Reading instructions

- Chapters for this lecture
  - 12.1 – 12.2 in Gonzalez-Woods

Recognition and interpretation

- Machine learning techniques
  - Supervised learning
  - Unsupervised learning
  - Reinforcement learning
  - ...
- Supervised learning
  - Learn classification rules from examples and apply to new unknown examples
- Unsupervised learning
  - Model the input data without examples with known class
Intelligence

- The ability to separate the relevant information from the background of irrelevant details
- The ability to learn from examples and generalise the knowledge so that it can be used in new situations
- The ability to draw conclusions from incomplete information

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

Classification

- An object or pattern is an individual image region or an individual pixel
- A pattern is described using a vector of $N$ descriptors or features – a feature vector.
- Each feature vector is a point in the $N$ dimensional feature space
- Patterns are placed in $W$ classes based on their position in the feature space using discriminant functions

Feature vector and feature space

$$\bar{X} = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{pmatrix}$$

Example of 2D feature space

Two features, four classes
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 \( j \)
  \[ d_i(x) - d_j(x) = 0 \]

Object-wise and pixel-wise

- Object-wise classification
  - Use shape, size, mean intensity, mean colour etc
- Pixel-wise classification
  - Use intensity, colour, texture, spectral information etc

Object-wise classification

Example

- 48 objects (regions in the image)
- 5 classes
- 1 feature (object radius)
- One-dimensional feature space (the histogram)

Steps

- Segment the image into regions and label them. These are the patterns to be classified.
- Extract (calculate) features for each pattern.
- Train the classifier on examples with known class to find the discriminant functions in feature space.
- For new examples decide what class they belong to using the discriminant functions.
Pixel-wise classification

Example: Colour image

- 256 x 256 patterns (pixels)
- Three features (red, green and blue band)
- Four classes (stamen, leaf, stalk and background)
- Three-dimensional feature space

Example: Multispectral image

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

Steps

- The pattern is a pixel in a non-segmented image
- Extract (calculate) features for each pattern (pixel) such as colour (R,G,B,...), greylevel representation of texture, temporal changes
- Train the classifier on examples with known class to find the discriminant functions in feature space
- For new examples decide what class they belong to using the discriminant functions
- 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
  - First apply knowledge, then classify
Train and classify

- Regions in the image are used as training examples in the case of pixel-wise classification.
- The separability of the features can be inspected in a scatterplot.

Original image  
Training areas  
Classification

Scatterplot

Thresholding (simple classification)

- Classify image in foreground and background

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

Box classification

- Generalised thresholding – multispectral thresholding
- Intervals for each class and feature
- All objects with feature vectors within the same box belong to the same class
Common classification methods

- Bayes classifiers
  - Maximum Likelihood
  - Minimum Distance
- Neural Networks

Bayes Classification

- A priori knowledge of class probability
- Cost of errors

These are combined to obtain an optimal classification result.
Different assumptions simplify the 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 performed by calculating the mean of the feature vectors of each class
- New patterns are classified by finding the closest mean vector
Reading instructions

- Chapters for next lectures
  - Object Descriptors II
  - Classification II
  - 11.3 – 11.4 in Gonzalez-Woods
  - 12.1 – 12.2 in Gonzalez-Woods

Matching

- Locate known objects in the image or search for specific patterns
- Part of image understanding
- Can be used for segmentation

Matching by correlation

- Use correlation to match subimage $w(x,y)$ of size $J \times K$ with image $f(x,y)$ of size $M \times N$

$$c(x,y) = \sum_{s} \sum_{t} f(s,t) w(x+s, y+t)$$

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