Classification Lectures

Today

- Object-wise (shape, size, mean colour)
- Pixel-by-pixel (spectral, temporal, artificial)
- Supervised and unsupervised classification
- Decision-theoretic methods
  - Optimum statistical classifiers (Bayes)
    - Maximum likelihood
    - Minimum distance

Tomorrow

- Box classification
- Neural networks
- Clustering
- How to choose classifier
- How to choose features
- Why limit the number of features
- “Ground truth” and training data
Classification

Image acquisition
Preprocessing
Segmentation
Representation
Classification

Intelligence

- The ability to separate the relevant information from a 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.
Classification/Recognition

- We want to create an “intelligent system” that can draw conclusions from our image data.
- No classification, recognition or interpretation is possible without some kind of knowledge.

Object-wise Classification

Definitions

Object A region of interest in a segmented image. We want to recognise, interpret or classify the object.

Feature/Pattern A descriptor (such as shape, size, intensity etc) which can be described by a numerical value. Several features of a single object are often described as a feature vector $\mathbf{x} = [x_1, x_2, \ldots, x_n]^T$, where $n$ is the number of features.

Class A collection of objects that share some common pattern or properties (features). Classes are denoted $w_1, w_2, \ldots, w_M$, where $M$ is the number of classes.

Feature space The space where we draw decision lines between different classes.
Object-wise Classification

- 48 objects.
- One feature (object radius).
- Four classes of objects (0.50, 1, 5 and 10kr).
- One-dimensional feature space (the histogram).

Object-wise Classification

Steps

1. Segment the image into regions.
2. Label the regions.
3. Extract (calculate) features.
4. Based on training on some kind of known data, draw decision lines in feature space.
5. Identify new objects by deciding what class they belong to.

In computer exercise 2 you used step 1 to 4, but you used intuition (instead of training) to draw lines in feature space.
Pixel-by-Pixel Classification

Definitions

Object A pixel in a non-segmented image.

Feature/Pattern The pixel intensity. When using a colour or multispectral image, pixel values from several bands can be combined to form a feature vector \( \mathbf{x} = [x_1, x_2, \ldots, x_n]^T \), where \( n \) is the number of bands.

Class A collection of objects that share some common pattern or properties (features). Classes are denoted \( w_1, w_2, \ldots, w_M \), where \( M \) is the number of classes.

Feature space The space where we draw decision lines between different classes.

Pixel-by-Pixel Classification

Colour Image

- 256×256 objects (pixels).
- Three features (red, green and blue band).
- Four classes of objects (stamen, leaf, stalk, and background).
- Three-dimensional feature space.
Pixel-by-Pixel Classification

Multispectral Image

- Each type of material on the ground reflects electromagnetic waves differently: it has its own spectra.

![Reflectance of spectral bands for different materials.](image)

**Spectral bands:**
- Blue
- Green
- Red
- Near infrared
- Thermal infrared

**Figure:** Reflectance of spectral bands for different materials.

- Let the reflectance for each band represent the feature value:
  \[ \mathbf{x} = [r_1, r_2, r_3, r_4, r_5]^T. \]
- \( \Rightarrow \) We get a 5-dimensional feature space.

Pixel-by-Pixel Classification

Steps

1. Each pixel is considered as an object and is classified based on features such as colour, greylevel representation of texture, temporal changes, etc.
2. Based on training on some kind of known data, draw decision lines in feature space.
3. Identify new pixels by deciding what class they belong to.
4. Perform relaxation (optional).

**No segmentation used in pixel-by-pixel classification!**
### Training and Testing

- **Figure:** Original image.
- **Figure:** Training areas.
- **Figure:** Classification.

Train by assigning objects to known classes.

- When having more than one image in your data set, use half of your data set for training, and half for testing.

### Classification Methods

#### A Selection

**Supervised methods**
- Bayes Classifiers
  - Maximum Likelihood
  - Minimum Distance
- Box Classifier
- Neural Network

**Unsupervised methods**
- Clustering
  - \(k\)-Means Clustering
  - Hierarchical Clustering
Unsupervised Classification

- Assume that objects that have feature vectors that lie close together in feature space belong to the same class.
- Order the feature vectors into “natural” clusters representing the classes.
- After clustering:
  - Compare with reference data.
  - Identify the classes.

First classify, then apply knowledge.

Supervised Classification

- Objects/pixels belonging to a known class are used for training of the system and drawing decision lines between different classes.
- New objects/pixels are classified using the decision lines.

First apply knowledge, then classify.
Bayes Classification

- A priori knowledge of class probabilities.
- Cost of errors.

These are weighted together to achieve an optimal classification result.

Different kinds of 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

\[ x_1 = \frac{P^2}{A} \]

- Each class is represented by its mean vector.
- Training is done by 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.

\[ x_2 = \text{grey-variation} \]

\[ d_2 - d_1 = 0 \]

decision border