

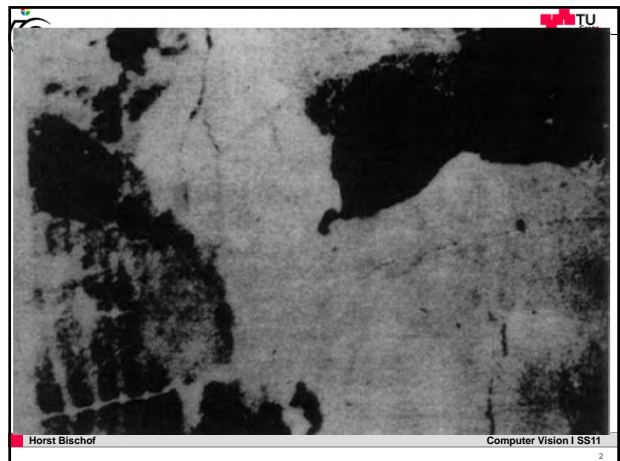
SEGMENTATION

Readings:

Szeliski: Chapter 5 (5.2,5.3,5.4)
Chapter 4 (4.2.2, 4.3.2)

Some Slides adapted from Univ. of Washington
<http://www.cs.washington.edu/education/courses/cse576/08sp/>

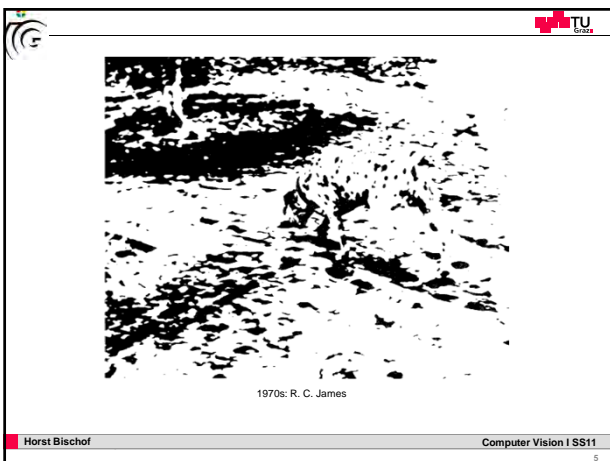
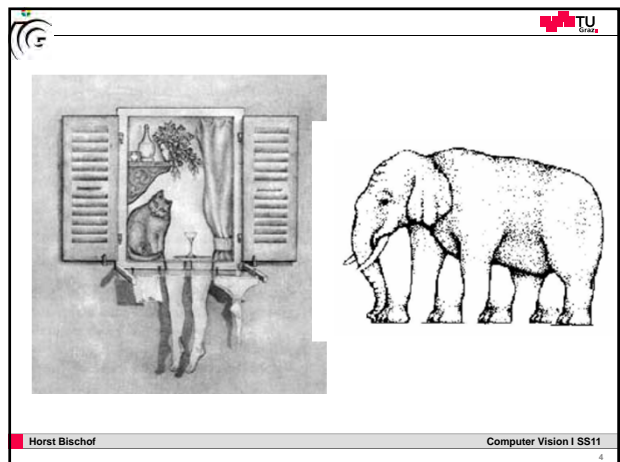
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It can get a lot harder

Brady, M. J., & Kersten, D. (2003). Bootstrapped learning of novel objects. J Vis, 3(6), 413-422

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From images to objects

- What Defines an Object?
 - Subjective problem, but has been well-studied
 - Gestalt Laws seek to formalize this
 - proximity, similarity, continuation, closure, common fate

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Extracting objects



- How could this be done?

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Segmentation

• Definition:
Partition Image in Regions S_i such that following conditions are satisfied (H is homogeneity Criterion)

1. $I = \bigcup_{i=1}^m S_i$
2. $S_i \cap S_j = \emptyset$ for all $i \neq j$
3. $H(S_i) = TRUE$ For all i
4. $H(S_i \cup S_j) = FALSE$ for neighboring S_i and S_j , $i \neq j$

- Neither partition nor number of Segments (m) needs to be unique
- m need not be minimal

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Segmentation

Thresholding
– Simple & Fast

Edge based segmentation
– How to find closed edges

Region-based Methods

- Region Growing
- Split & Merge
- Clustering
- Mean-Shift

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Thresholding

Partition image according to homogeneity (gray value, color, etc.)

Partition according to gray value (i.e. partition Histogram
→ cf. Relation to Quantization

Main Question:
– How to determine the Threshold

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Thresholding

$g(i,j) = 1$ for $f(i,j) > T$
 $= 0$ otherwise

Global Threshold

$T = T(f)$

Local Threshold

$T = T(f, f_c)$ (f_c part of image where T is determined)

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Methods for Thresholding

If **a priori** information is known the selection of the threshold is simplified

Example1: Printed Text p% of page are covered with letters
→ set Threshold (p-tile thresholding) such that %p Pixels are black

Example2: Knowledge about line width
→ set Threshold such that lines have required width

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Threshold Selection

- More complex methods are based on histogram analysis
- If object is uniform (in gray value) and differs from background gray value
 - ➔ Histogram is **bimodal**
 - ➔ Object pixels form Peak in Histogram
 - ➔ Background Pixels form a second Peak in Histogram
 - ➔ Gray values in between peaks are not common (border pixels between the object and background)
 - ➔ Select Threshold according to minimum histogram value between maxima

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Histogram-based segmentation

- Goal
 - Break the image into K regions (segments)
 - Solve this by reducing the number of colors to K and mapping each pixel to the closest color

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Histogram-based segmentation

- Goal
 - Break the image into K regions (segments)
 - Solve this by reducing the number of colors to K and mapping each pixel to the closest color

Here's what it looks like if we use two colors

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Threshold Selection

- Difficult to interpret significance of maxima/minima
- Bimodal Algorithms, detect first highest maxima, select threshold as minimum between these local (**mode method**)
- Minimum Distance between Maxima is enforced.
- Histogram smoothing, helps in detecting significant Maxima/Minima
- When constructing histogram use also local neighborhood information (pixels without/with high gradient) to get clearer maxima/minima

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Optimal Thresholding

Assume distribution (normal) of gray-values
→ Fit distributions and determine Threshold

Figure 5.4 Gray level histograms approximated by two normal distributions: the threshold is set to give minimum probability of segmentation error: (a) Probability distributions of background and objects, (b) corresponding histograms and optimal threshold.

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Iterative Optimal Thresholding

1. Assume corner pixels contain background
2. Step t compute μ_B^t and μ_O^t mean BG & Object gray-level where B and O is obtained using threshold T^t

$$\mu_B^t = \sum_{(i,j) \in B} f(i,j) / |B|$$

$$\mu_O^t = \sum_{(i,j) \in O} f(i,j) / |O|$$
3. Set $T^{t+1} = \frac{\mu_B^t + \mu_O^t}{2}$
4. If $T^{t+1} = T^t$ halt, otherwise go to 2

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Color Image Segmentation

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Segmentation as clustering

- E.g. Color image segmentation
- Group pixels with similar color
- Feature space representation of images (cf. Classification/Recognition)

- 2D (N-D Histogram of colors (features)

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Segmentation as clustering

- Clusters in Feature space correspond to segmentations in image space
- Same as Thresholding but in higher dim. Spaces

- How to find clusters?

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Segmentation as clustering

- Cluster together (pixels, tokens, etc.) that belong together
- Agglomerative clustering
 - attach closest to cluster it is closest to
 - repeat
- Divisive clustering
 - split cluster along best boundary
 - repeat
- Point-Cluster distance
 - single-link clustering
 - complete-link clustering
 - group-average clustering
- Dendrograms
 - yield a picture of output as clustering process continues

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Squared Error

$$se_{K_i} = \sum_{j=1}^m \|t_{ij} - C_k\|^2$$

$$se_K = \sum_{j=1}^k se_{K_j}$$

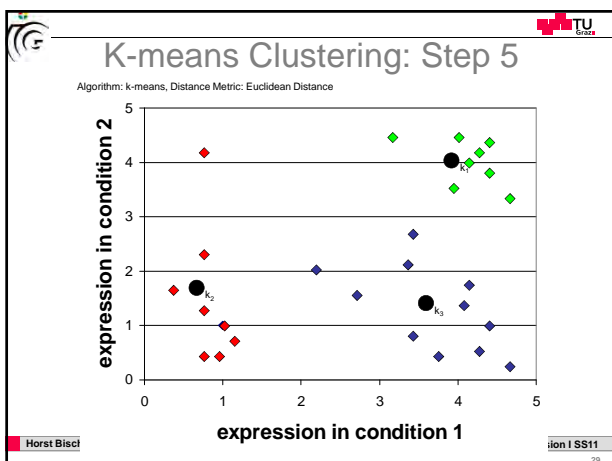
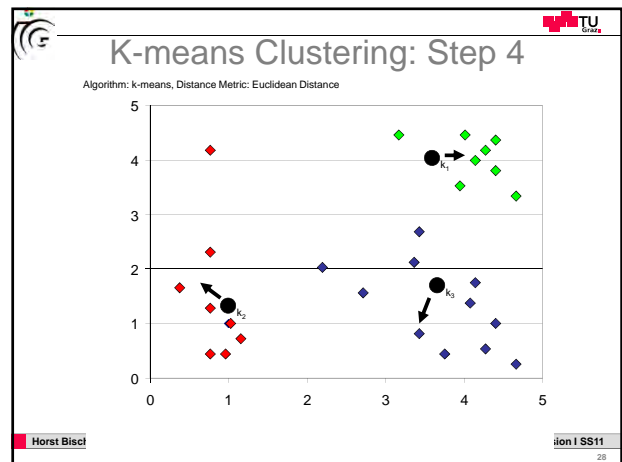
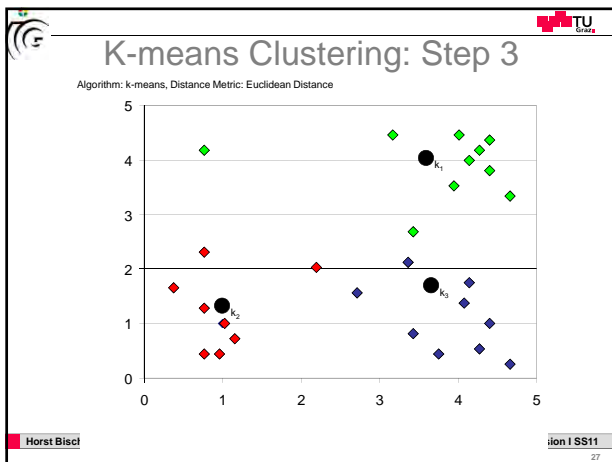
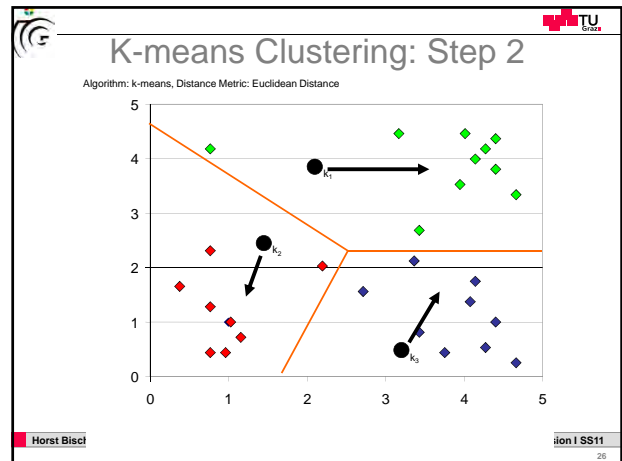
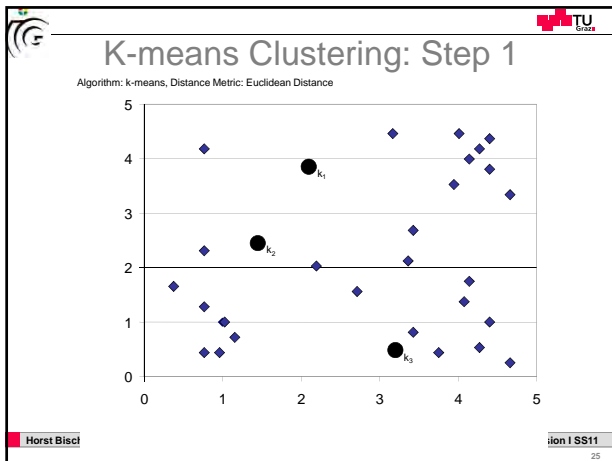
Objective Function

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Algorithm *k*-means

- Decide on a value for *k*.
- Initialize the *k* cluster centers (randomly, if necessary).
- Decide the class memberships of the *N* objects by assigning them to the nearest cluster center.
- Re-estimate the *k* cluster centers, by assuming the memberships found above are correct.
- If none of the *N* objects changed membership in the last iteration, exit. Otherwise goto 3.

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Comments on the *K-Means* Method

Strength

- Relatively efficient: $O(tkn)$, where n is # objects, k is # clusters, and t is # iterations. Normally, $k, t \ll n$.
- Often terminates at a *local optimum*. The *global optimum* may be found using techniques such as: *deterministic annealing* and *genetic algorithms*

Weakness

- Need to specify k , the *number* of clusters, in advance
- Unable to handle noisy data and *outliers*
- Not suitable to discover clusters with *non-convex shapes*

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Image Clusters on intensity Clusters on color

K-means clustering using intensity alone and color alone

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Including spatial relationships

Augment data to be clustered with spatial coordinates.

$$z = \begin{pmatrix} Y \\ u \\ v \\ x \\ y \end{pmatrix} \begin{array}{l} \text{color coordinates} \\ \text{spatial coordinates} \end{array}$$

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Mean Shift

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Finding Modes in a Histogram

- How Many Modes Are There?
 - Easy to see, hard to compute

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Mean Shift [Comaniciu & Meer]

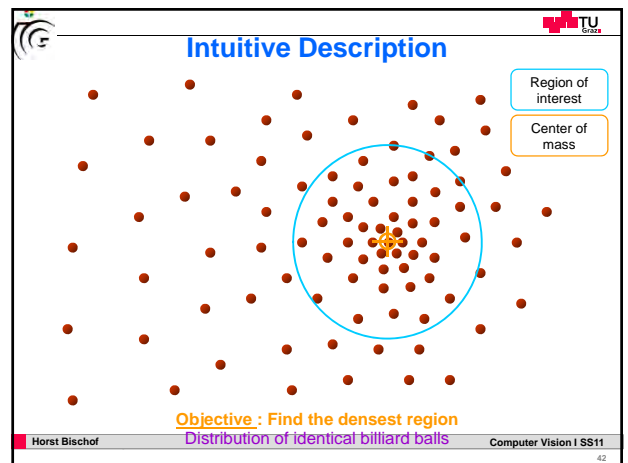
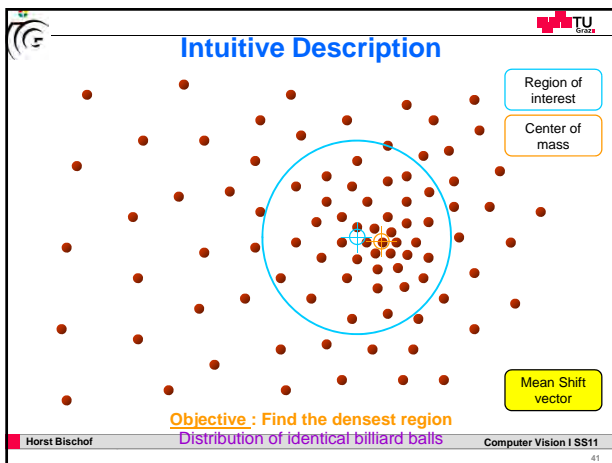
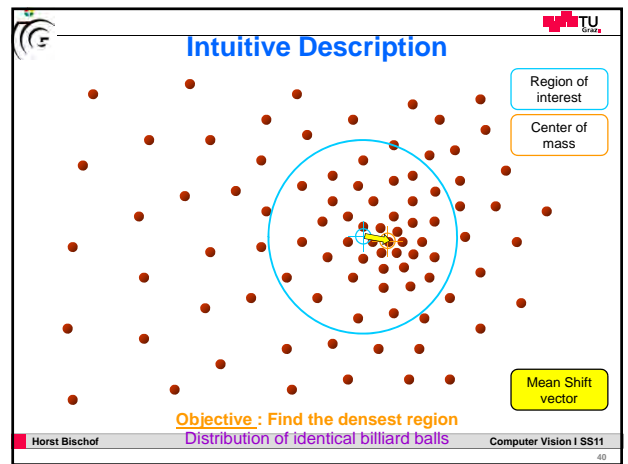
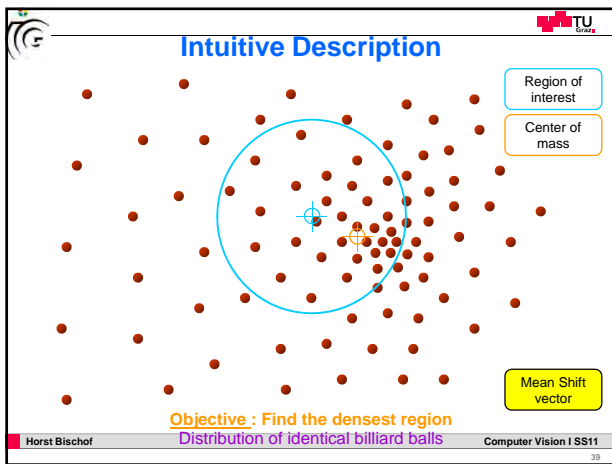
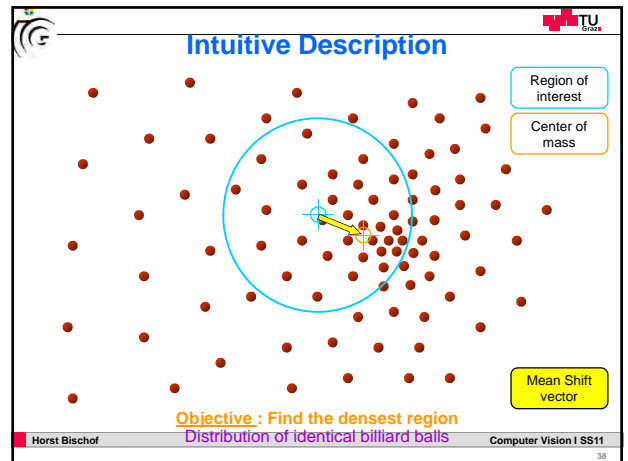
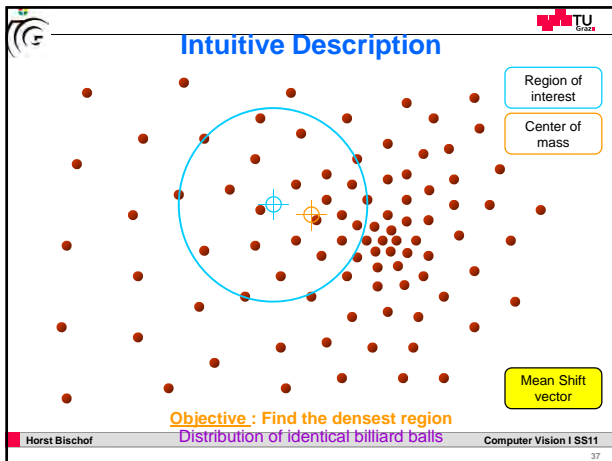
- Iterative Mode Search
 1. Initialize random seed, and window W
 2. Calculate center of gravity (the "mean") of W : $\sum_{x \in W} xH(x)$
 3. Translate the search window to the mean
 4. Repeat Step 2 until convergence

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Intuitive Description

Objective: Find the densest region
Distribution of identical billiard balls

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What is Mean Shift ?

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

PDF in feature space

- Color space
- Scale space
- Actually any feature space you can conceive

Data \rightarrow **Non-parametric Density GRADIENT Estimation (Mean Shift)** \rightarrow PDF representation

PLU Analysis
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Clustering Real Example

L*u*v space representation

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Clustering Real Example

2D (L*u) space representation

Final clusters

Not all trajectories in the attraction basin reach the same mode

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Segmentation Example

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Segmentation Example

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Segmentation Example

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Segmentation Example

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A different way of thinking about segmentation...

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Graph-Theoretic Image Segmentation

Build a weighted graph $G=(V,E)$ from image

V: image pixels
E: connections between pairs of nearby pixels

Segmentation = graph partition

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Graphs Representations

	a	b	c	d	e
a	0	1	0	0	1
b	1	0	0	0	0
c	0	0	0	0	1
d	0	0	0	0	1
e	1	0	1	1	0

Adjacency Matrix

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A Weighted Graph and its Representation

Affinity Matrix					
1	.1	.3	0	0	
.1	1	.4	0	.2	
.3	.4	1	.6	.7	
0	0	.6	1	1	
0	.2	.7	1	1	

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Affinity between pixels

Similarities among pixel descriptors

$$W_{ij} = \exp(-\|z_i - z_j\|^2 / s^2)$$

Scale factor... it will hunt us later

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Affinity between pixels

Similarities among pixel descriptors

$$W_{ij} = \exp(-\|z_i - z_j\|^2 / \sigma^2)$$

σ = Scale factor... it will hunt us later

Interleaving edges

$$W_{ij} = 1 - \max(P_{ij})$$

Line between i and j
With P_{ij} = probability of boundary

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Feature grouping by "relocalisation" of eigenvectors of the proximity matrix

Guy L. Scott
Robotics Research Group
Department of Engineering Sciences
University of Oxford

H. Christopher Longuet-Higgins
University of Sussex
Falmer
Brighton

$$W_{ij} = \exp(-\|z_i - z_j\|^2 / \sigma^2)$$

With an appropriate σ

	A	B	C
A	1.00	0.63	0.03
B	0.63	1.00	0.0
C	0.03	0.0	1.00

The eigenvectors of W are:

	E_1	E_2	E_3
Eigenvalues	1.63	1.00	0.37
A	-0.71	-0.01	0.71
B	-0.71	-0.05	-0.71
C	-0.03	1.00	-0.03

The first 2 eigenvectors group the points as desired...

Three points in feature space

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Example eigenvector

points

eigenvector

matrix

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Example eigenvector

points

eigenvector

matrix

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Scale affects affinity

$$W_{ij} = \exp(-\|z_i - z_j\|^2 / \sigma^2)$$

$\sigma = 2$

$\sigma = 1$ $\sigma = 2$ $\sigma = 1$

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Global optimization

- In this formulation, the segmentation becomes a global process.

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Boundaries of image regions defined by a number of attributes

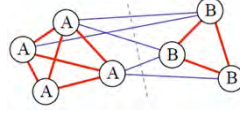
- Brightness/color
- Texture
- Motion
- Stereoscopic depth
- Familiar configuration



[Malik]

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Some Terminology for Graph Partitioning



Cut: sum of the weight of the cut edges:

$$cut(A, B) = \sum_{u \in A, v \in B} W(u, v)$$

with $A \cap B = \emptyset$

Association: sum of the weights of the edges connecting two sets:

$$assoc(A, B) = \sum_{u \in A, v \in B} W(u, v)$$

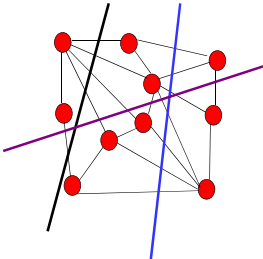
A and B not necessarily disjoint

	A	B	sum
A	$assoc(A, A)$	$cut(A, B)$	$assoc(A, V)$
B	$cut(B, A)$	$assoc(B, B)$	$assoc(B, V)$
sum	$assoc(A, V)$	$assoc(B, V)$	

With V = the set of all nodes

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Minimum Cut



A cut of a graph G is the set of edges S such that removal of S from G disconnects G .

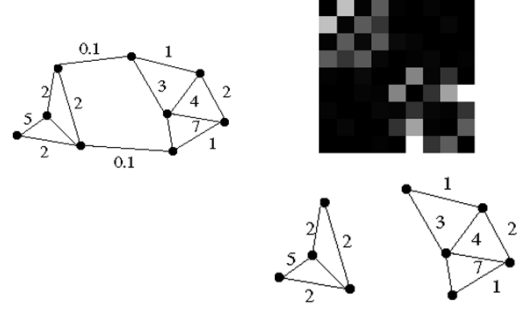
Minimum cut is the cut of minimum weight, where weight of cut $\langle A, B \rangle$ is given as

$$w(\langle A, B \rangle) = \sum_{x \in A, y \in B} w(x, y)$$

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* From Khurram Hassan-Shafique CAPS415 Computer Vision 2003

Minimum Cut and Clustering

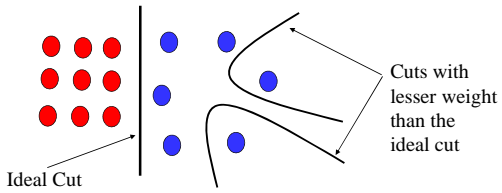


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* From Khurram Hassan-Shafique CAPS415 Computer Vision 2003

Drawbacks of Minimum Cut

- Weight of cut is directly proportional to the number of edges in the cut.



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* Slide from Khurram Hassan-Shafique CAPS415 Computer Vision 2003

Normalized cuts

- First eigenvector of affinity matrix captures within cluster similarity, but not across cluster difference
- Min-cut can find degenerate clusters
- Instead, we'd like to maximize the within cluster similarity compared to the across cluster difference
- Write graph as V , one cluster as A and the other as B

- Minimize $\frac{cut(A, B)}{assoc(A, V)} + \frac{cut(A, B)}{assoc(B, V)}$

where $cut(A, B)$ is sum of weights with one end in A and one end in B ;
 $assoc(A, V)$ is sum of all edges with one end in A .
 i.e. construct A, B such that their within cluster similarity is high compared to their association with the rest of the graph

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Solving the Normalized Cut problem

- Exact discrete solution to Ncut is NP-complete even on regular grid,
 - [Papadimitriou'97]
- Drawing on spectral graph theory, good approximation can be obtained by solving a generalized eigenvalue problem.

[Malik]

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Normalized Cut As Generalized Eigenvalue problem

$$Ncut(A, B) = \frac{cut(A, B)}{assoc(A, V)} + \frac{cut(A, B)}{assoc(B, V)} \quad D_{ii} = \sum_j A_{ij}$$

$$= \frac{(1+x)^T (D-W)(1+x)}{k^T D 1} + \frac{(1-x)^T (D-W)(1-x)}{(1-k)^T D 1}; \quad k = \frac{\sum_{i,j>0} D(i,i)}{\sum_i D(i,i)}$$

= ...
after simplification, Shi and Malik derive

$$Ncut(A, B) = \frac{y^T (D-W)y}{y^T D y}, \quad \text{with } y_i \in \{1, -b\}, y^T D 1 = 0.$$

W = affinity matrix, "A" [Malik]

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Normalized cuts

- Instead, solve the generalized eigenvalue problem

$$\max_y (y^T (D - W)y) \text{ subject to } (y^T D y = 1)$$
- which gives

$$(D - W)y = \lambda D y$$
- They show that the 2nd smallest eigenvector solution y is a good real-valued approx to the original normalized cuts problem. Then you look for a quantization threshold that maximizes the criterion -- i.e. all components of y above that threshold go to one, all below go to -b

Horst Bischof <http://www.cs.berkeley.edu/~malik/papers/SM-ncut.pdf> Computer Vision I SS11 69

$$w_{ij} = \begin{cases} \frac{|F_i - F_j|}{|X_i - X_j|} & \text{if } |X_i - X_j| \leq r \\ 0 & \text{otherwise} \end{cases}$$

brightness location

N pixels = ncols * nrows

W = $\begin{bmatrix} & N \\ N & \end{bmatrix}$

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Figure 12: Subplot (1) plots the smallest eigenvectors of the generalized eigenvalue system (11). Subplot (2) - (9) shows the eigenvectors corresponding the 2nd smallest to the 9th smallest eigenvalues of the system. The eigenvectors are reshaped to be the size of the image.

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Edge-based Segmentation

Describe the border of region

- Dual to region

Edge Detector (+ Threshold selection)

How to obtain closed curve (border tracing)

How to fill holes on contour

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Edge-based Segmentation

- Large group of methods based on information about edges in the image
- Rely on edges found in an image by edge detecting operators
- Edges mark image locations of discontinuities in gray level, color, texture, ..
- Edge detection results cannot be used as a segmentation result
- Edge segments → borders

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Edge Thresholding

- Global Threshold
- Histogram Analysis
- p-tile Threshold
- Non maximum suppression (directional data)
- Hysteresis to filter output

cf. Canny Edge Detector

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Edge-Aggregation

- Local edges (edgels) shall be aggregated to longer segments
- Global Method
 - Formulate Problem as search problem for minimal cost path (A*-Algorithm)
 - Costs based on Magnitude, Distance, Orientation
- Local Methods
 - Iteratively add edgels
 - Take best among neighbors

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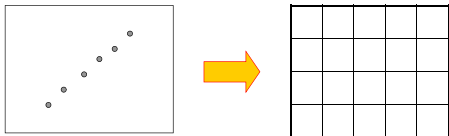
Parametric Model Fitting

- Fit a parametric representation to edgels
 - Line, Circle, etc.
- Hough Transform
 - Aggregation of local information
 - Lines, Circles

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Hough transform

- An early type of voting scheme
- General outline:
 - Discretize parameter space into bins
 - For each feature point in the image, put a vote in every bin in the parameter space that could have generated this point
 - Find bins that have the most votes



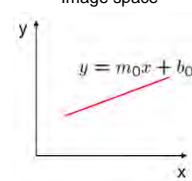
P.V.C. Hough, *Machine Analysis of Bubble Chamber Pictures*, Proc. Int. Conf. High Energy Accelerators and Instrumentation, 1959

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Parameter space representation

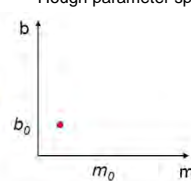
- A line in the image corresponds to a point in Hough space

Image space



→

Hough parameter space



Horst Bischof Computer Vision I SS11 Source: S. Seitz 78

Parameter space representation

- What does a point (x_0, y_0) in the image space map to in the Hough space?

Image space: x, y axes, point (x_0, y_0) .

Hough parameter space: m, b axes.

Source: S. Seltz 70

Parameter space representation

- What does a point (x_0, y_0) in the image space map to in the Hough space?
 - Answer: the solutions of $b = -x_0m + y_0$
 - This is a line in Hough space

Image space: x, y axes, point (x_0, y_0) .

Hough parameter space: m, b axes, line $b = -x_0m + y_0$.

Source: S. Seltz 80

Parameter space representation

- Where is the line that contains both (x_0, y_0) and (x_1, y_1) ?

Image space: x, y axes, points (x_0, y_0) and (x_1, y_1) .

Hough parameter space: m, b axes.

Source: S. Seltz 81

Parameter space representation

- Where is the line that contains both (x_0, y_0) and (x_1, y_1) ?
 - It is the intersection of the lines $b = -x_0m + y_0$ and $b = -x_1m + y_1$

Image space: x, y axes, points (x_0, y_0) and (x_1, y_1) .

Hough parameter space: m, b axes, lines $b = -x_0m + y_0$ and $b = -x_1m + y_1$.

Source: S. Seltz 82

Parameter space representation

- Problems with the (m, b) space:
 - Unbounded parameter domain
 - Vertical lines require infinite m

Source: S. Seltz 83

Parameter space representation

- Problems with the (m, b) space:
 - Unbounded parameter domain
 - Vertical lines require infinite m
- Alternative: polar representation

Equation: $x \cos \theta + y \sin \theta = \rho$

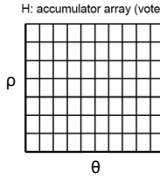
Each point will add a sinusoid in the (θ, ρ) parameter space

Source: S. Seltz 84

Algorithm outline

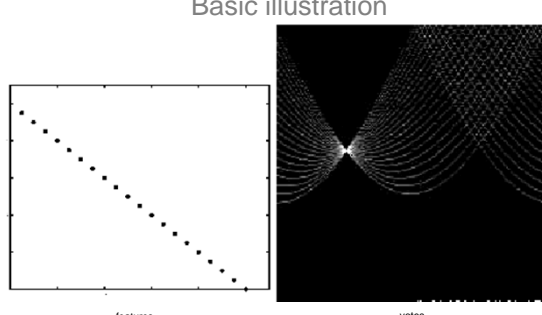
- Initialize accumulator H to all zeros
- For each edge point (x,y) in the image
 - For $\theta = 0$ to 180
 - $\rho = x \cos \theta + y \sin \theta$
 - $H(\theta, \rho) = H(\theta, \rho) + 1$
 - end
- Find the value(s) of (θ, ρ) where $H(\theta, \rho)$ is a local maximum
 - The detected line in the image is given by $\rho = x \cos \theta + y \sin \theta$

H: accumulator array (votes)



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Basic illustration



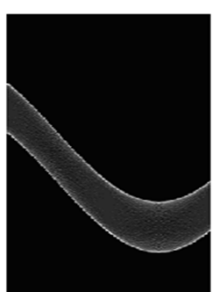
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Other shapes

Square

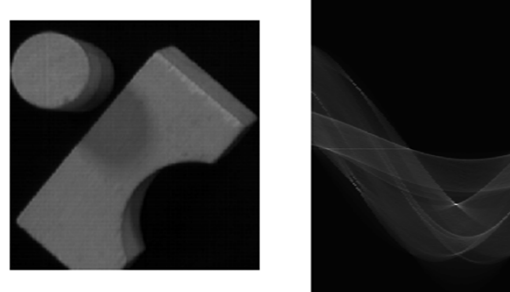


Circle



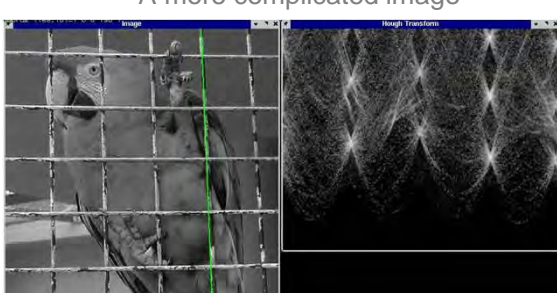
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Several lines



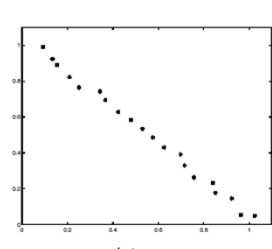
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A more complicated image

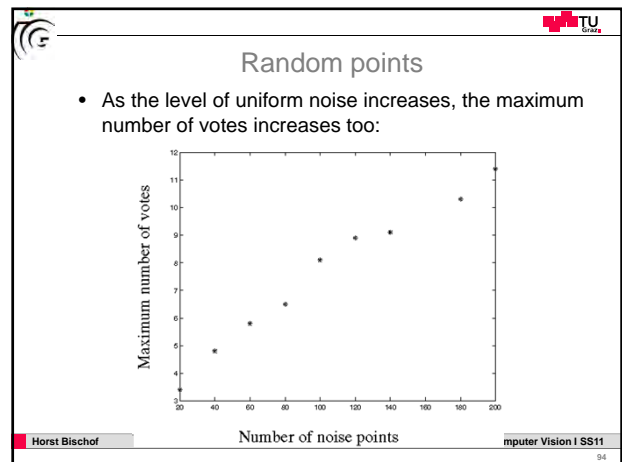
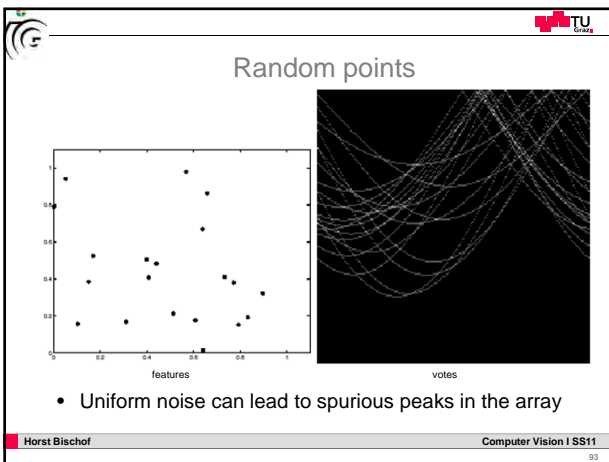
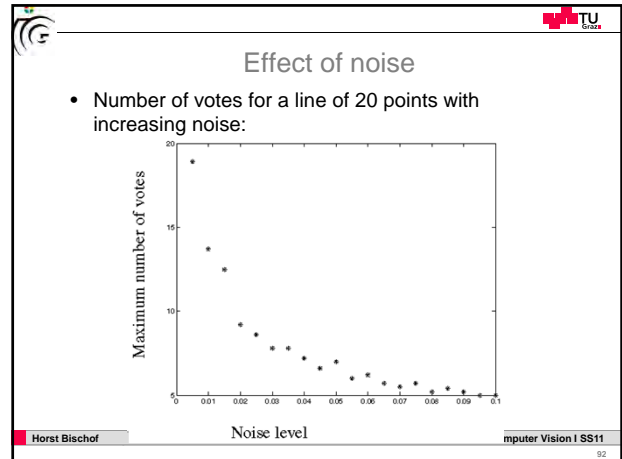
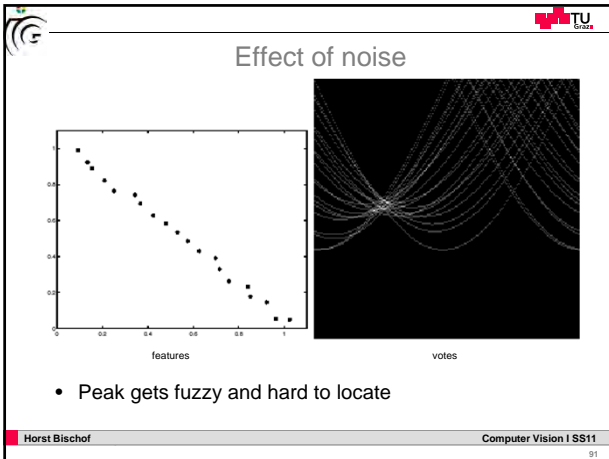


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Effect of noise



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Dealing with noise

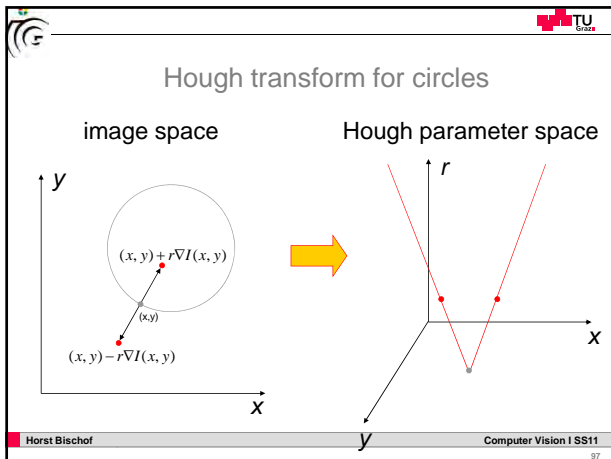
- Choose a good grid / discretization
 - Too coarse: large votes obtained when too many different lines correspond to a single bucket
 - Too fine: miss lines because some points that are not exactly collinear cast votes for different buckets
- Increment neighboring bins (smoothing in accumulator array)
- Try to get rid of irrelevant features
 - Take only edge points with significant gradient magnitude

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Hough transform for circles

- How many dimensions will the parameter space have?
- Given an oriented edge point, what are all possible bins that it can vote for?

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Hough-Transformation: Erweiterungen

- Das Prinzip der Geraden-Detektion kann erweitert werden zu höheren Merkmalen
 - z.B. **Parabeln** $y = ax^2 + bx + c$
 - Kreise** $(x-a)^2 + (y-b)^2 = r^2$
- Berechnungskomplexität und die Akkumulatorgröße steigen polynomiell mit der Anzahl der Parameter → klassische Hough-Technik ist nur für einfache Kurven praktisch einsetzbar
- Beschleunigungen:**
 - Hierarchical Hough-Transform:** Verarbeitung in mehreren Auflösungen
 - Randomized Hough-Transform:** Auf Grund der Robustheit wird nur eine zufällig ausgewählte Untermenge der Features berücksichtigt.

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- ### Region-based Segmentation
- Edge-based segmentation: borders between regions
 - Region-based segmentation: direct construction of regions
 - Easy to construct regions from their borders and easy to detect borders of regions
 - Combination of results may be a good idea
 - Region growing techniques are generally better in noisy images where edges are extremely difficult to detect
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- ### Region-based Segmentation
- Homogeneity of regions is used as the main segmentation criterion in region growing
 - The criteria for homogeneity:
 - gray level
 - color, texture
 - shape
 - model
 - etc.
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- ### Region Definition
- 4 Conditions
 - $I = \bigcup_{i=1}^m S_i$
 - $S_i \cap S_j = \emptyset$ for all $i \neq j$
 - $H(S_i) = TRUE$ for all i
 - $H(S_i \cup S_j) = FALSE$ neighboring S_i and S_j , $i \neq j$
 - Resulting regions of the segmented image must be both homogeneous and maximal
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- ### Region Merging
- Start at small segment (e.g. one pixel) satisfying homogeneity criterion
 - Merge adjacent regions that satisfy merging criterion
 - If no regions can be merged stop
 - Different algorithms depending on starting and order and merging criterion
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Region Splitting

Start with whole
 Split region if not homogeneous
 Stop if no region can be split anymore

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Split-and-Merge Algorithm

- Combination of splitting and merging advantages of both approaches.
- Split-and-merge use pyramid image representations; regions are square-shaped and correspond to elements of the appropriate pyramid level.

Figure 5.44 Split-and-merge in a hierarchical data structure.

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Split-and-Merge Algorithm

Data Structure is Pyramid/Quadtree
 If region is not homogeneous split (4 children)
 If all 4 regions with same parent can be merged, then merge.
 If no split or merge is possible, merge any two adjacent regions that are homogeneous (even on different pyramid levels)

Merge

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Quadtree Representation

Figure 5.45 Segmentation quadtree.

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Split-and-Merge Algorithm

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