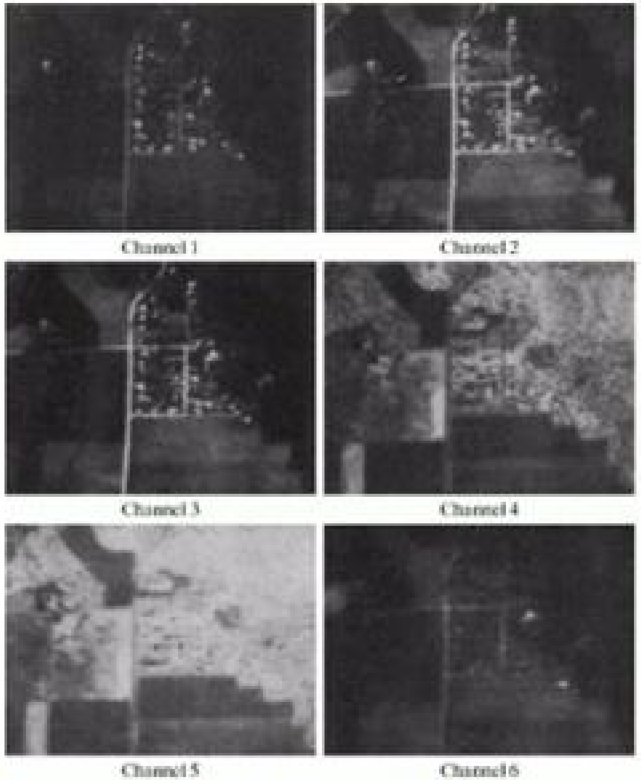
It is a technique for reducing the dimensionality of a multidimensional dataset.

- Involves a mathematical procedure that transforms a number of possibly correlated variables into a smaller number of uncorrelated variables called principal components.
- PCA is an orthogonal linear transformation that transforms the data to a new coordinate system such that the greatest variance by any projection of the data comes to lie on the first coordinate (called the first principal component), the second greatest variance on the second coordinate, and so on.

Principal Components for Descriptions

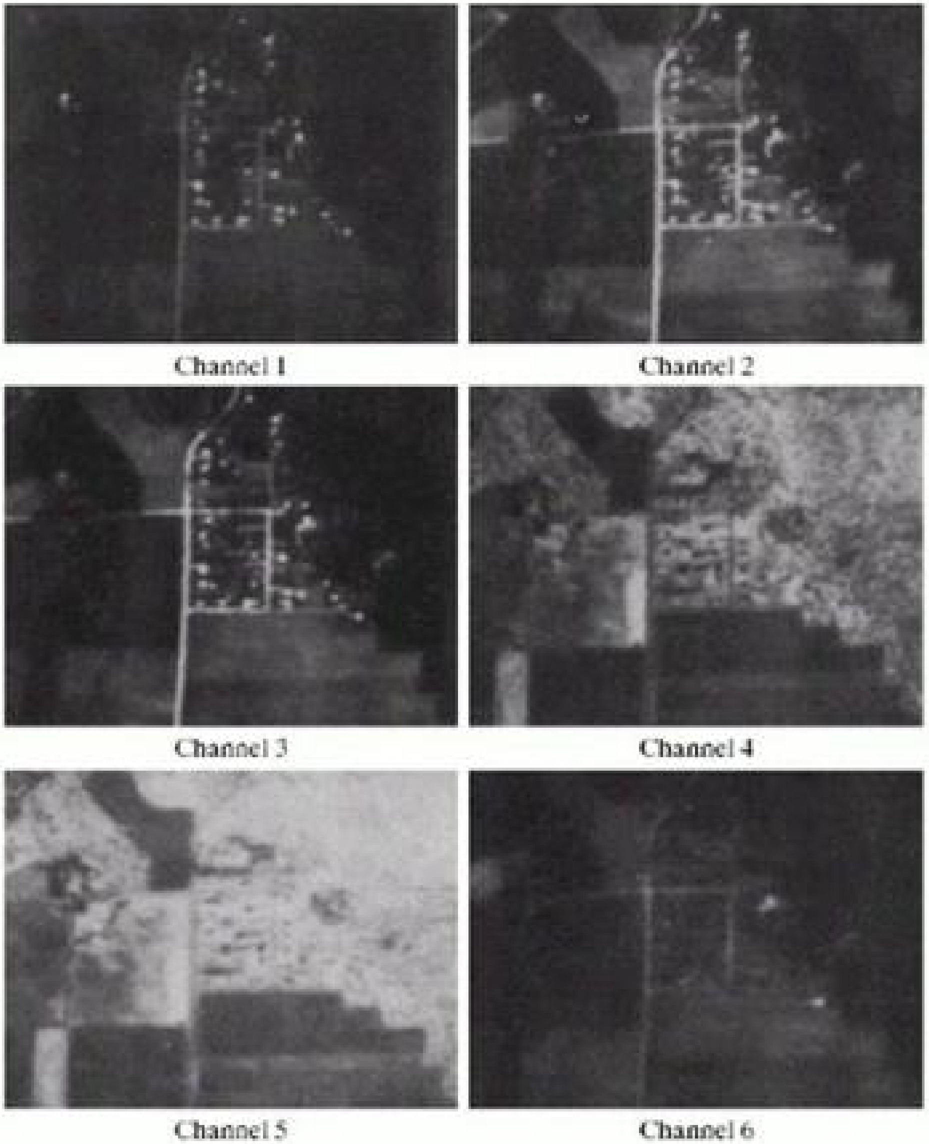
Suppose a set of 1000 hyper-spectral images. These images look similar but differ from each other at some positions (i.e., some of the interesting details appear in different image at different places) Since the images are highly correlated we do not wish to spend time analyzing them all but rather rearranging the information into much fewer components that contain the resting information.

Channel	Wavelength band (microns)
1	0.40–0.44
2	0.62–0.66
3	0.66–0.72
4	0.80–1.00
5	1.00–1.40
6	2.00–2.60



A set of 6 channel Multispectral remote images.

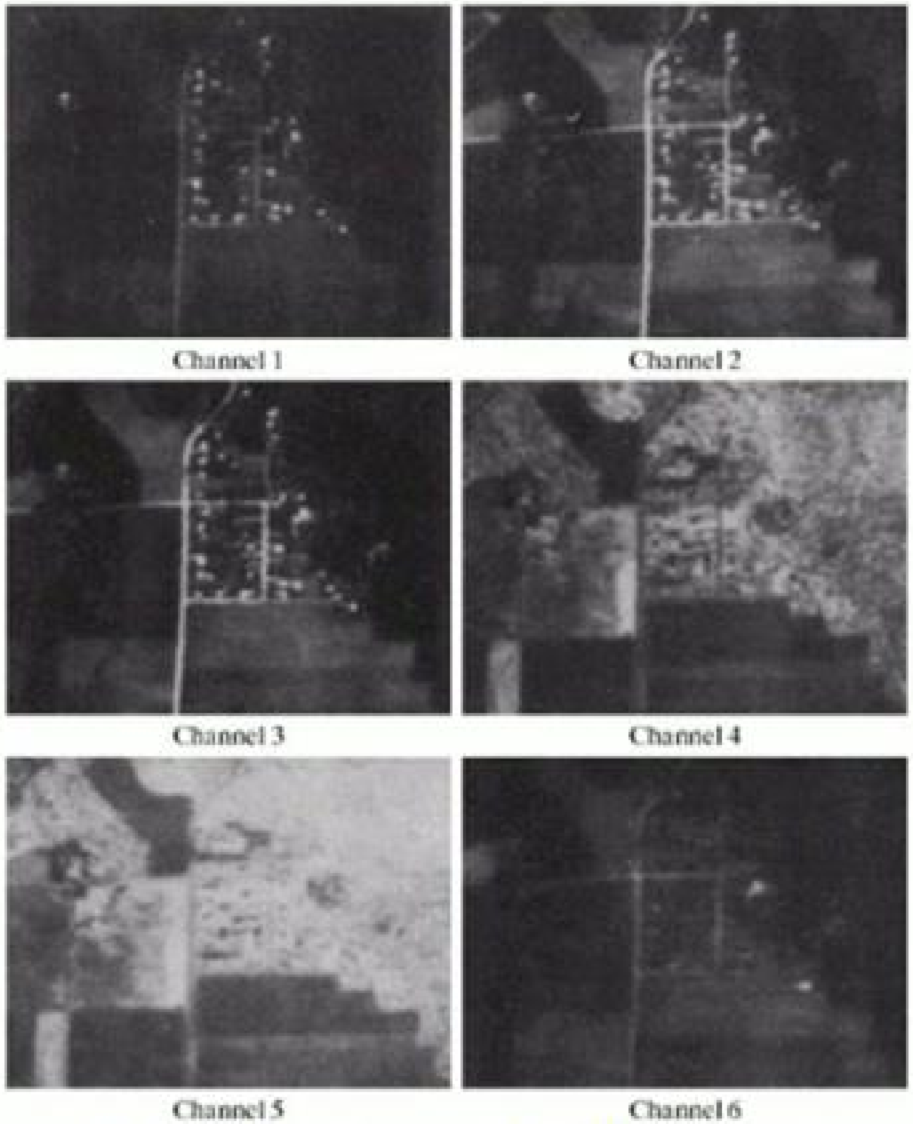
Example-6 Spectral images from an airborne Scanner



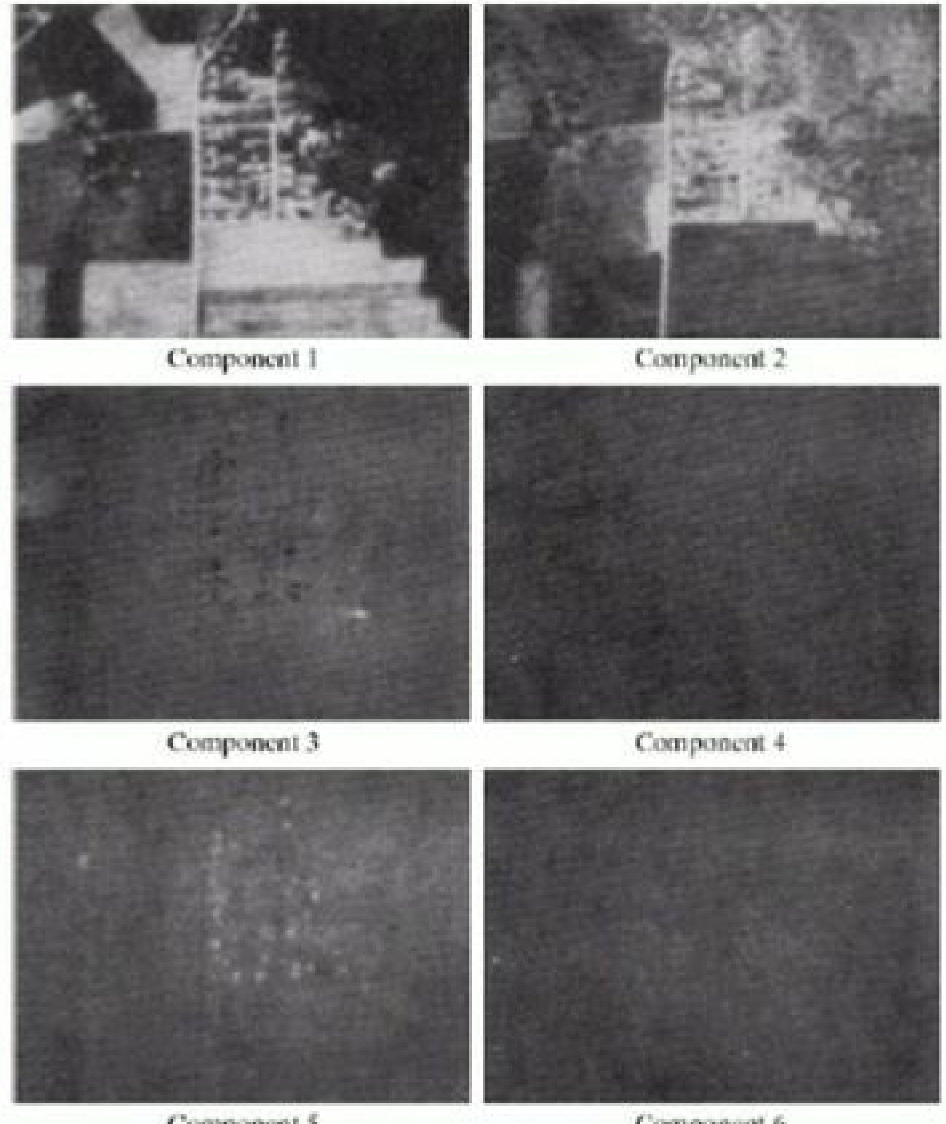
Component	λ
1	3210
2	931.4
3	118.5
4	83.88
5	64.00
6	13.40

TABLE 11.5
Eigenvalues of the covariance matrix obtained from the images in Fig. 11.26.

Principal Components Images



A set of 6 channel Multispectral remote images.



Principal Components Images

Suppose a set of 6 hyper-spectral images X are acquired.

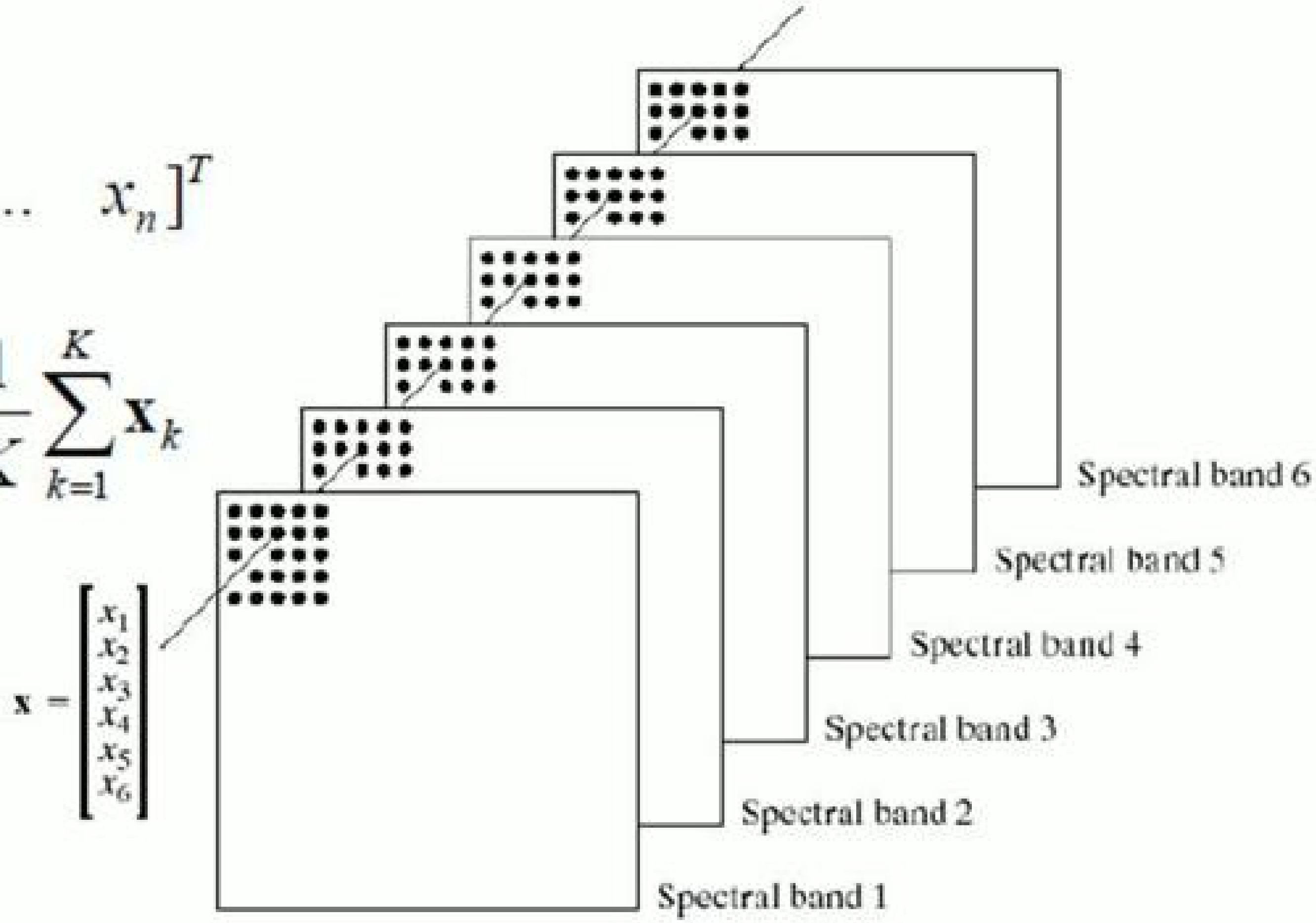
Find the PCA values for these images.

Let

$$\mathbf{x} = [x_1 \quad x_2 \quad \dots \quad x_n]^T$$

Mean:

$$\mathbf{m}_x = E\{\mathbf{x}\} = \frac{1}{K}\sum_{k=1}^{K}\mathbf{x}_k$$



Covariance matrix $\mathbf{C}_x = E\{(\mathbf{x}-\mathbf{m}_x)(\mathbf{x}-\mathbf{m}_x)^T\} = \frac{1}{K}\sum_{k=1}^{K}\mathbf{x}_k\mathbf{x}_k^T - \mathbf{m}_x\mathbf{m}_x^T$

Example

Considering 4 vectors $x_1=(0,0,0)^T$, $x_2=(1,0,0)^T$, $x_3=(1,1,0)^T$ and $x_4=(1,0,1)^T$

$$X = \begin{bmatrix} 0 & 1 & 1 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Find the covariance matrix of this data X and interpretate its elements.

Example

Considering 4 vectors $x_1=(0,0,0)^T$, $x_2=(1,0,0)^T$, $x_3=(1,1,0)^T$ and $x_4=(1,0,1)^T$

$$X = \begin{bmatrix} 0 & 1 & 1 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Mean vector and covariance matrix are

$$m_x = \frac{1}{4}\begin{bmatrix} 3 \\ 1 \\ 1 \end{bmatrix} \qquad C_x = \frac{1}{16}\begin{bmatrix} 3 & 1 & 1 \\ 1 & 3 & -1 \\ 1 & -1 & 3 \end{bmatrix}$$

Example

covariance matrix

$$C_x = \frac{1}{16}\begin{bmatrix} 3 & 1 & 1 \\ 1 & 3 & -1 \\ 1 & -1 & 3 \end{bmatrix}$$

covariance matrix

$$C_x = \frac{1}{16}\begin{bmatrix} 3 & 1 & 1 \\ 1 & 3 & -1 \\ 1 & -1 & 3 \end{bmatrix}$$

$$\begin{bmatrix} \operatorname{cov}(x_1, x_1) & \operatorname{cov}(x_1, x_2) & \operatorname{cov}(x_1, x_3) \\ \operatorname{cov}(x_2, x_1) & \operatorname{cov}(x_2, x_2) & \operatorname{cov}(x_2, x_3) \\ \operatorname{cov}(x_3, x_1) & \operatorname{cov}(x_3, x_2) & \operatorname{cov}(x_3, x_3) \end{bmatrix}$$

How to interpret entries of the covariance matrix?

$$\begin{bmatrix} \text{cov}(x_1, x_1) & \text{cov}(x_1, x_2) & \text{cov}(x_1, x_3) \\ \text{cov}(x_2, x_1) & \text{cov}(x_2, x_2) & \text{cov}(x_2, x_3) \\ \text{cov}(x_3, x_1) & \text{cov}(x_3, x_2) & \text{cov}(x_3, x_3) \end{bmatrix}$$

If covariance is positive, both dimensions increase together. If negative, as one increases, the other decreases. Zero: independent of each other.

Introduction to Medical Imaging

Medical imaging systems construct an (output) image in response to (input) signals from diverse types of objects for example, take input signals which arise from various properties of the body of a patient, such as its attenuation of x-rays or reflection of ultrasound.

Medical imaging systems can be classified in a number of ways, e.g. according to the radiation or field used, the property being investigated, or whether the images are formed directly or indirectly.

Introduction to Medical Imaging

- Medical imaging of the human body requires some form of energy.
  - In radiology, the energy used to produce the image must be capable of penetrating tissues.
    - The electromagnetic spectrum outside the visible light region is used for
      - x-ray imaging,
      - magnetic resonance imaging, and
      - nuclear medicine.
  - Mechanical energy, in the form of high-frequency sound waves, is used in ultrasound imaging.

Introduction to Medical Imaging

Medical imaging requires that the energy used to penetrate the body's tissues also interact with those tissues.

- Absorption
- Attenuation
- Scattering

Introduction to Medical Imaging

If energy were to pass through the body and not experience some type of interaction (e.g., absorption, attenuation, scattering), then the detected energy would not contain any useful information regarding the internal anatomy, and thus it would not be possible to construct an image of the anatomy using that information.

Medical Image Analysis

1. Deterministic Studies:

   - distortion
   - impulse response
   - transfer functions

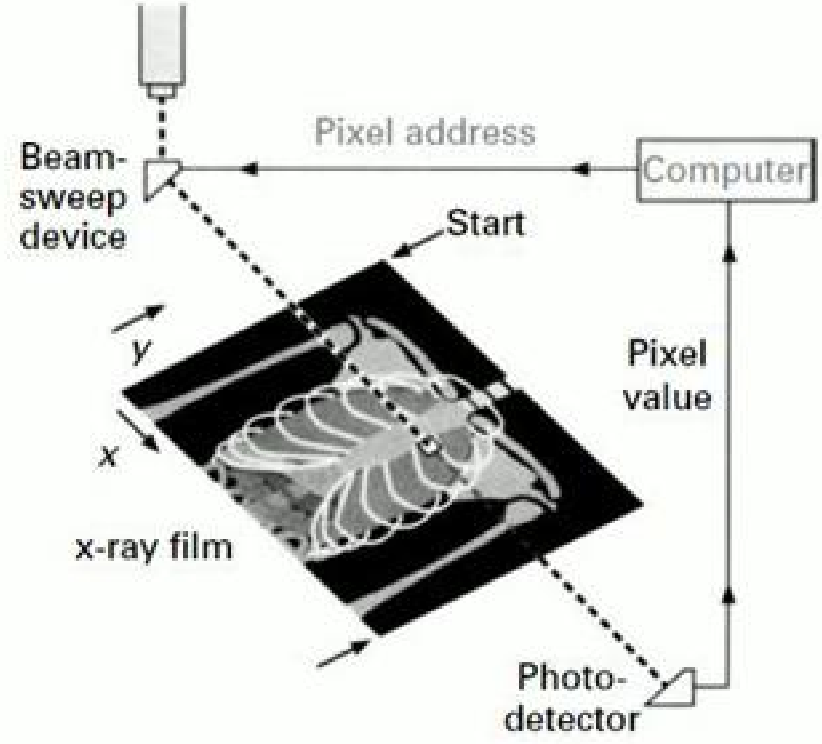
All modalities are non-linear and space variant to some degree. Approximations are made to yield a linear, space-invariant system.

2. Stochastic Studies:

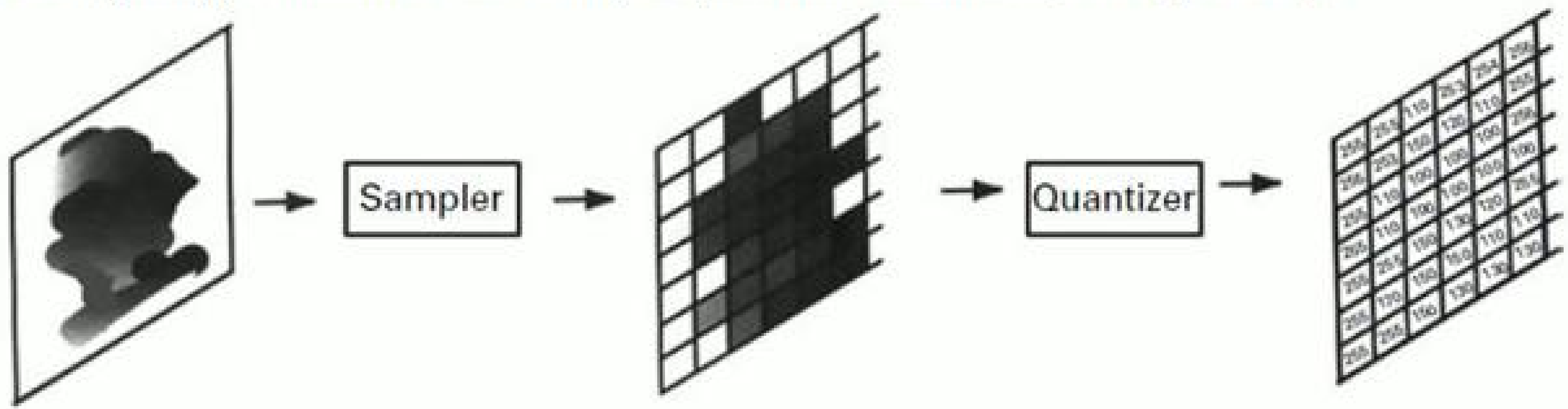
   -SNR (signal to noise ratio) of the resultant image
   - mean and variance

Medical Image Processing

Physicists and engineers have initiated new developments in Medical Imaginary technology, rather than physicians.



Scanning an analog image in a raster fashion. (Adapted from Wolbarst, 1993, p. 207.)



The relationship between an analog image and a digitized image.

The challenge is to obtain an output image that is an accurate representation of the input signal, and then to analyze it and extract as much diagnostic information from the image as possible.

Medical Imaging Developments

Time-line

1940's, 1950's

Background laid for ultrasound and nuclear medicine

1960's

Revolution in imaging – ultrasound and nuclear medicine

1970's

CT (Computerized Tomography)

- true 3D imaging

(instead of three dimensions crammed into two)

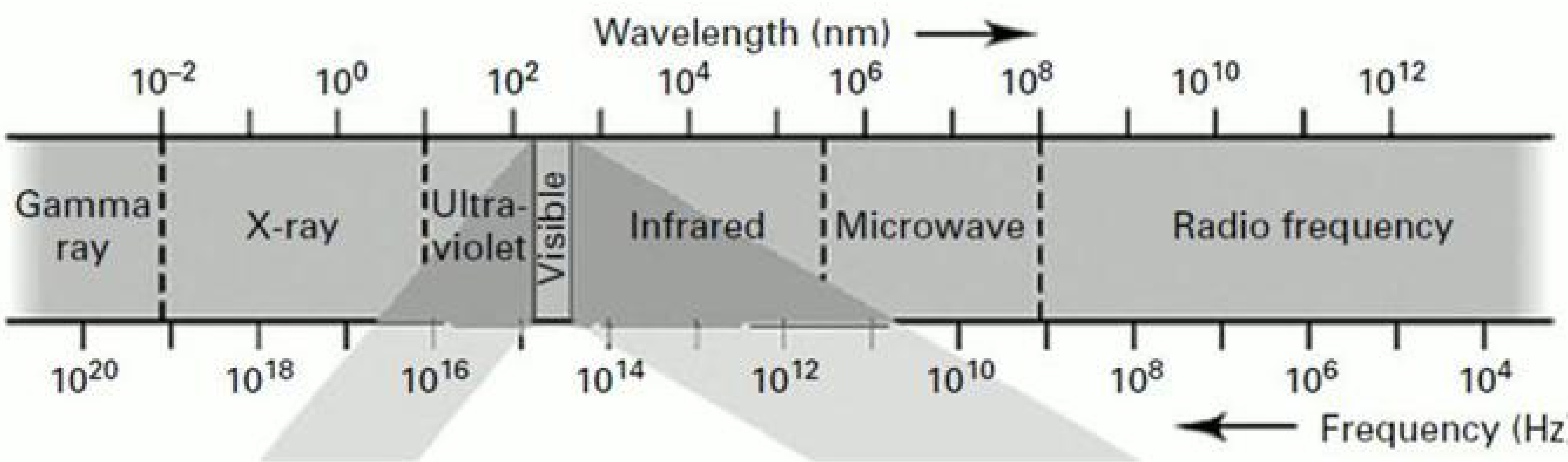
1980's

MRI (Magnetic Resonance Imaging)

PET (Positron Emission Tomography)

Classification of imaging systems by type of radiation or field used.

Type of radiation or field	Examples
Electromagnetic waves	Radio, microwaves, infrared, visible light, ultraviolet, (soft) x-rays
Other waves	Water, sonar, seismic, ultrasound, gravity
Particles	Neutrons, protons, electrons, heavy ions, (hard) x-rays, γ-rays
Quasistatic fields	Geomagnetic, biomagnetic, bioelectric, electrical impedance



Comparison of Modalities

Why do we need multiple modalities?

Each modality measures the interaction between energy and biological tissue.

- Provides a measurement of physical properties of tissue.
- Tissues similar in two physical properties may differ in a third.

Note:

- Each modality must relate the physical property it measures to normal or abnormal tissue function if possible.
- However, anatomical information and knowledge of a large patient base may be enough.
  - i.e. A shadow on lung or chest X-rays is likely not good.

Other considerations for multiple modalities include:

- cost
- safety
- portability/availability

Measures attenuation coefficient

Safety: Uses ionizing radiation
- risk is small, however, concern still present.
- 2-3 individual lesions per 10^6

Use: Principal imaging modality
Used throughout body

Distortion: X-Ray transmission is not distorted.

Measures acoustic reflectivity

Safety: Appears completely safe

Use: Used where there is a complete soft tissue and / or fluid path

Severe distortions at air or bone interface

Distortion:

Reflection: Variations in c (speed) affect depth estimate

Diffraction: $\lambda \approx$ desired resolution (~0.5 mm)

Clinical Applications

	Chest	Abdomen	Head
X-Ray/ CT	+ widely used + CT - excellent	– needs contrast + CT - excellent	+ X-ray - is good for bone – CT - bleeding, trauma
Ultrasound	– no, except for + heart	+ excellent – problems with gas	– poor
Nuclear	+ extensive use in heart	Merge w/ CT	+ PET
MR	+ growing cardiac applications	+ minor role	+ standard

Clinical Applications

	Cardiovascular	Skeletal / Muscular
X-Ray/ CT	+ X-ray – Excellent, with catheter-injected contrast	+ strong for skeletal system
Ultrasound	+ real-time + non-invasive + cheap – but, poorer images	– not used
Nuclear	+ functional information on perfusion	+ functional - bone marrow
MR	+ getting better High resolution Myocardium viability	+ excellent

Clinical Applications

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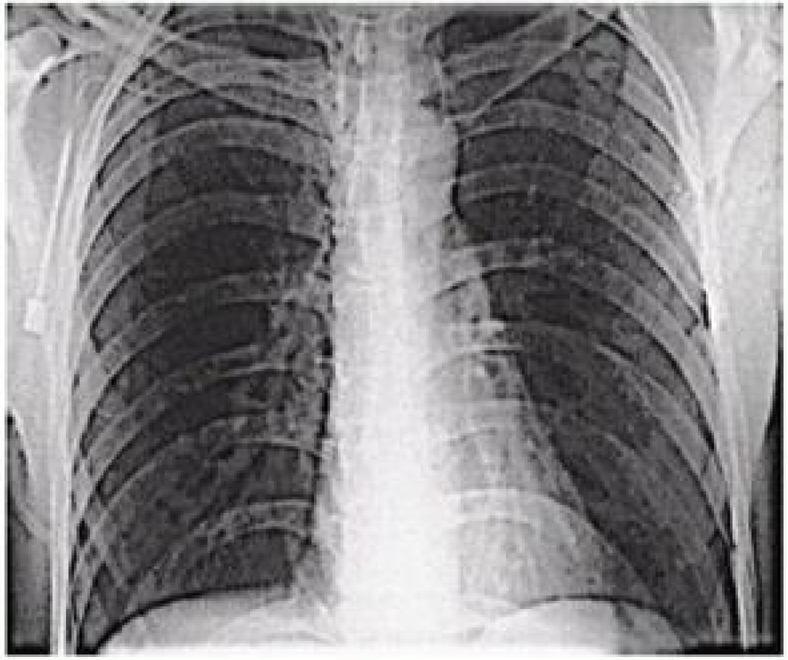
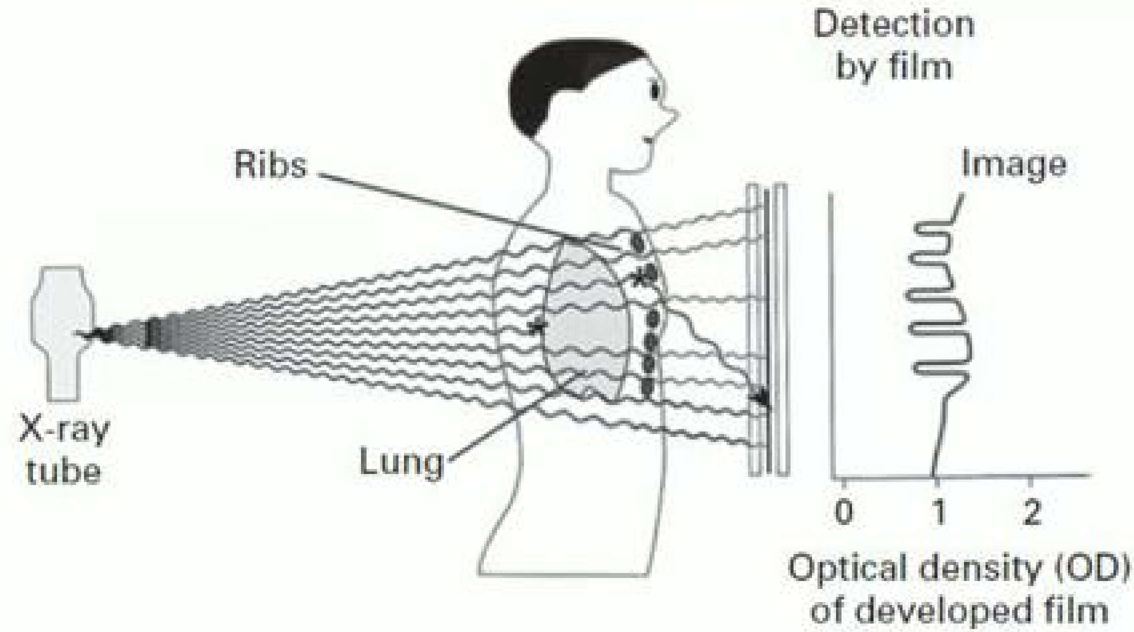
Nuclear	+ functional information on perfusion	+ functional - bone marrow
MR	+ getting better High resolution Myocardium viability	+ excellent

The most common uses of DIP techniques
Improve quality, remove noise etc



X-ray imaging

Basic Principle of X-Ray



Attenuation coefficient $\mu(x, y, z) = \mathrm{f}(\text{electron density, } \mathrm{Z})$

$\mathrm{I_d} = \mathrm{I_o} e^{-\int \mu(x,y,z)\mathrm{dl}}$ Measures line integrals of attenuation

Film shows intensity as a negative (dark areas) for high x-ray detection

X-ray:

X-ray experience some type of interaction with tissues. Tissues with greater density will absorb more of the x-ray so less of the beam reaches the film plate. The resultant image is therefore lighter. Tissues with less density will allow more x-ray to reach the film so it will be darker.

This is called radio density and is determined by:

1. Composition of the structure
2. Thickness of the structure

X-ray response as image for these elements

Air: Black -- trachea, lungs, stomach, digestive tract
Fat: Gray black -- subcutaneously along muscle sheaths; around viscera
Water: Gray -- Muscles, nerves, tendons, ligaments, vessels (All of these structures have the same density and therefore are hard to distinguish on plain x-rays)
Bone: Gray/White
Contrast Medium: White Outline
Heavy Metal: White Solid

X-ray Image Processing Techniques:

❖ **Brightness / Contrast adjustment**

X-ray Image Processing Techniques:

- Contrast inversion

X-ray Image Processing Techniques:

- Image zoom and pan

X-ray Image Processing Techniques:

- Edge detection
- Enhancement
- Measurement and annotation
- Subtraction

X-ray Image Processing Techniques:

- **Subtraction**

Image Processing Techniques in MRI:

- Window / level manipulation
- Image zoom / pan
- Measurement / annotations
- Multi-plannar reconstruction
- Maximum intensity projection
- Shaded surface display
- 3D volume rendering
- 3D Object editing
- Image fusion

Image Processing Techniques in MRI:

- Window / level manipulation

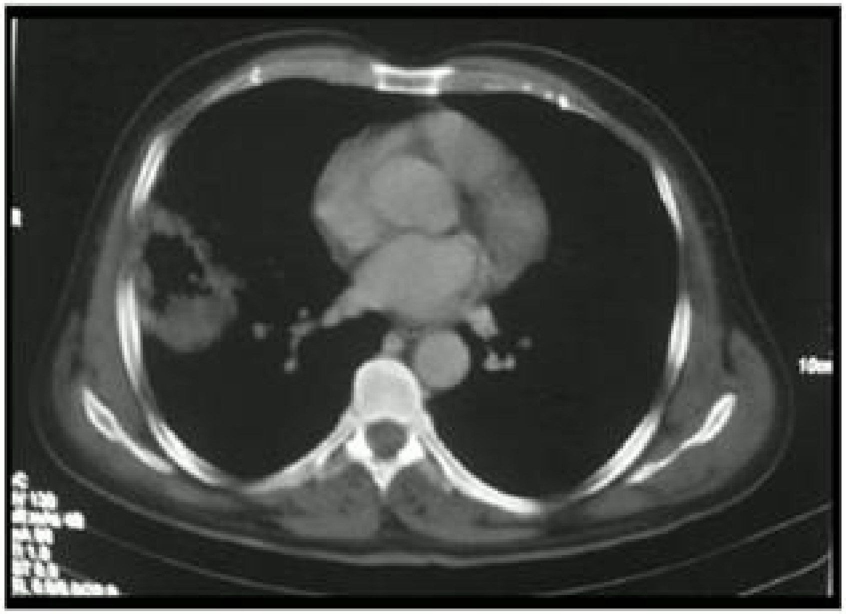


Image Processing Techniques in MRI:

- Multi-plannar reconstruction

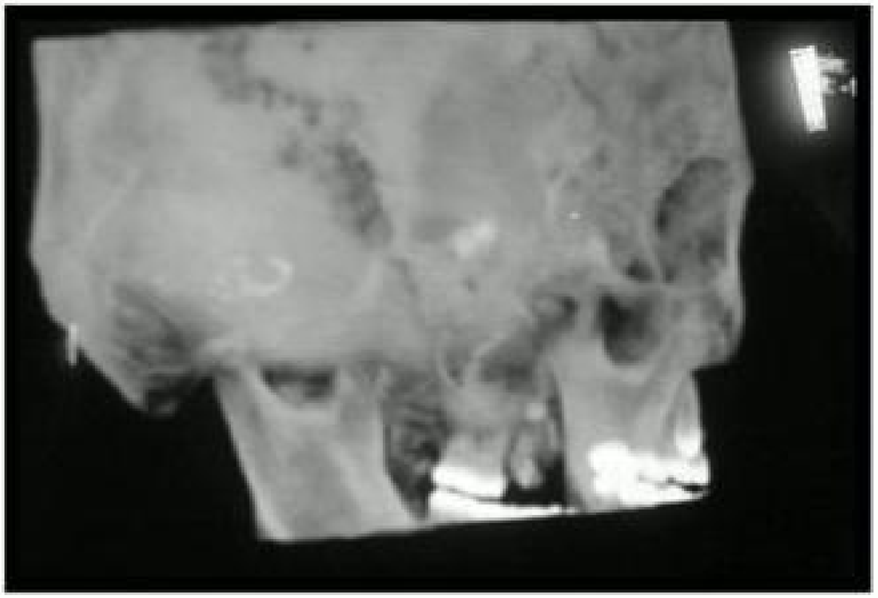


Image Processing Techniques in MRI:

- Shaded surface display

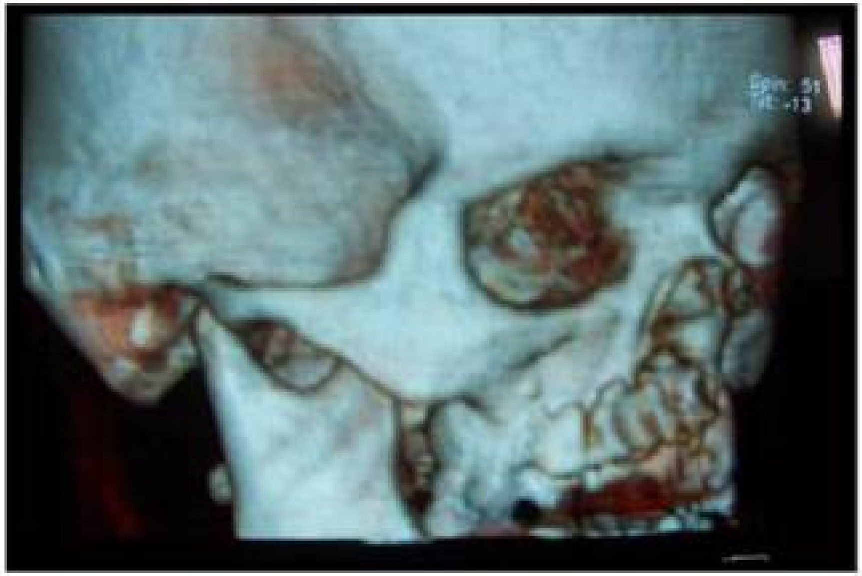


Image Processing Techniques in MRI:

- 3D volume rendering

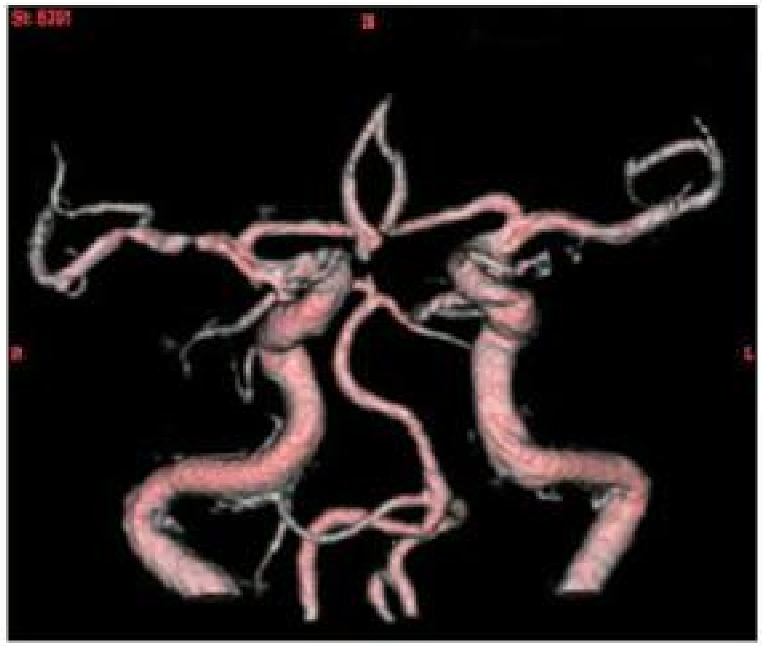


Image Processing Techniques in MRI:

❖ Image fusion

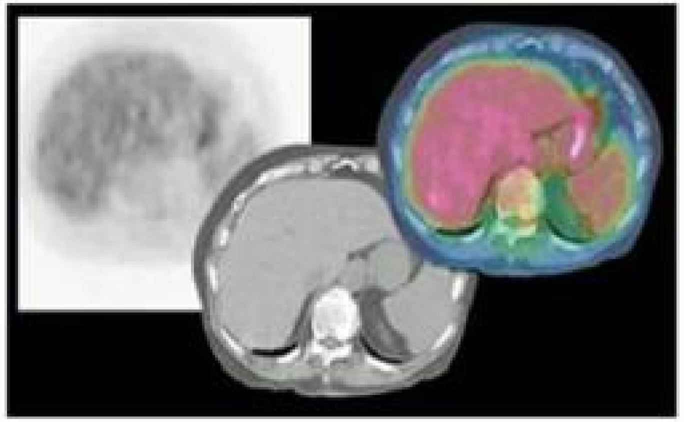


Image Processing Techniques in Ultrasonography:

- ❖Automatic gain compensation mode
- ❖Photopic Imaging
- ❖Measurement / Annotations
- ❖Cine loop
- ❖3D Reconstruction
- ❖Extended field of view

Image Processing Techniques in Ultrasonography:

- Automatic gain compensation mode
- Photopic Imaging
- Measurement / Annotations
- Cine loop
- 3D Reconstruction
- Extended field of view

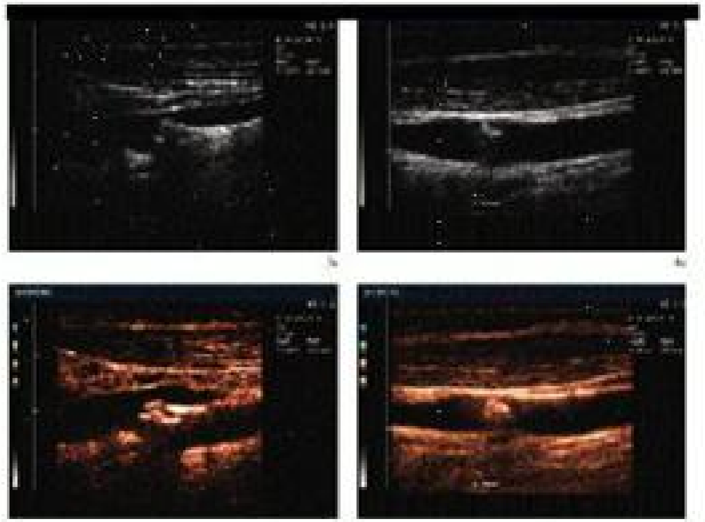


Image Processing Techniques in Ultrasonography:

- Automatic gain compensation mode
- Photopic Imaging
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Image Processing Techniques in Ultrasonography:

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- **Extended field of view**

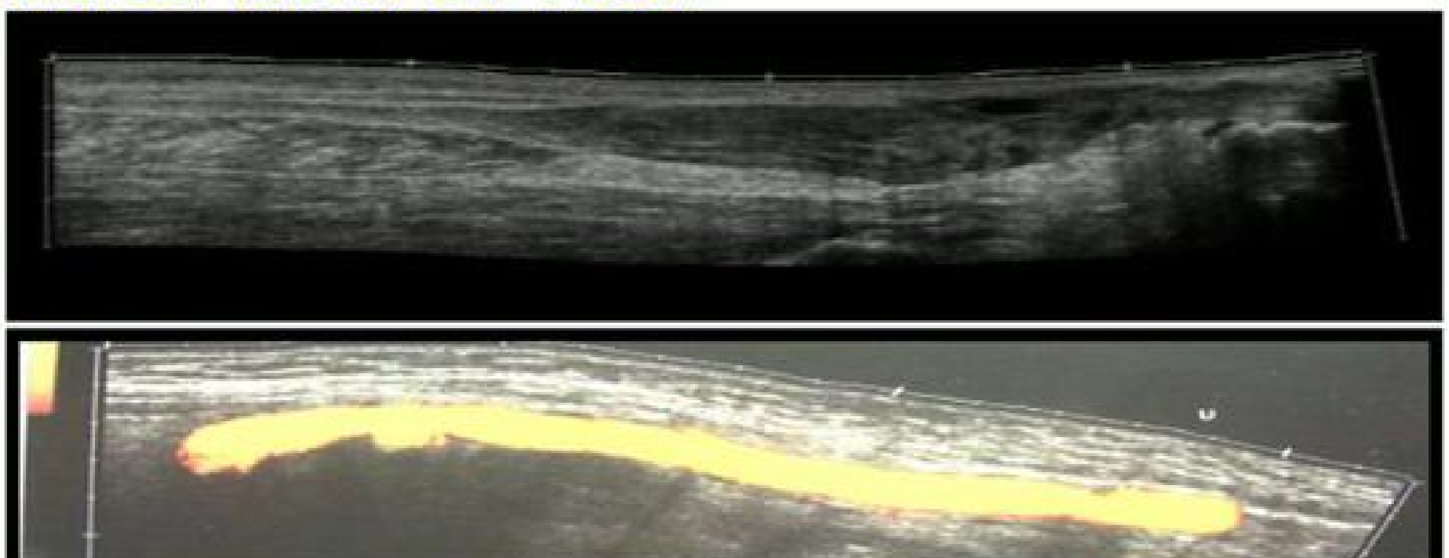


Image artifacts in Computer Tomography:

3. Noise artifacts. Noise causes grainy images and is the result of a low signal-to noise ratio. As a remedy, the signal-to-noise ratio can be increased by higher tube current and tube voltage.

4. Motion artifacts are caused by movements of the patient during image acquisition. These appear as local blurs and streaks on the reconstructed image. Shorter acquisition times are the simplest and most effective way to avoid such artifacts although there are sophisticated algorithms available which can partially correct this effect.

Image artifacts in Computer Tomography:

5. Beam hardening artifacts result from high attenuation coefficients. This is corrected for radiologically water equivalent tissues. Nevertheless, especially bone will harden radiation, resulting in dark streaks in the image.

6. Metal artifacts. If the attenuation is so large that the measured signal is dominated by electronic noise (as it is with metallic objects within the body) the image shows overall deterioration. Dark lines appear which radiate from sharp corners of the object.

Ultrasound Artifacts:

- *Noise: One of the most obvious ultrasound artifacts is speckle. It is a consequence* of the reflection of sound waves on microscopic tissue inhomogeneities.

- Shadowing: Objects with strong echos reflect sound waves in a way that produces a shadow behind the reflecting object while the object is displayed with greater brightness.

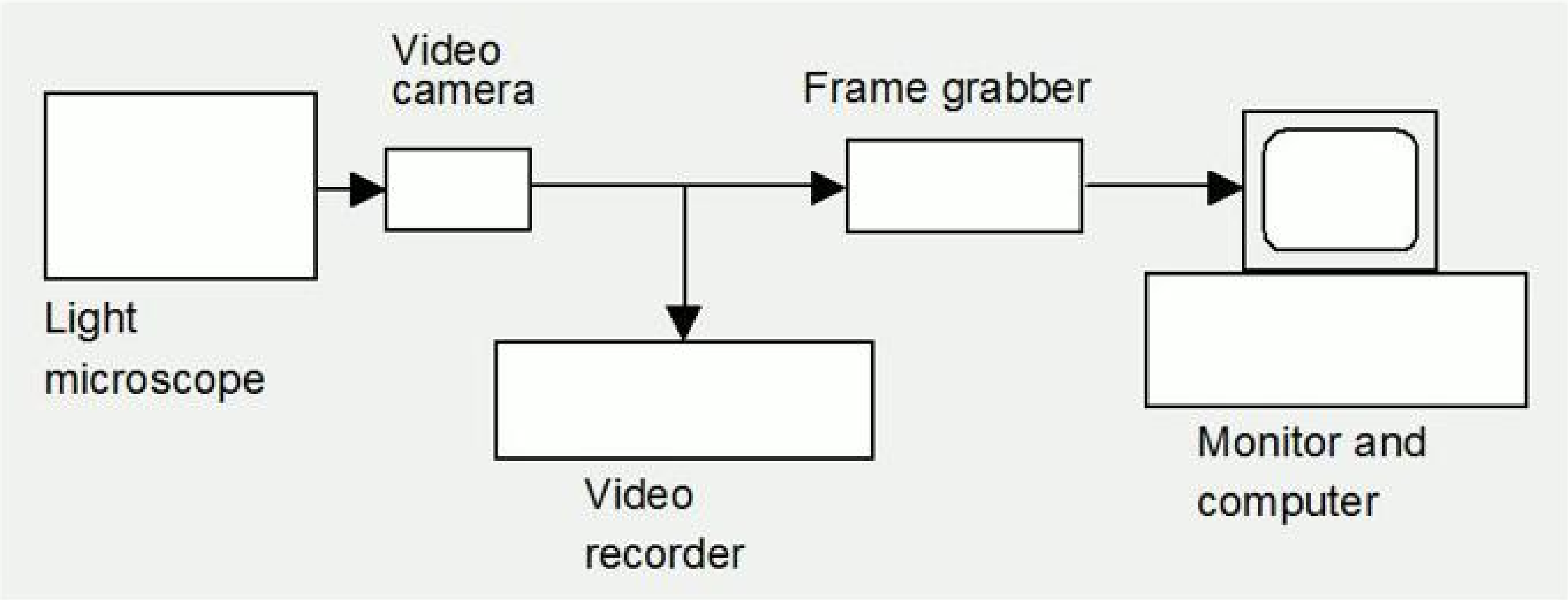
- Multiple reflections between two strong reflectors are displayed as multiple echos where the distance between each of the echo artifacts correlates to the distance between the two reflectors.

- Mirroring: If an object is placed between the transducer and a strongly reflecting layer, the object is mirrored.

Magnetic Resonance Imaging Artifacts:

- Aliasing artifacts occur when the field of view is smaller than the object being imaged. Anatomical structures outside the FOV are mapped to the opposite side of the image. Therefore, the simplest way to compensate for aliasing is to enlarge the FOV to encompass the entire anatomical dimension of the object.

- Chemical shift artifacts occur in the frequency encoding direction when signals from tissues with slightly different resonance frequency compared to water (for instance, fat) are mistaken as signals from water molecules.



Video enhanced contrast microscope (VECM) system.