Reading instructions

• Chapters for this lecture
  – 12.1–12.2 in Gonzales-Woods
The teacher

Research: Cervical cancer screening
Image analysis
What is classification?

Classification is a procedure in which individual **items** (objects/patterns/image regions/pixels) are grouped based on the similarity between the item and the description of the group.
Some important concepts

- Arrangements of descriptors are often called patterns.
- Descriptors are often called features.
- The most common pattern arrangement is a feature vector with $n$-dimensions.
- Patterns are placed in classes of objects which share common properties. A collection of $W$ classes are denoted $\omega_1, \omega_2, \ldots, \omega_W$.
Feature vectors and feature space

\[ \mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \]

Example of a feature space (N=2)

Two features, three classes
Feature vectors and feature space

- Flower example

![Graph of petal length vs petal width with Iris virginica, Iris versicolor, and Iris setosa marked with different symbols.](image)
Object-wise and pixel-wise classification

• Object-wise classification
  – Uses shape, size, mean intensity, mean color etc. to describe patterns.

• Pixel-wise classification
  – Uses intensity, color, texture, spectral information etc.
Object-wise classification

• Example

- 48 objects
- 1 feature (radius)
- 4 (5) classes
- 1-D feature space
Object-wise classification

• Segment the image into regions and label them. These are the patterns to be classified.
• Extract (calculate) features for each pattern. (Lecture 9 and 10)
• Train a classifier on examples with known class to find discriminant functions in the feature space.
• For new examples decide their class using the discriminant function.
Matching by correlation

- Variant of object-wise classification.
- Locate specific objects or patterns.
- Can be used for segmentation.

http://vicos.fri.uni-lj.si/leegle/
Matching by correlation

- Use correlation to match mask $w(x,y)$ with image $f(x,y)$.
- Slide the mask over the image and calculate correlation at each position.

\[ c(x,y) = \sum_{s} \sum_{t} w(s,t) f(x+s, y+t) \]
Matching by correlation

• Example
Pixel-wise classification

- Color image example.
- 256 x 256 patterns (pixels).
- 3 features (red, green and blue band).
- 4 classes (stamen, leaf, stalk and background).

\[
X_{ij} = [r_{ij} g_{ij} b_{ij}]^T
\]

R-layer

G-layer

B-layer
Pixel-wise classification

- Multispectral example
- Five materials with different spectra in a multispectral image.
- Let the reflectance in each band be a feature value for the pixel

\begin{itemize}
  \item Five dimensional feature space (n=5).
  \item Five classes (W=5).
\end{itemize}
Pixel-wise classification

- The pattern is a pixel in a non-segmented image.
- Extract (calculate) features for each pattern (pixel), e.g., color, gray-level representation of texture, temporal changes (Lecture 10).
- Train classifier.
- New samples are classified by classifier.
- Perform relaxation (optional).
Train and classify

• Training
  – Find rules and discriminant functions that separate the different classes in the feature space using known examples.

• Classification
  – Take a new unknown example and put it into the correct class using the discriminant functions.
Train and classify

- Regions in the image are used as training examples (pixel-wise classification).
Discriminant functions

- A **discriminant function** for a class is a function that will yield larger values than functions for other classes if the pattern belongs to the class.

\[ d_i(x) > d_j(x) \quad j = 1, 2, ..., W; \quad j \neq i \]

- For \( W \) pattern classes, we have \( W \) discriminant functions.

- The **decision boundary** between class \( i \) and \( j \)

\[ d_i(x) - d_j(x) = 0 \]
Decision boundary

\[ d_2 - d_1 = 0 \]
Thresholding (simple classification)

- Classify image into foreground and background.

\[ f(x, y) \]

\[ g(x, y) = \begin{cases} 
1 & \text{if } f(x, y) \geq T; \\
0 & \text{if } f(x, y) < T.
\end{cases} \]
Box classification

• Generalized thresholding
  – Multispectral thresholding
• Intervals for each class and feature
• All objects with feature vectors within the same box belong to the same class
Other classification methods

- Bayesian classifiers
  - Maximum likelihood
  - Minimum distance
- Artificial Neural Networks (ANNs)
- Clustering
  - Partitional clustering (K-means)
  - Hierarchical clustering
Bayesian classifiers

- Thomas Bayes 1702 – 1761
- Based on *a priori* knowledge of class probability
- Cost of errors
- Combination gives an optimum statistical classifier (in theory)
- Assumptions to simplify classifier
  - Maximum likelihood (ML) classifier
  - Minimum distance (MD) classifier
Maximum likelihood classifier

• Classify according to the greatest probability (taking variance and covariance into consideration)
• Assume that the distribution within each class is Gaussian
• The distribution within each class can be described by a mean vector and a covariance matrix
Minimum distance classifier

• Each class is represented by its mean vector
• Training is done using the objects/pixels of known class and calculate the mean of the feature vectors for the objects within each class
• New objects are classified by finding the closest mean vector
Reading instructions

• Chapters for next lecture:
  – 12.1–12.2 in Gonzales-Woods
• But! Start preparing L13
  – Chapter 4 in Gonzales-Woods