

Lecture Narrative: Image Segmentation

Recording Notes

Each subsection corresponds to one slide in the Image Segmentation lecture. Slide numbers follow the order of the presentation from title to the final clustering discussion.

Slide 1: Image Segmentation

This lecture introduces image segmentation, which is the task of partitioning an image into meaningful regions. Segmentation is a foundational problem in computer vision and often serves as the first step toward higher-level understanding.

Slide 2: Source

This material is adapted from lecture notes available at Imperial College London. The focus here is on classical segmentation methods rather than modern deep learning approaches.

Slide 3: Introduction to Image Segmentation

The goal of image segmentation is to divide an image into regions that are meaningful for a particular application. The definition of “meaningful” depends heavily on the task we are trying to solve.

Slide 4: Measurements Used for Segmentation

Segmentation can be based on many different image measurements, including greylevel intensity, color, texture, depth, or motion. Different applications require different cues.

Slide 5: Segmentation as an Initial Step

Segmentation is usually an early and crucial step in a larger vision pipeline. Errors at this stage can propagate and negatively affect later processing.

Slide 6: Applications of Segmentation

Applications include identifying objects for measurement, segmenting moving objects for video compression, and separating objects by depth for robotic navigation.

Slide 7: Greyscale-Based Segmentation Example

This example shows segmentation based purely on greyscale intensity. Using a very simple intensity model often leads to incorrect object labeling.

Slide 8: Limitations of Greyscale Segmentation

Greyscale-based segmentation struggles when object and background intensities overlap, resulting in ambiguous boundaries.

Slide 9: Texture-Based Segmentation Example

Segmentation based on texture can distinguish regions even when greyscale values vary within objects.

Slide 10: Motivation for Texture Segmentation

Texture allows us to capture local patterns rather than raw intensity, making segmentation more robust in complex scenes.

Slide 11: Motion-Based Segmentation

Segmentation based on motion requires estimating optical flow, which introduces uncertainty. The segmentation relies on estimated motion rather than true motion.

Slide 12: Challenges in Motion Segmentation

Errors in optical flow estimation directly affect segmentation accuracy, making this a challenging problem.

Slide 13: Depth-Based Segmentation

Depth segmentation uses distance measurements, often from sensors like laser range finders, to separate objects by distance.

Slide 14: Robotics Motivation

Depth-based segmentation is especially useful in robotics, where understanding object distance enables navigation and path planning.

Slide 15: Example Images

This slide shows an original image, its corresponding range image, and the resulting segmented image.

Slide 16: Histogram-Based Segmentation

We now focus on simple segmentation techniques based on the greylevel histogram of an image, specifically thresholding and clustering.

Slide 17: Test Images

We will examine noise-free, low-noise, and high-noise images to understand how noise affects segmentation performance.

Slide 18: Histogram Interpretation

Histograms allow us to visualize the distribution of greylevels and assess how well object and background are separated.

Slide 19: Noise-Free Histogram

In the noise-free case, the histogram consists of two spikes corresponding to object and background intensities.

Slide 20: Low-Noise Histogram

With low noise, the spikes become broader peaks, but the object and background are still distinguishable.

Slide 21: High-Noise Histogram

With high noise, the peaks merge into a single distribution, making segmentation much harder.

Slide 22: Signal-to-Noise Ratio

We define the signal-to-noise ratio in terms of the mean greylevels of object and background and the noise standard deviation.

Slide 23: SNR for Test Images

For the noise-free image, the SNR is infinite. For the low-noise image, it is approximately 5, and for the high-noise image, it drops to around 2.

Slide 24: Greylevel Thresholding

Thresholding is one of the simplest segmentation methods. A single threshold value separates object from background.

Slide 25: Histogram Valley

In the low-noise case, there is a clear valley between the object and background peaks where a threshold can be placed.

Slide 26: Threshold Definition

The thresholding rule assigns pixels to object or background depending on whether their greylevel is below or above the threshold.

Slide 27: Choosing the Threshold

The key challenge is selecting an appropriate threshold value. Several strategies exist, including interactive and adaptive methods.

Slide 28: Minimization Approach

We focus on a minimization approach that selects the threshold by minimizing the within-group variance.

Slide 29: Idealized Histogram

An ideal object-background histogram helps illustrate how thresholding divides pixels into two groups.

Slide 30: Within-Group Variance

Each threshold defines two groups, each with its own mean and variance. The goal is to make each group as homogeneous as possible.

Slide 31: Optimal Threshold

The optimal threshold minimizes the weighted sum of variances within the object and background groups.

Slide 32: Group Definitions

Object pixels have greylevels less than or equal to the threshold, while background pixels exceed it.

Slide 33: Prior Probabilities

The prior probabilities of object and background are computed directly from the histogram.

Slide 34: Group Statistics

The mean and variance of each group can be derived from the histogram and threshold.

Slide 35: Optimization

The within-group variance is evaluated for all possible thresholds, requiring only 256 comparisons for an 8-bit image.

Slide 36: Threshold Result

For the low-noise image, the optimal threshold is approximately 124, roughly midway between the two peaks.

Slide 37: Applying the Threshold

Applying this threshold segments both the low-noise and high-noise images.

Slide 38: Low-Noise Segmentation Result

The segmentation works reasonably well for the low-noise image.

Slide 39: High-Noise Segmentation Result

In the high-noise case, significant pixel misclassification is visible.

Slide 40: Misclassification Analysis

Misclassification arises from overlap between object and background histograms.

Slide 41: Fundamental Limitation

No threshold can perfectly separate object and background when their greylevel distributions overlap.

Slide 42: Error Probability

The probability of error increases as histogram overlap increases.

Slide 43: Introduction to Greylevel Clustering

We now consider greylevel clustering as an alternative to thresholding.

Slide 44: Clustering Idea

Clustering separates greylevels into groups based on proximity to cluster centers.

Slide 45: Cluster Centers

Two cluster centers represent object and background intensities.

Slide 46: Nearest Neighbor Assignment

Each greylevel is assigned to the cluster whose center is closest.

Slide 47: Relation to K-Means

This approach is a simple case of K-means clustering, which is widely used in practice.

Slide 48: Partitioning the Data

The greylevels are partitioned into two sets corresponding to object and background.

Slide 49: Updating Cluster Means

Cluster centers are updated as the mean greylevel of assigned pixels.

Slide 50: Chicken-and-Egg Problem

Cluster assignments depend on cluster means, and cluster means depend on assignments.

Slide 51: Iterative Solution

This dependency is resolved using an iterative algorithm.

Slide 52: Iterative Algorithm Steps

The algorithm alternates between updating cluster means and reassigning pixels.

Slide 53: Convergence Questions

Two key questions arise: does the algorithm converge, and what does it converge to?

Slide 54: Cost Function

We define a cost function measuring within-cluster variance.

Slide 55: Updating the Cost

Each iteration reduces or maintains the cost function value.

Slide 56: Proof of Convergence

Because the cost is non-increasing and bounded below, the algorithm must converge.

Slide 57: Interpretation of the Result

The algorithm converges to a local minimum of within-cluster variance.

Slide 58: Relation to Thresholding

For well-separated clusters, clustering and thresholding yield similar results.

Slide 59: Performance Comparison

Both methods degrade as object and background distributions overlap.

Slide 60: Key Takeaways

Simple histogram-based methods are intuitive and efficient but fundamentally limited by noise and overlap.

Slide 61: Transition Forward

These limitations motivate more advanced segmentation methods based on spatial context, texture, and learning-based models.