Lecture 11: Image Segmentation

CAP5415-Computer Vision
Lecture 11-Image Segmentation (BASICS): Thresholding, Region Growing, Clustering

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Lecture 11: Image Segmentation

Image Segmentation

• **Aim:** to partition an image into a collection of set of pixels
  – Meaningful regions (coherent objects)
  – Linear structures (line, curve, ...)
  – Shapes (circles, ellipses, ...)
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  - Meaningful regions (coherent objects)
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- Content based image retrieval
- Machine Vision
- Medical Imaging applications (tumor delineation,..)
- Object detection (face detection,...)
- 3D Reconstruction
- Object/Motion Tracking
- Object-based measurements such as size and shape
- Object recognition (face recognition,...)
- Fingerprint recognition,
- Video surveillance
...
In computer vision, image segmentation is one of the oldest and most widely studied problems.

- Early techniques -> region splitting or merging
- More recent techniques -> Energy minimization
Image Segmentation Methods

- Thresholding
- Region based methods (region growing,..)
- Machine Learning based methods
- Clustering (k-means, mean shift,..)
- Energy minimization methods (MRF,..)
- Shape based methods (level set, active contours)
- Graph-based methods (graph-cut, random walk,..)
• **Definition:** *Image segmentation* partitions an image into regions called *segments.*
Basics of Image Segmentation

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Image segmentation creates segments of connected pixels by analyzing some *similarity criteria:*

*intensity, color, texture, histogram, features, ...*
Image Binarization

- Image binarization applies often just one global threshold $T$ for mapping a scalar image $I$ into a binary image
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$$J(x, y) = \begin{cases} 
0 & \text{if } I(x, y) < T \\
1 & \text{otherwise.}
\end{cases}$$
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- The **global threshold** can be identified by an optimization strategy aiming at creating “large” connected regions and at reducing the number of small-sized regions, called *artifacts*. 
**Image Binarization**

- **Thresholding:** Most frequently employed method for determining threshold is based on histogram analysis of intensity levels.

  - Peak on the left of the histogram corresponds to dark objects
  - Peak on the right of the histogram corresponds to brighter objects

**DIFFICULTIES**
1. The valley may be so broad that it is difficult to locate a significant minimum
2. Number of minima due to type of details in the image
3. Noise
4. No visible valley
5. Histogram may be multi-modal
Thresholding Example

Original Image

Thresholded Image
Thresholding Example 2

Threshold Too Low

Threshold Too High
Thresholding Example 3
Thresholding Example-4

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(a) Image of cells with varying intensities.
(b) Histogram showing the distribution of intensities.
(c) Image with threshold set to 110, showing some cells are below the threshold.
(d) Image with threshold set to 147, showing more cells are now below the threshold.
(e) Image with threshold set to 185, showing all cells are below the threshold.
Otsu Thresholding

- **Definition:** The method uses the grey-value histogram of the given image $I$ as input and aims at providing the best threshold in the sense that the “overlap” between two classes, set of object and background pixels, is minimized (i.e., by finding the best balance).
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- Otsu’s algorithm selects a threshold that maximizes the between-class variance $\sigma_b^2$. In the case of two classes,

$$
\sigma_b^2 = P_1 (\mu_1 - \mu)^2 + P_2 (\mu_2 - \mu)^2 = P_1 P_2 (\mu_1 - \mu_2)^2
$$

where $P_1$ and $P_2$ denote class probabilities, and $\mu_i$ the means of object and background classes.
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• Let $c_I$ be the relative cumulative histogram of an image I, then $P_1$ and $P_2$ are approximated by $c_I(u)$ and $1 - c_I(u)$ respectively.

• $u$ is assumed to be the chosen threshold.
Otsu Thresholding Algorithm

1: Compute histogram \( H_I \) for \( u = 0, \ldots, G_{\text{max}} \);
2: Let \( T_0 \) be the increment for potential thresholds; \( u = T_0; T = u; \) and \( S_{\text{max}} = 0; \)
3: \textbf{while} \( u < G_{\text{max}} \) \textbf{do}
4: \hspace{1em} Compute \( c_I(u) \) and \( \mu_i(u) \) for \( i = 1, 2 \);
5: \hspace{1em} Compute \( \sigma_b^2(u) = c_I(u)[1 - c_I(u)][\mu_i(u) - \mu_2(u)]^2; \)
6: \hspace{1em} \textbf{if} \( \sigma_b^2(u) > S_{\text{max}} \) \textbf{then}
7: \hspace{2em} \( S_{\text{max}} = \sigma_b^2(u) \) and \( T = u; \)
8: \hspace{1em} \textbf{end if}
9: \hspace{1em} Set \( u = u + T_0 \)
10: \textbf{end while}

\[
\begin{align*}
\mu_1 &= \sum_{i=0}^{u} ip(i)/P_1 \\
\mu_2 &= \sum_{i=u+1}^{G_{\text{max}}} ip(i)/P_2 \\
\sigma_b^2 &= \sum_{i=0}^{G_{\text{max}}} (i - \mu_1)^2 p(i) / P_1 \\
\end{align*}
\]

\( P_1 = \sum_{i=0}^{u} p(i) \quad \mu_1 = \sum_{i=0}^{u} ip(i)/P_1 \)

\( P_2 = \sum_{i=u+1}^{G_{\text{max}}} p(i) \quad \mu_2 = \sum_{i=u+1}^{G_{\text{max}}} ip(i)/P_2 \)

\text{probabilities} \quad \text{Class means}

(a) Two distinct modes \quad (b) Overlapped modes
Example: Otsu Thresholding
Region Based Segmentation
Region Based Segmentation - Basics

Region:
A group of connected pixels with similar properties.

Closed boundaries

Computation of regions is based on similarity.

Regions may correspond to Objects in a scene or parts of objects.

Spatial proximity + similarity
Region Growing

• For segment generation in grey-level or color images, we may start at one seed pixel \((x,y, I(x,y))\) and add recursively adjacent pixels that satisfy a “similarity criterion” with pixels contained in the so-far grown region around the seed pixel.
Region Growing

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- Defining similarity criteria alone is not an effective basis for segmentation
- It is necessary to consider the adjacency spatial relationship between pixels
Region Growing

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Algorithm

1. The absolute intensity difference between candidate pixel and the seed pixel must lie within a specified range
2. The absolute intensity difference between a candidate pixel and the running average intensity of the growing region must lie within a specified range;
3. The difference between the standard deviation in intensity over a specified local neighborhood of the candidate pixel and that over a local neighborhood of the candidate pixel must (or must not) exceed a certain threshold
Seeded Segmentation (Region Growing)

1. Choose the seed pixel
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2. Check the neighboring pixels and add them to the region if they are similar to the seed
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3. Repeat step 2 for each of the newly added pixels; stop if no more pixels can be added

\[ |\text{neighboring pixels} - \text{seed}| < \text{Threshold} \]
Ex: Muscle/Bone Segmentation in CT Scans
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**Region Growing Implementation**

*growRegion*: red nodes are the "active_front" (queue or stack)

- Add seed into *active_front*
- Stop when *active_front* is empty

**Algorithm:**
- Remove pixel \( p \) from *active_front*
- Mark it as \( \text{region}[p] = 1 \)
- Add all neighbors \( q \) such that:
  \[ \text{region}[q] = 0, \quad |I_p - I_q| < T \]
- Set \( \text{region}[q] = -1 \)

Object with small intensity variation within the image.
Limitations of Region Growing

Note that a complete segmentation of an image must satisfy a number of criteria:

1) All pixels must be assigned to regions
2) Each pixel must belong to a single region only
3) Each region must be a connected set of pixels
4) Each region must be uniform
5) Any merged pair of adjacent regions must be non-uniform
Comparison of Thresholding and Region Growing

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region growing with variance of 2 in respect to value 11 with reference to threshold $T \geq 11$
Region splitting and Merging Segmentation

• Region splitting:
  – Unlike region growing, which starts from a set of seed points, region splitting starts with the whole image as a single region and subdivides it into subsidiary regions recursively while a condition of homogeneity is not satisfied.
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  – Region merging is the opposite of splitting, and works as a way of avoiding over-segmentation
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• Region merging:
  – Region merging is the opposite of splitting, and works as a way of avoiding over-segmentation
  – Start with small regions (2x2 or 4x4 regions) and merge the regions that have similar characteristics (such as gray level, variance).
Region splitting and Merging Segmentation

- RAG: region adjacency graph
- Quadtree for splitting (top-down) procedure

RAG with adjacency relations (in red) for big black region.
Algorithm:

- If a region R is inhomogeneous (P(R) = FALSE), then R is split into four sub-regions.
- If two adjacent regions $R_i, R_j$ are homogeneous (P($R_i \cup R_j$) = TRUE), they are then merged.
- The algorithm stops when no further splitting or merging is possible.
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Region splitting and Merging Segmentation

- Original image:
- Split 1:
- Split 2:
- Split 3:
Clustering Based Segmentation Methods
What is Clustering?

• Organizing data into classes such that:
  – High intra-class similarity
  – Low inter-class similarity

• Finding the class labels and the number of classes directly from the data (as opposed to classification tasks)
What is a natural grouping?
What is a natural grouping?

Clustering is subjective

Simpson's Family  School Employees  Females  Males
What is similarity?
What is similarity?

Cluster by features

• Color
• Intensity
• Location
• Texture
• ....
Distance metrics

0.23

3

342.7
K-means Clustering
K-means Clustering
K-means Clustering
K-means Clustering
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K-means Clustering
Mean-Shift Segmentation

- **Mean-shift** is a variant of an iterative steepest-ascent method to seek stationary points (i.e., peaks) in a density function, which is applicable in many areas of multi-dimensional data analysis.

[Segmented "landscape 1" and "landscape 2"]

[http://www.caip.rutgers.edu/~comanici/MSPAMI/msPamiResults.html](http://www.caip.rutgers.edu/~comanici/MSPAMI/msPamiResults.html)
Mean-Shift Segmentation

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- openCV -> meanShift method available.
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- Attempts to find all possible cluster centers in feature space (unlike k-means, where there is a requirement to know the number of different clusters).
Mean-Shift Segmentation

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- The mean shift algorithm seeks *modes* or *local maxima* of density in the feature space.
Mean-Shift

A tool for:
Finding modes in a set of data samples, manifesting an underlying probability density function (PDF) in $\mathbb{R}^N$
Density Estimation

- What is the distribution that generated these points?
Density Estimation

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• **Parametric model:** Can express distr. with a few parameters (mean and variance)
Density Estimation

• What is the distribution that generated these points?
• **Parametric model:** Can express distr. with a few parameters (mean and variance)
• Limited in flexibility!
Non-parametric density estimation

• Focus on kernel density estimates, using the data to define the distribution
• Build distribution by putting a little mass of probability around each data-point
Nonparametric Density Estimation

Determining parameters of unknown number of probability functions of an unknown type will be difficult!
Basics Assumptions

- The probability density functions of the mixture models have only one max and that this maximum represents the mean of the function.
- Combining the probability functions in the mixture model preserves the maxima, local maxima are the modes of the density functions.
- The local minima of the mixture model segment the feature space so that each segment contain only one of the local maxima.
Recap: Nonparametric Density Estimation

• Consider image pixels as data points \( (x) \).
Recap: Nonparametric Density Estimation

- Consider image pixels as data points (x).
- Probability that x belongs to a sub-domain D

\[ P = \int_{D} p(x) \, dx \]
Recap: Nonparametric Density Estimation

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Recap: Nonparametric Density Estimation

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\[
P \approx p(x) \int_D dx
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Recap: Nonparametric Density Estimation

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  \[
P \approx p(x) \int_D dx = p(x) V
  \]
Recap: Nonparametric Density Estimation

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Recap: Nonparametric Density Estimation

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• If \(D\) is small, pdf is fairly constant inside, so
  \[
  P \approx p(x) \int_D dx
  \]
  \[
  P \approx p(x) \int_D dx = p(x)V \Rightarrow p(x) = \frac{P}{V}
  \]
Mean-Shift Basics

- **Mean-Shift** is a procedure for locating maxima of a density function given discrete data samples from that function.
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- This is an iterative method, and we start with an initial estimation of $x$. 
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• The weighted mean of the density in the window determined by $K$
Mean-Shift Basics

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- Let a kernel function \( K(x_i - x) \) be given, determining the weight of nearby points for re-estimation of the mean.
- The weighted mean of the density in the window determined by \( K \)

\[
m(x) = \frac{\sum_{x_i \in N(x)} K(x_i - x) x_i}{\sum x_i \in N(x) K(x_i - x)}
\]

N(x): neighborhood of x
m(x) – x: mean shift
Mean-Shift

FIND DENSEST REGION!
Mean-Shift

Search window
Center of mass

Mean Shift vector

Slide by Y. Ukrainitz & B. Sarel
Mean-Shift

Search window
Center of mass

Mean Shift vector

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Slide by Y. Ukrainitz & B. Sarel
Mean-Shift

Search window
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Mean-Shift

Mean Shift vector

Search window

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Mean-Shift

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Center of mass

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Slide by Y. Ukrainitz & B. Sarel
Practical Knowledge

Tessellate the space with windows

Run the procedure in parallel
Mean-Shift Clustering

- Find features (color, gradients, texture, etc)
- Initialize windows at individual feature points
- Perform mean shift for each window until convergence
- Merge windows that end up near the same “peak” or mode
Mean-Shift Clustering
Trajectory: $x, m(x), (m(m(x))), \ldots$
Mean-Shift Clustering

- Gradient ascent requires computing a gradient of the density function.
- Density function is only approximated by a distribution of samples, the gradient can only be approximated as well!!!
- This is done by a kernel window estimator.
Practical Knowledge-2

- The most popular kernel is Gaussian! (i.e., $K$)

$$K(x) = \exp(-|x|^2)$$

- Epanechnikov kernel

$$K(x) = \begin{cases} 
3(1-x^2)/4 & \text{if } |x| \leq 1 \\
0 & \text{else} 
\end{cases}$$
Practical Knowledge-3

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Parameters of the Mean-Shift Segmentation

- $h_s$: spatial resolution parameter
  - Affects the smoothing, connectivity of segments
- $h_r$: range resolution parameter
  - Affects the number of segments
- $M$: size of smallest segment
  - Should be chosen based on size of noisy patches
Parameters of the Mean-Shift Segmentation

Original

(hs, hr) = (8, 4)

(hs, hr) = (8, 7)
Ex: Mean-Shift Segmentation
Ex: Mean-Shift Segmentation
Mean-shift pros and cons

• **Pros**
  – Does not assume spherical clusters
  – Just a single parameter (window size)
  – Finds variable number of modes
  – Robust to outliers

• **Cons**
  – Output depends on window size
  – Computationally expensive
  – Does not scale well with dimension of feature space
Slide Credits and References

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