Karlsruhe Institute of Technology

Machine Vision

Chapter 6: Segmentation

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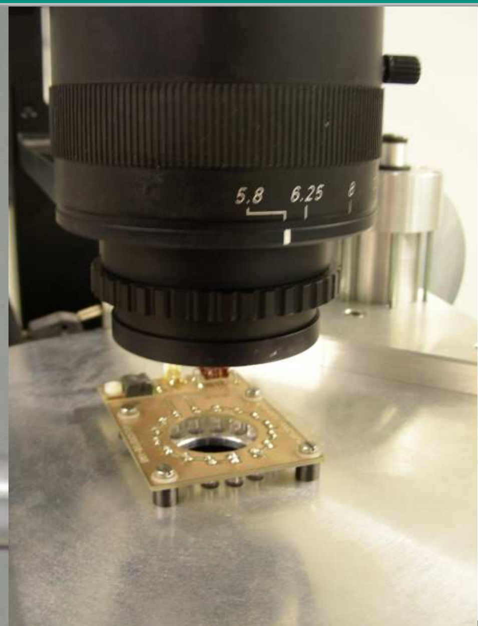
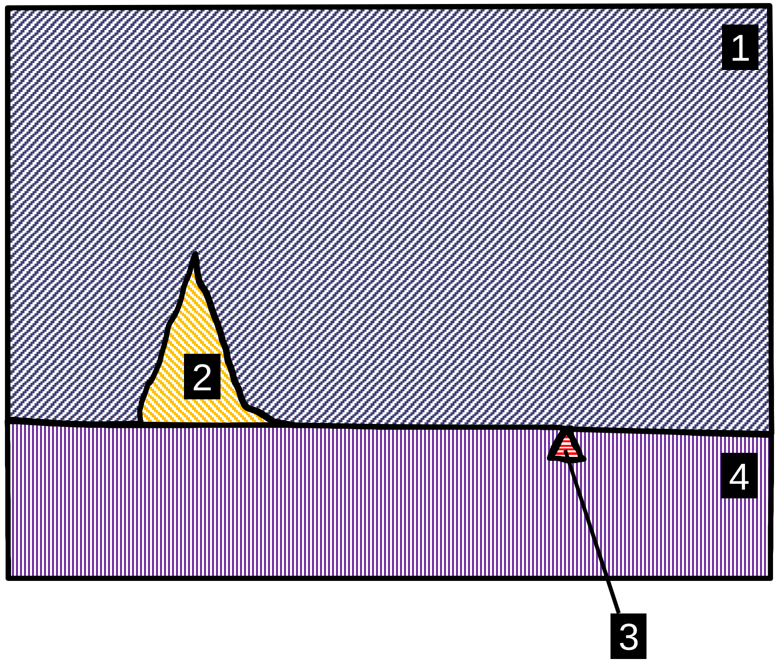


Segmentation

- partitioning the image into areas of similar color
  - image driven
  - no semantics for segments

- what we need for segmentation:
  - a criterion that defines which pixels belong to a segment and which don't
  - an algorithm that efficiently subdivides pixels into segments



Criteria for Segmentation

- criteria for segmentation:
  - *predefined color criterion*
  - *neighborhood criterion*
  - *homogeneity criterion*
  - *connectedness criterion*
  - *spatial criterion*
  - *boundary smoothness criterion*
  - *size criteria*
  - *…*

Criteria for Segmentation

– *predefined color criterion*

pixel color belongs to a predefined set of “interesting” colors

1. specify which color values are relevant
2. check which pixels are colored

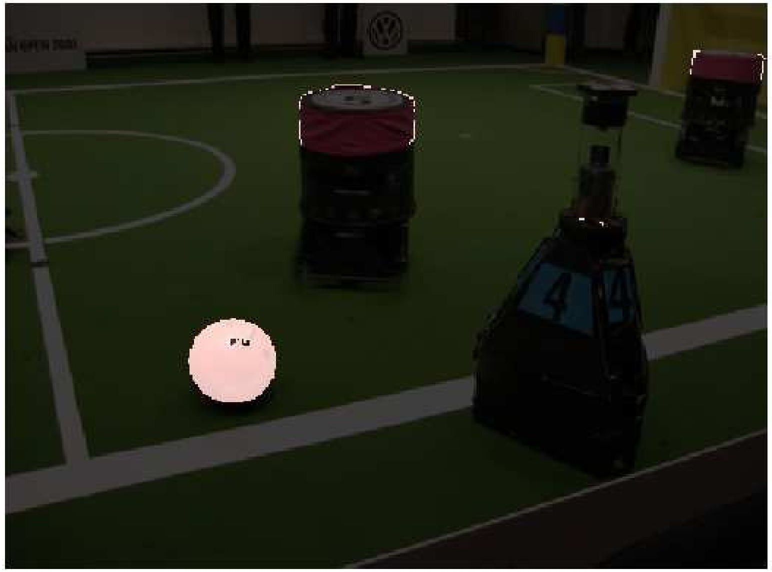
example:

find the orange ball on a soccer robot field

orange pixels are those with HSV values in the interval: $0^o \leq H \leq 24^o$, $0.4 \leq S \leq 1$, $0.4 \leq V \leq 1$

advantages and disadvantages:

- very simple, very fast
- can be applied if color of objects is known in advance and color is discriminative
- not applicable if different objects share the same colors
- finding appropriate color specification is often cumbersome



Criteria for Segmentation

– *neighborhood criterion*

pixel color is similar to color of neighboring pixels

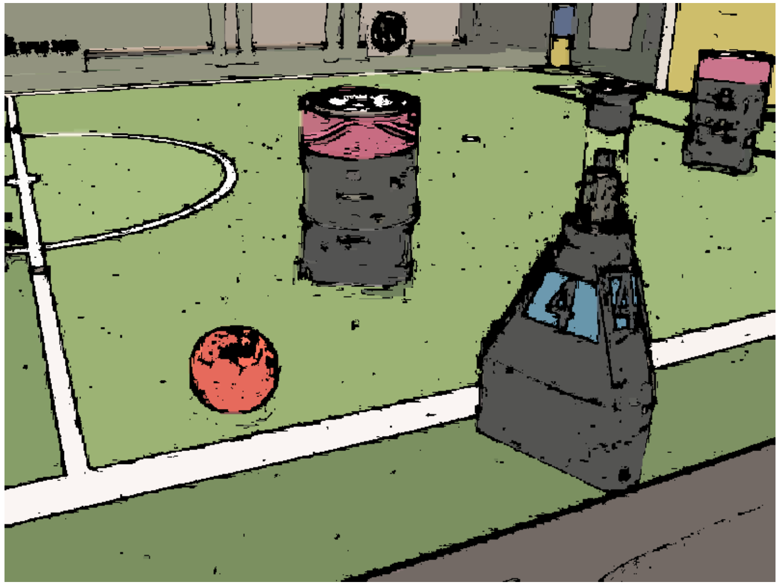
1. specify which colors are similar
2. group all pixels in one segment which have at least one similar neighbor which already belongs to the segment

example:

pixels are neighboring if Euclidean distance of RGB triplets is less than 7/255

advantages and disadvantages:

- simple
- objects colors don’t need to be known
- object boundaries must be high-contrast, the inside must be low-contrast
- blurry images might lead to undersegmentation, noisy images to oversegmentation



Criteria for Segmentation

– *homogeneity criterion*

pixel color is similar to the average color of a segment

1. specify how to compute the average color and decide whether two colors are similar
2. group all pixels in one segment which are similar to the average color of a segment

example:

pixels that are similar to the average ball color

advantages and disadvantages:

- objects colors don't need to be known
- objects must have similar color in all parts
- does not support low frequent color changes
- recurrent definition

Criteria for Segmentation

– *connectedness criterion*

all pixels in the same segment must be connected, i.e. between two pixels of the segment there is a path which does not leave the segment

example

advantages and disadvantages:

- criterion is combined with other criteria

same color, but different segments

Criteria for Segmentation

– *spatial criterion*

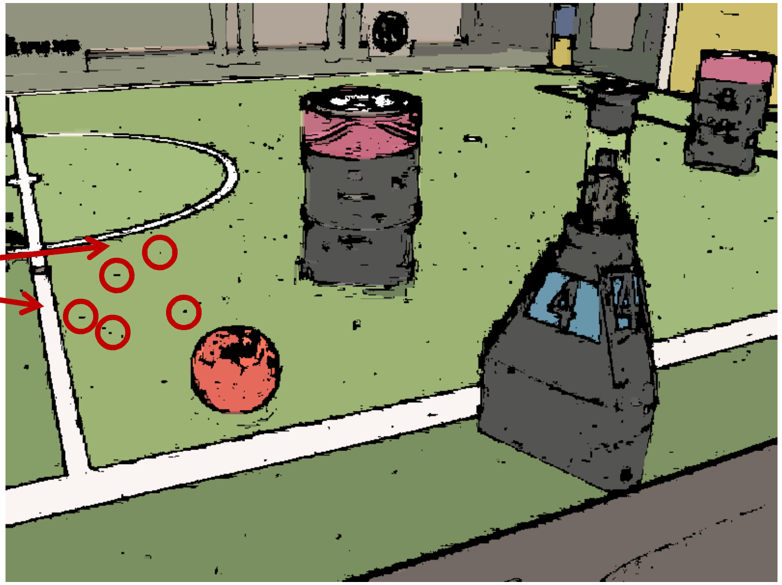
pixels which are surrounded by pixels of another segment should belong to that segment

example

advantages and disadvantages:

- criterion is combined with other criteria
- improves robustness w.r.t. noise

avoid/fill these gaps



Criteria for Segmentation

– *boundary smoothness criterion*

the boundary of segments should be smooth, not ragged.

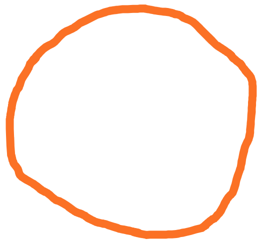
example

advantages and disadvantages:

- criterion is combined with other criteria
- improves robustness w.r.t. noise

ragged boundary – bad

smooth boundary – better



Criteria for Segmentation

– *size criteria*

the size of a segment should be within a range/not too small/not too large

Segmentation Algorithms

- basic segmentation algorithms:
  - *region growing*
  - *connected components labeling*
  - *k-means and mean-shift algorithm*
  - *morphological operations*

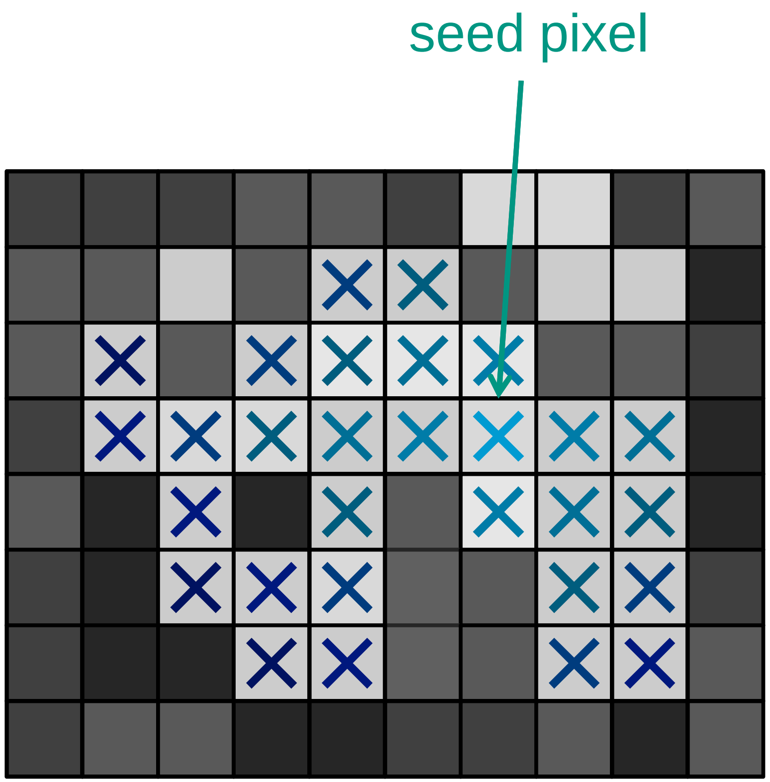
- more elaborated algorithms:
  - *level set methods*
  - *random fields*

Region Growing

– key idea:
  - start from one/more seed points (seed points must be provided)
  - incrementally expand segment until any pixel can be added

  - implements connectedness criterion + homogeneity or neighborhood criterion
  - yields single segment

– advantages and disadvantages:
  - easy to implement (breadth-first-search)
  - requires one or more seed points



no more extension possible

Region Growing cont.

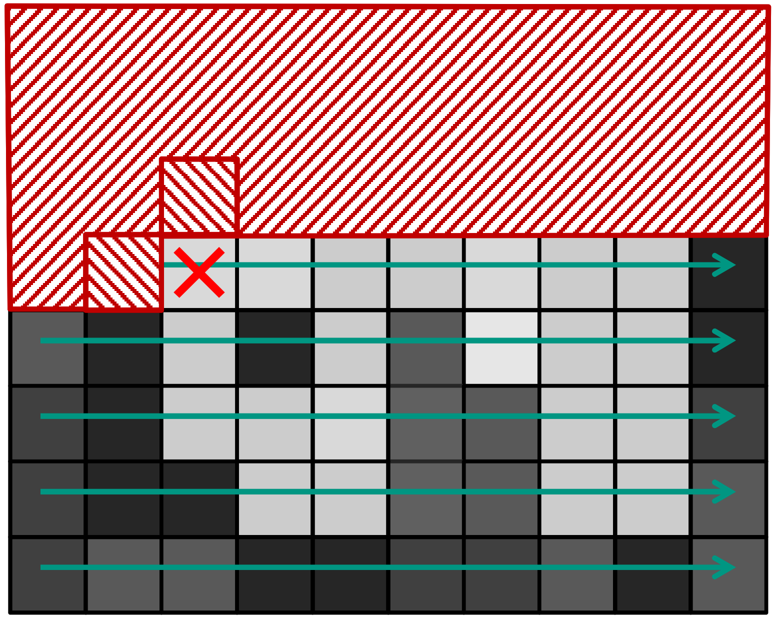
region growing on RGB

Connected Components Labeling (CCL)

– key idea:
  - create a full segmentation of the image
  - implements connectedness criterion + neighborhood criterion
  - assign each pixel to segment only by determining similarity with two neighboring pixels

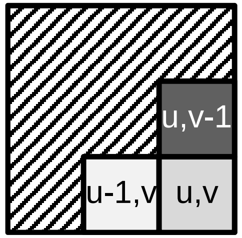
Connected Components Labeling (CCL)

– procedure:
- we visit pixels row-by-row from the left upper corner to the right lower corner and immediately assign them to a segment
- when we visit a pixel (u,v) we already visited (u-1,v) and (u,v-1)
- we compare color(u,v) with color(u-1,v), color(u,v-1). Five cases

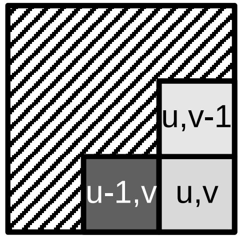


Connected Components Labeling (CCL)

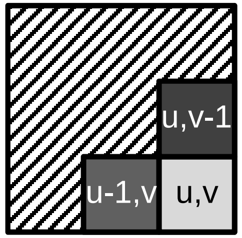
1. pixel colors at (u,v) and (u-1,v) are similar
   pixel colors at (u,v) and (u,v-1) are dissimilar
   → pixel (u,v) and (u-1,v) belong to the same segment
   → we assign pixel (u,v) to the segment of pixel (u-1,v)



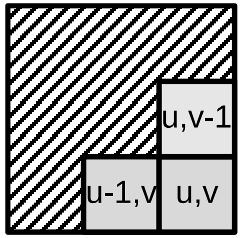
2. pixel colors at (u,v) and (u-1,v) are dissimilar
   pixel colors at (u,v) and (u,v-1) are similar
   → pixel (u,v) and (u,v-1) belong to the same segment
   → we assign pixel (u,v) to the segment of pixel (u,v-1)



3. pixel colors at (u,v) and (u-1,v) are dissimilar
   pixel colors at (u,v) and (u,v-1) are dissimilar
   → why should pixel (u,v) belong to the segments of (u-1,v) or (u,v-1)?
   → we create a new segment and assign pixel (u,v) to it

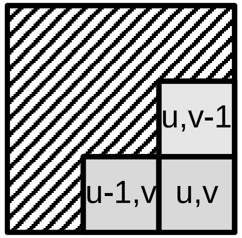


4. pixel colors at (u,v) and (u-1,v) are similar
   pixel colors at (u,v) and (u,v-1) are similar
   pixels (u-1,v) and (u,v-1) belong to the same segment
   → pixel (u,v) also belongs to that segment
   → we assign pixel (u,v) to that segment

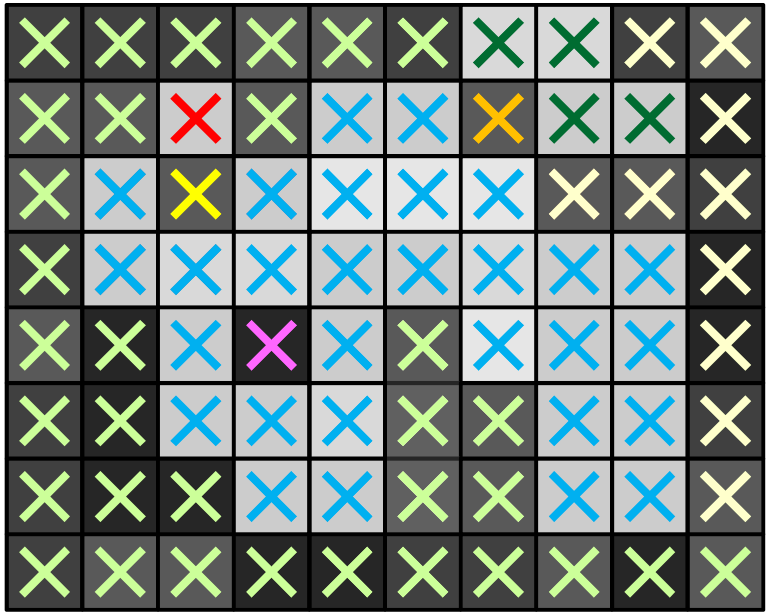


Connected Components Labeling (CCL)

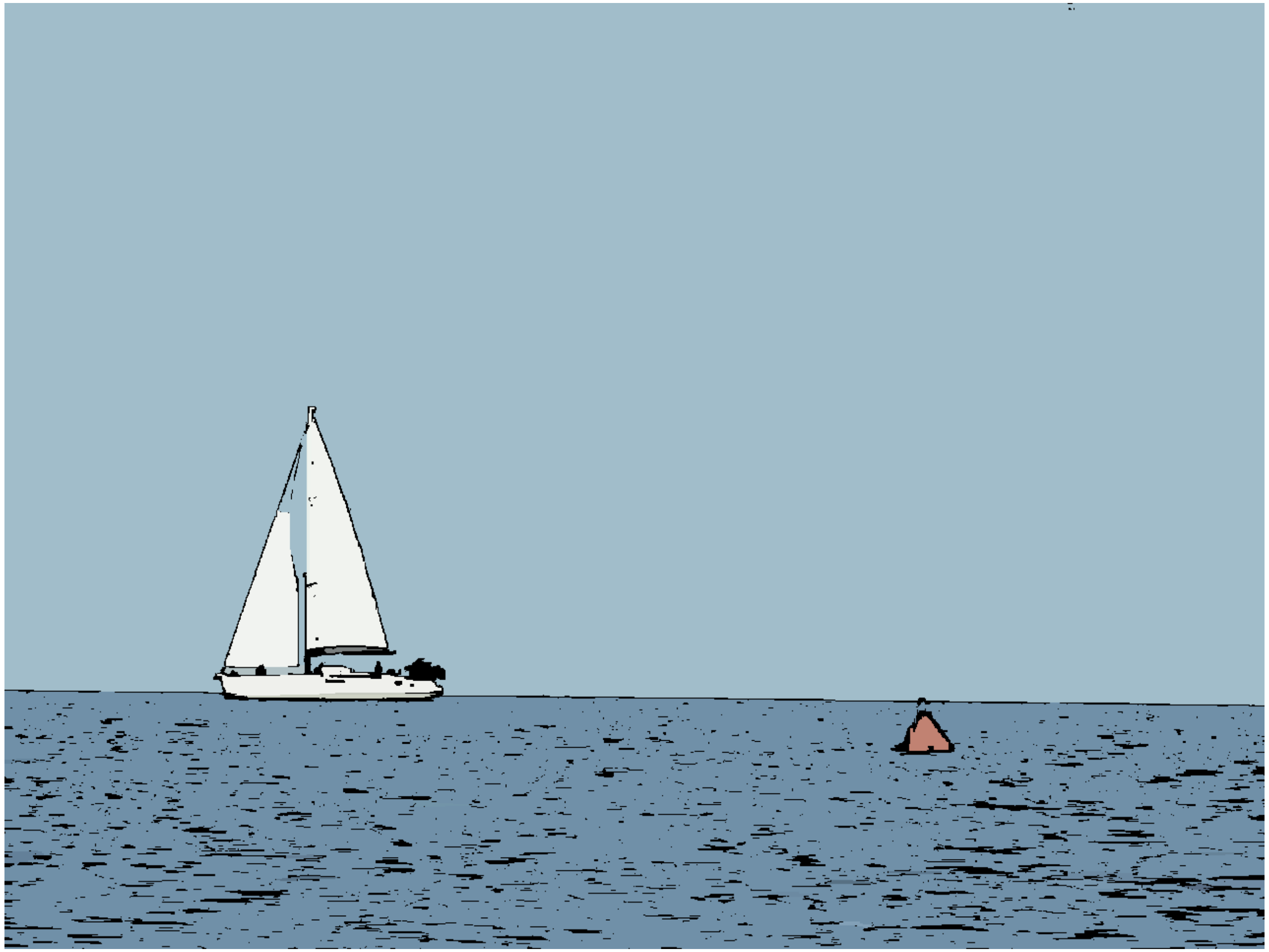
5. pixel colors at (u,v) and (u-1,v) are similar
   pixel colors at (u,v) and (u,v-1) are similar
   pixels (u-1,v) and (u,v-1) do not belong to the same segment
   → pixel (u,v) belongs to the segments of both neighbors
   → we merge the two neighboring segments and assign pixel (u,v) to the merged segment



- Example



Connected Components Labeling (CCL)



CCL on RGB values
pixels are similar if
Euclidean distance in color
space is below 10/255

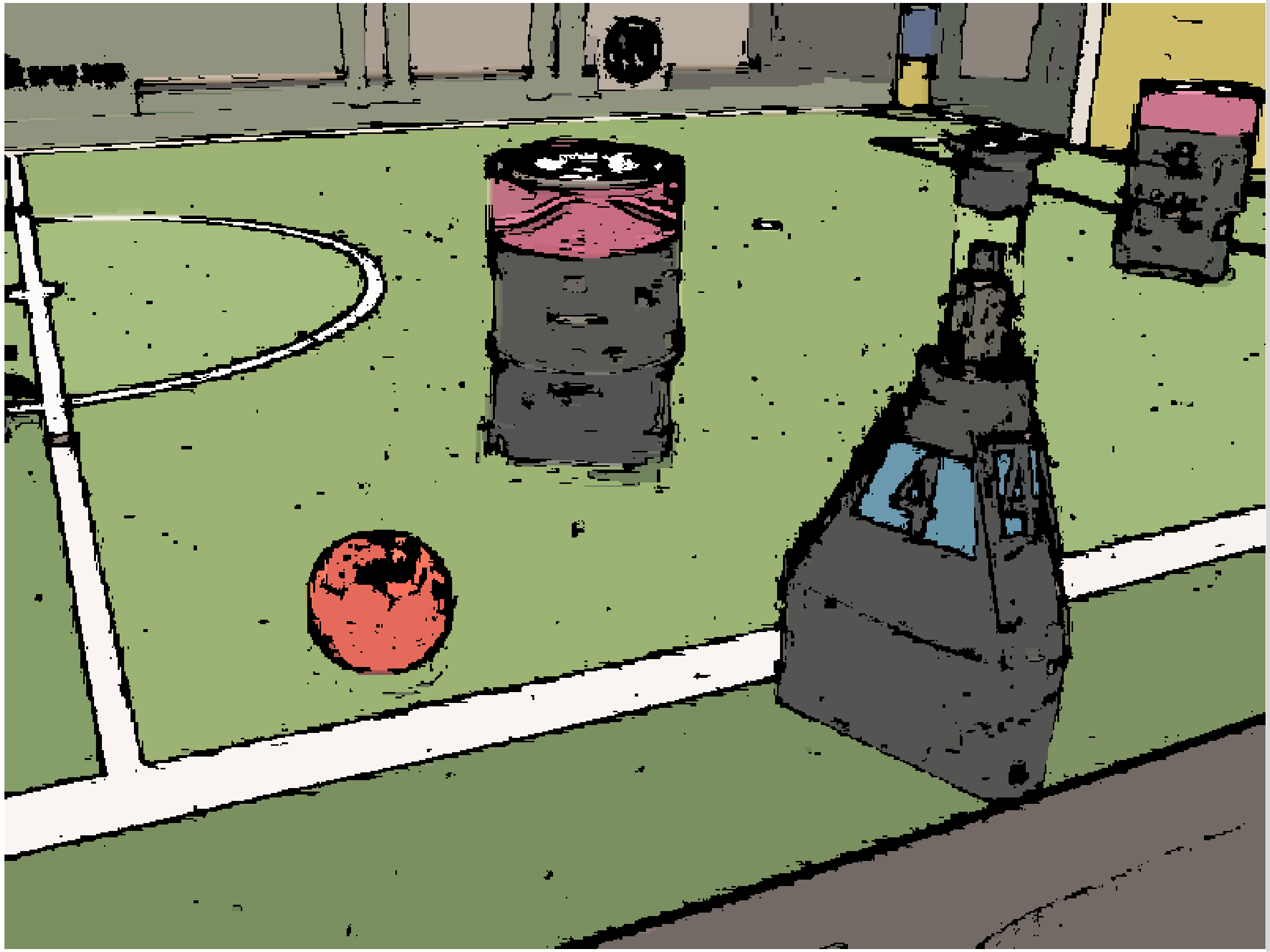
30 areas with more than
100 pixels

Connected Components Labeling (CCL)

CCL on RGB
θ=2/255 (Euclidean distance)
2418 areas with more than 10 pixels

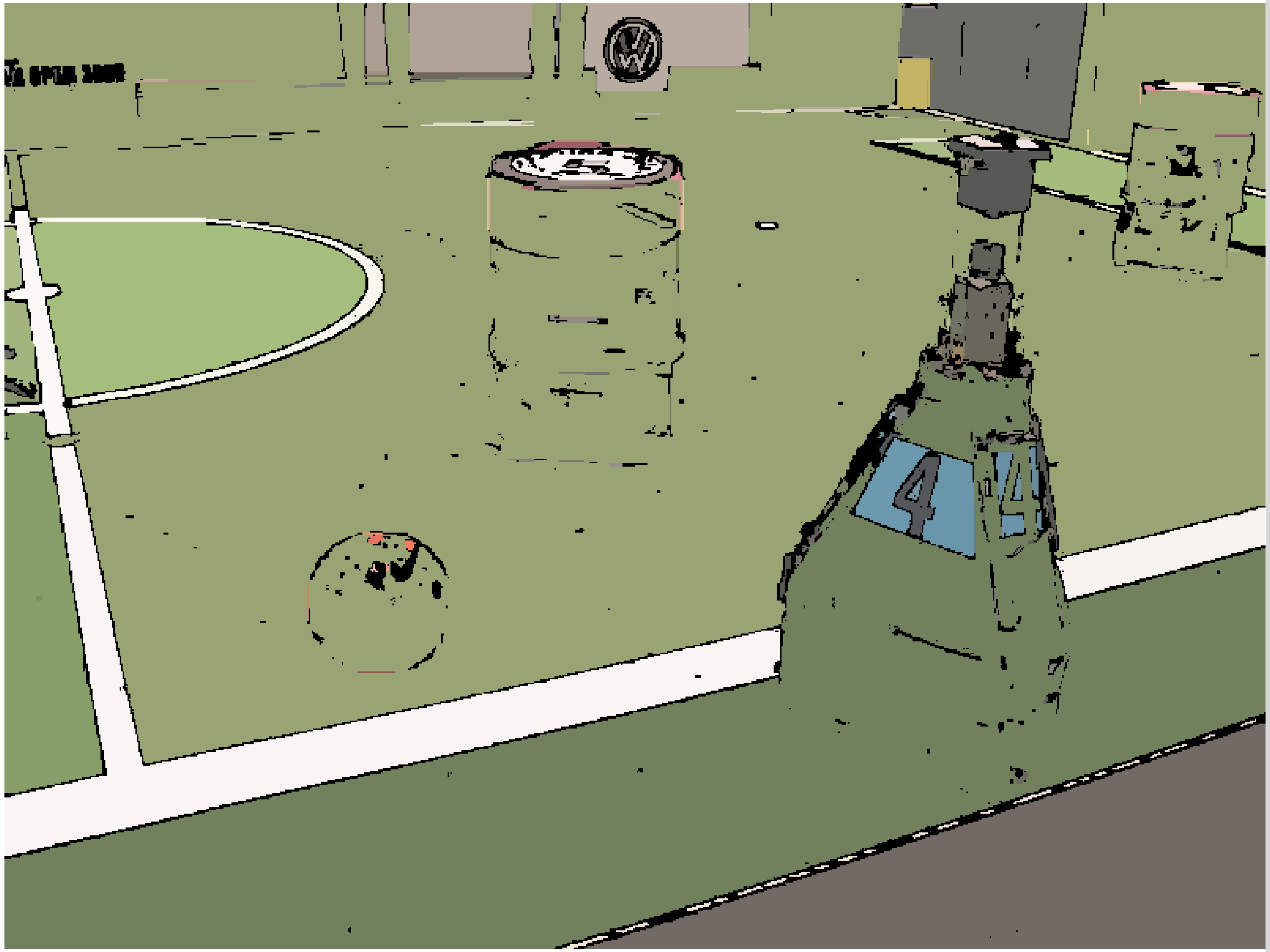
Connected Components Labeling (CCL)

CCL on RGB
θ=7/255 (Euclidean distance)
730 areas with more than 10 pixels



Connected Components Labeling (CCL)

CCL on RGB
θ=15/255 (Euclidean distance)
304 areas with more than 10 pixels



k-means

– key idea:
  - image is composed out of areas of similar color
  - find clusters of color
  - assign each pixel to its color cluster

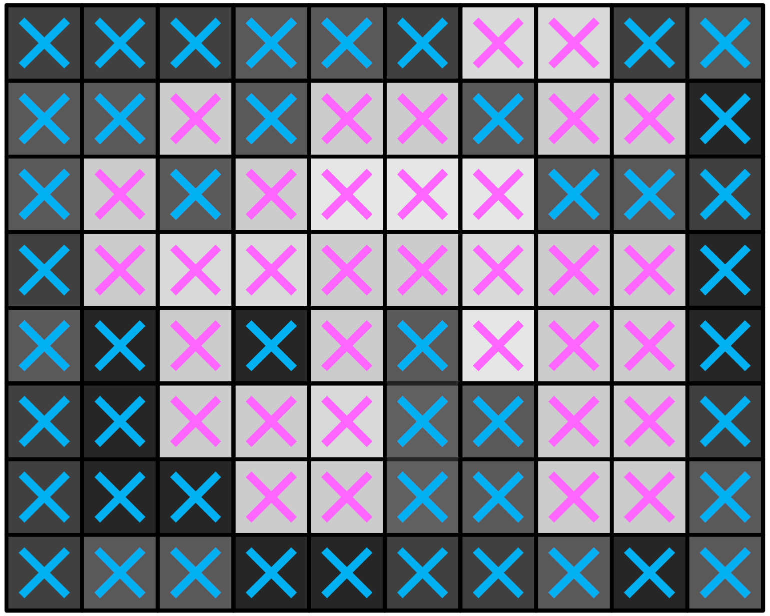
  - implements homogeneity criterion
  - creates full segmentation

color clusters in the robot soccer picture:
- green
- white
- orange
- black
- magenta
- blue
- yellow
- gray

k-means

- how can we find color clusters?
- if we know the number of clusters
  → k-means algorithm

1. initialize *k* prototype colors $c_1, c_2, \ldots, c_k$ randomly (e.g. by randomly picking pixels from image)
2. assign each pixel to the prototype color that is most similar
3. recalculate prototype colors by averaging over colors of pixel which have been assigned in step 2
4. repeat steps 2 and 3 until convergence (i.e. the assignments in step 2 do not change any more)



example: *k=2*

step 1: randomly pick colors from two pixels

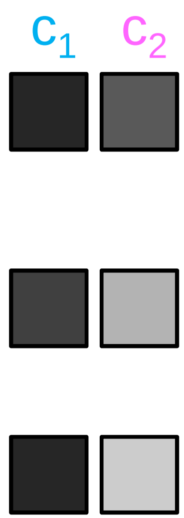
step 2: assign pixels to most similar cluster

step 3: recalculate prototype colors

step 2: reassign pixels

step 3: recalculate prototype colors

step 2: reassign pixels → convergence



k-means

- Examples:

original image

k=5, iteration=10

k-means

- Examples:

original image

k=10, iteration=10

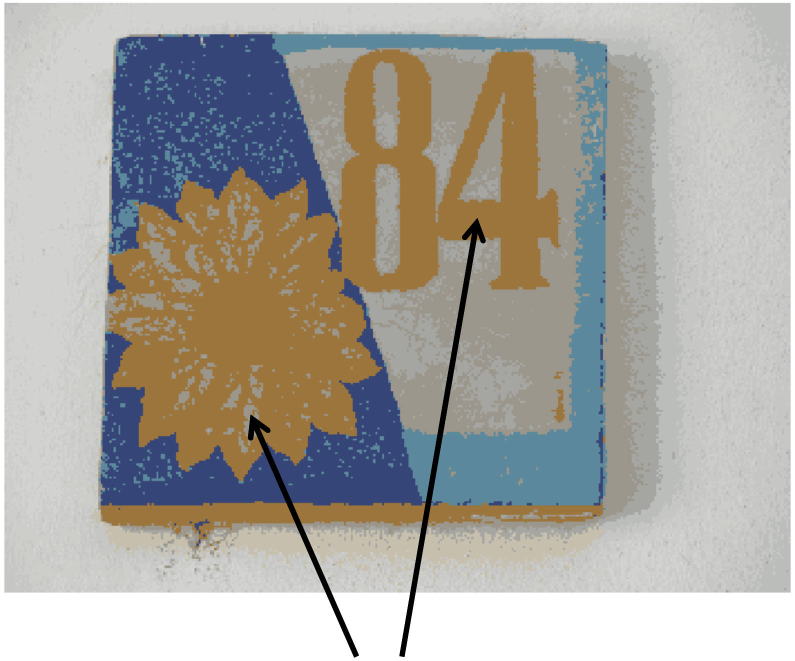
no light blue prototype

k-means

- Examples:

original image

k=10, iteration=10



suboptimal prototype colors: only one prototype for yellow+orange

Mean-Shift

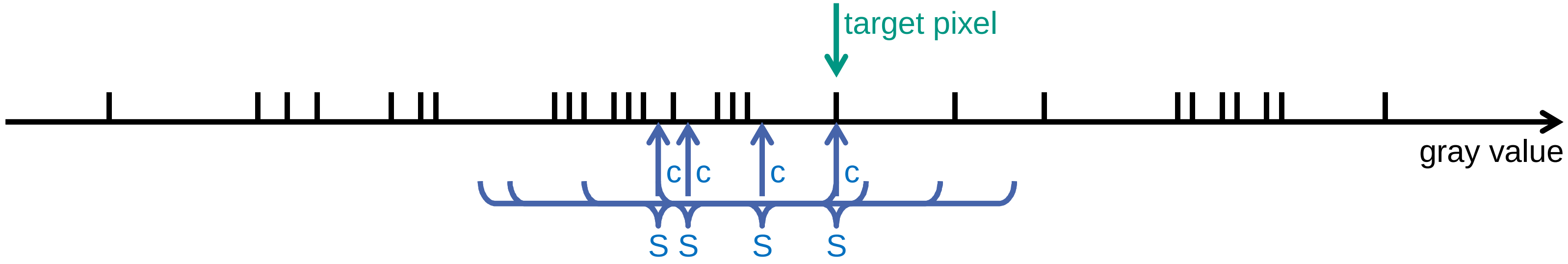
- k-means algorithm
  - advantage:
    - simple, easy to implement
  - disadvantages:
    - number of clusters *(k)* must be known
    - often converges into suboptimal clustering (depending on initial prototype colors)
- improvement for unknown number of clusters → mean-shift
  - requires a similarity measure for colors
  - for each pixel proceed as follows

1. determine color *c* of this pixel
2. find the set *S* of all pixels which are similar to *c*
3. calculate the average color of *S* and assign it to *c*
4. repeat steps 2 and 3 until convergence (i.e. until *S* remains unchanged in step 2)
5. finally, *c* is the prototype color of the segment which the pixel belongs to

Mean-shift

– example

arranged all pixel colors (gray values) along one axis



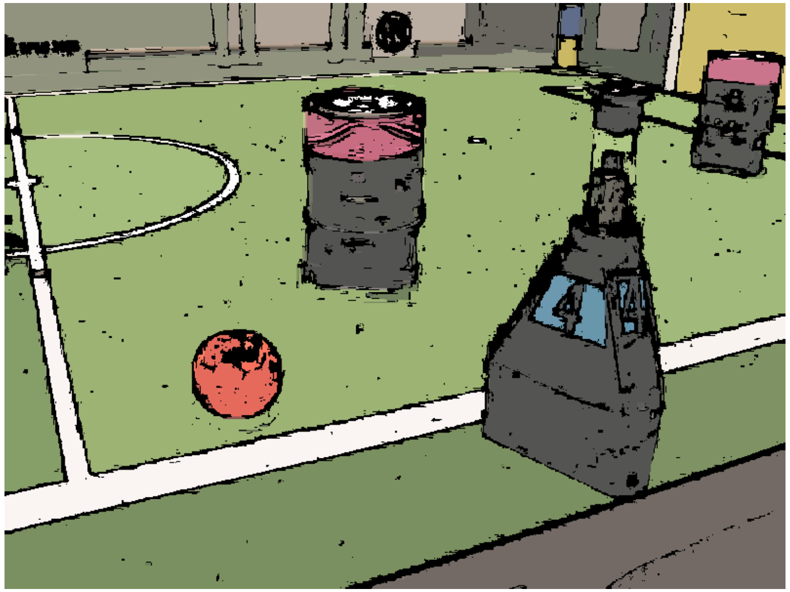
step 1: pick color of target pixel *c*
step 2: find the set of similar pixels *S*
step 3: calculate average color of *S* and assign it to *c*
step 2: recalculate *S*
step 3: recalculate average color of *S* and assign it to *c*
step 2: recalculate *S*
step 3: recalculate average color of *S* and assign it to *c*
step 2: recalculate *S* → convergence

Mean-shift

- Examples:

Morphological Operations

- problems:
  - holes
  - ragged contours
  - gaps
  - tiny areas



- extend/shrink areas
  - *erosion:* shrink area by one pixel
  - *dilation:* extend area by one pixel

- assumption
  - background pixels are encoded with 0
  - foreground pixels are encoded with numbers ≥1

Morphological Operations cont.

- Erosion:

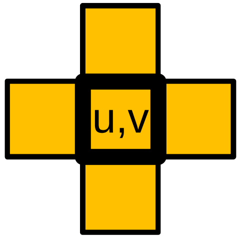
$$erode\{g\}(u,v) = \min\{g(u,v), g(u+1,v), g(u+1,v+1), g(u,v+1), g(u-1,v+1), g(u-1,v), g(u-1,v-1), g(u,v-1), g(u+1,v-1)\}$$

"take the minimal value of neighbors"

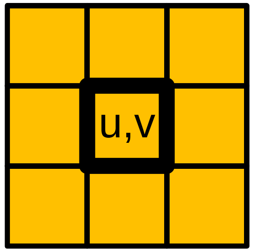
- Dilation:

$$dilate\{g\}(u,v) = \max\{g(u,v), g(u+1,v), g(u+1,v+1), g(u,v+1), g(u-1,v+1), g(u-1,v), g(u-1,v-1), g(u,v-1), g(u+1,v-1)\}$$

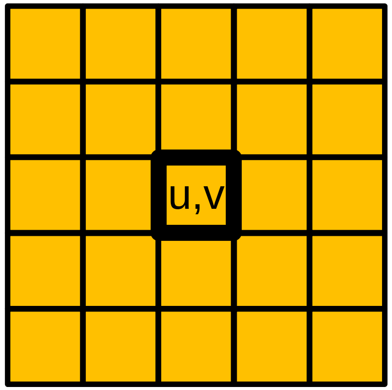
"take the maximal value of neighbors"



4-neighborhood of pixel (u,v)

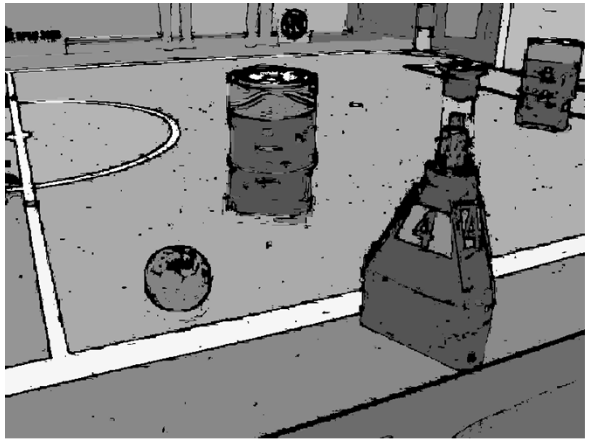


8-neighborhood of pixel (u,v)

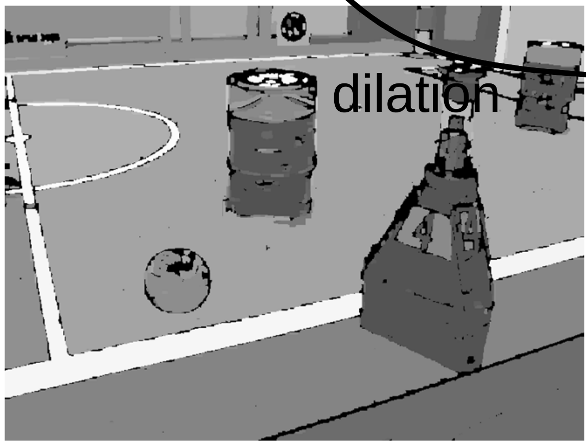


24-neighborhood of pixel (u,v)

Morphological Operations cont.



dilation



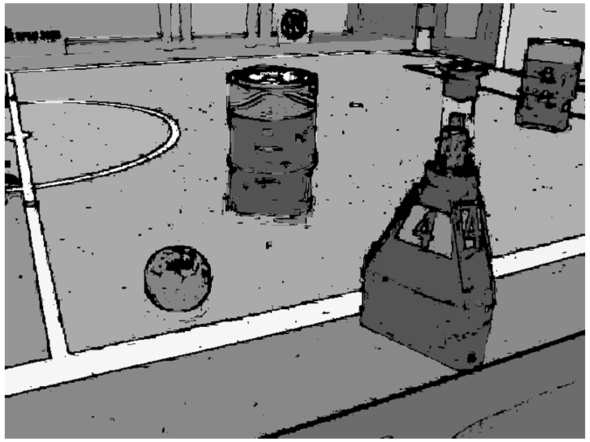
dilation

dilation

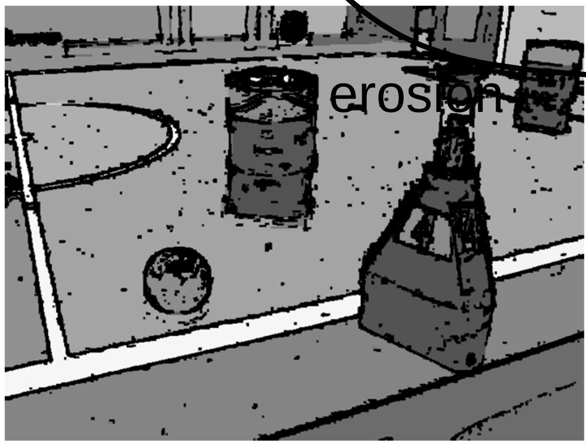
dilation fills holes and gaps

Morphological Operations cont.

erosion eliminates thin structures



erosion



erosion

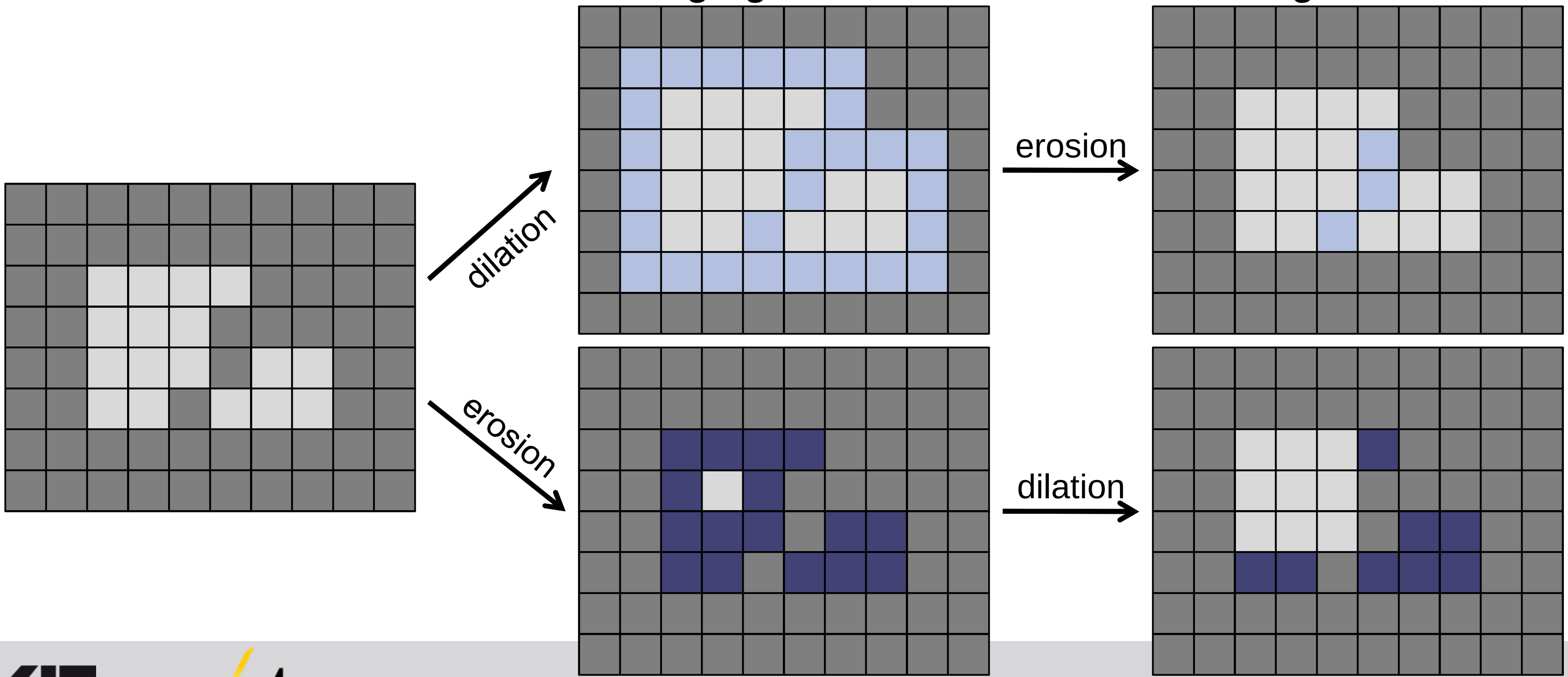
erosion

Morphological Operations cont.

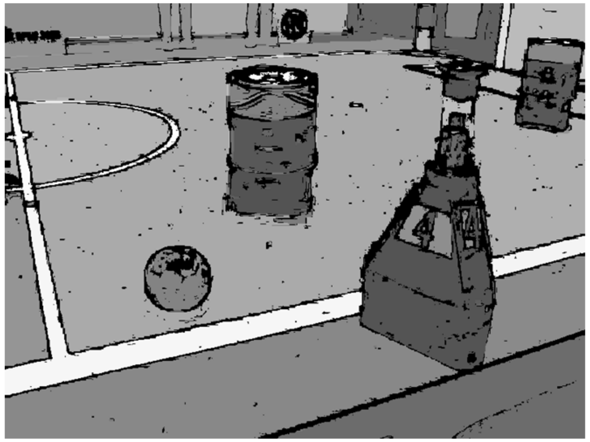
- erosion and dilation can be combined:
  - *closing:* first dilation, then erosion

    fill gaps and holes without changing the overall extension of areas
  - *opening:* first erosion, then dilation

    remove thin areas without changing the overall extension of large areas

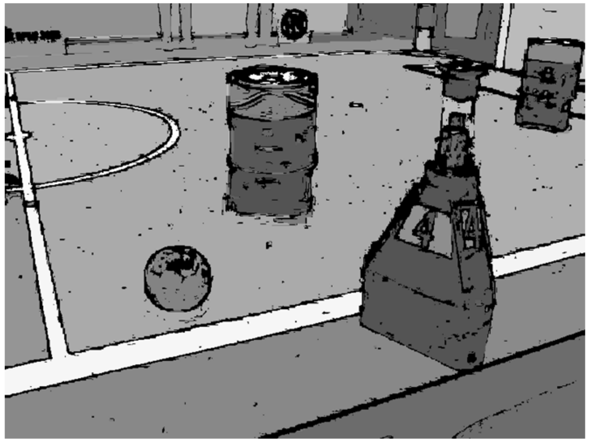


Morphological Operations cont.



closing

Morphological Operations cont.



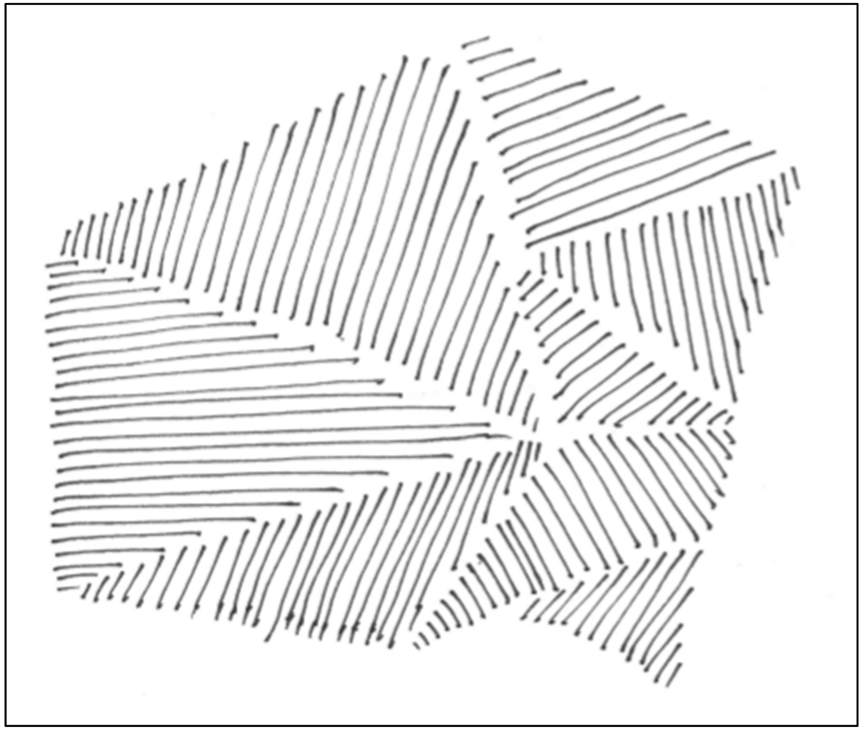
opening

Generic View on Segmentation

- So far:
  - segmentation was based on color (gray values)
  - different representation of color and different similarity measures

- Question:
  - how can we segment images in which colors are not salient?

- Example:
  - segment image into areas of same hatching



Generic View on Segmentation

- What do we need for image segmentation?
  - for every pixel: a description of the pixel (image features)
    - e.g. color
    - e.g. texture information
    - e.g. depth of point (3d scanner/stereo vision)
    - e.g. motion of pixel (optical flow)
    - e.g. features which characterize whether pixel belongs to certain object categories
    - e.g. a combination of those features
  - a measure of similarity of different pixels
    - e.g. Euclidean distance between feature vectors
    - e.g. other metric
  - one/more segmentation criteria

    → *cf. slide 3*
  - an efficient algorithm that implements the segmentation criteria

    → *cf. methods presented on previous slides*

Generic View on Segmentation

- Example:
  - segment image into areas of same hatching
  - image features:
    - color and gray level is not salient
    - orientation of lines is salient
    - e.g.
      - calculate gray level gradient
      - determine the dominant gradient direction in local environment around pixel
      - represent direction as 2d vector
      - length of vector is proportional to average gradient length
  - criteria and algorithm:
    - neighborhood criterion
    - minimal segment size
    - connected components labeling

input image

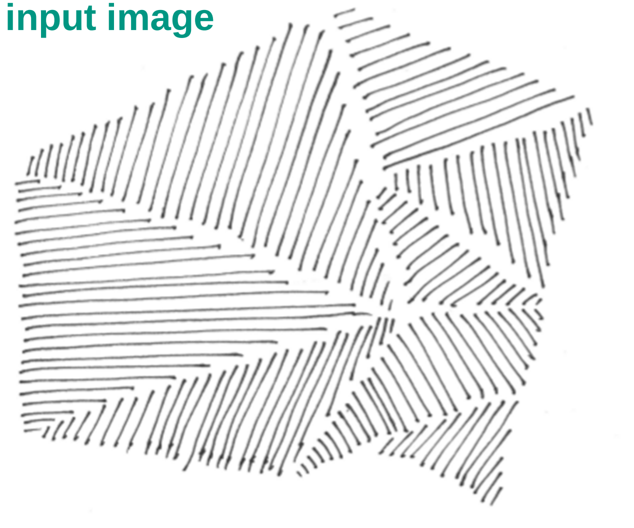
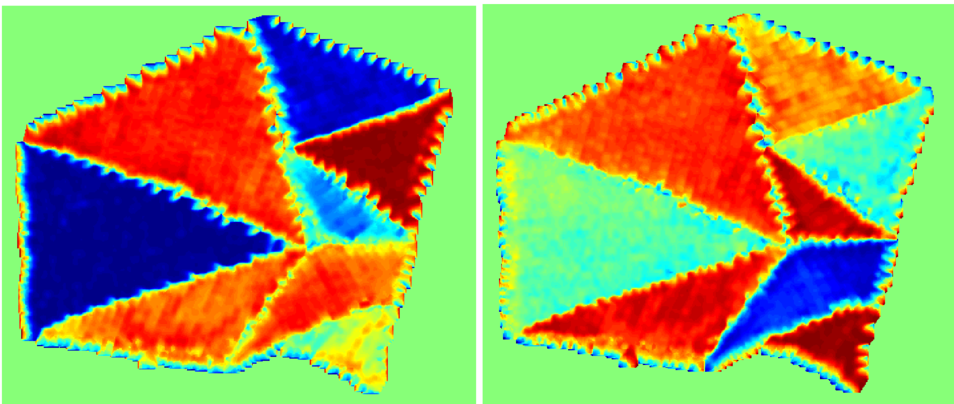


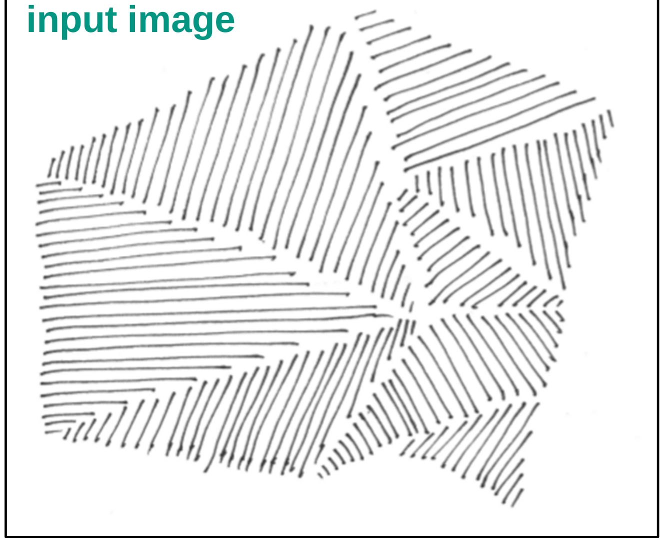
image features (illustrated as color images)



Generic View on Segmentation

- Example:
  - segment image into areas of same hatching

input image



segmentation result with CCL
(one color per segment)

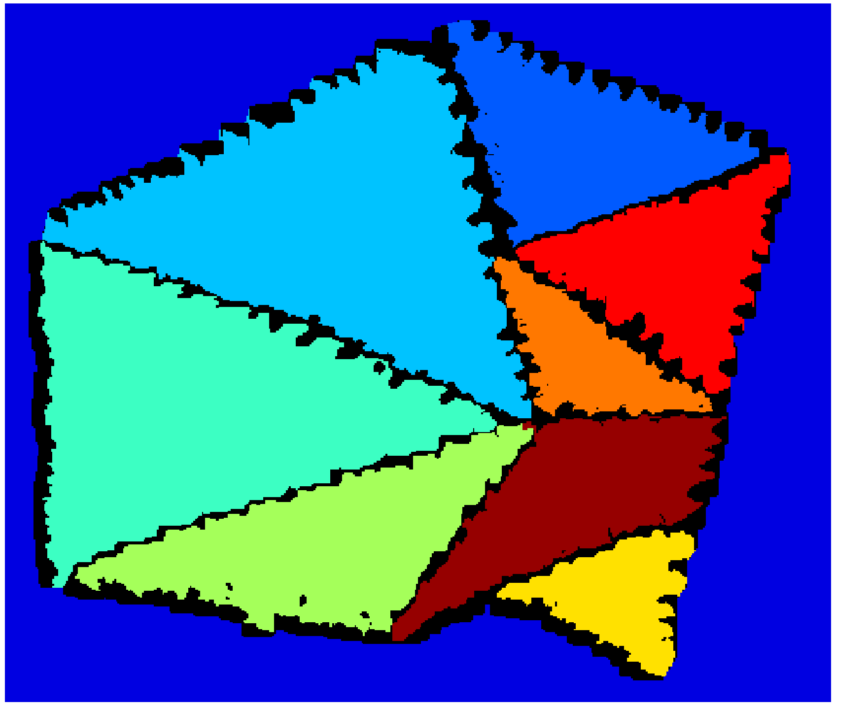
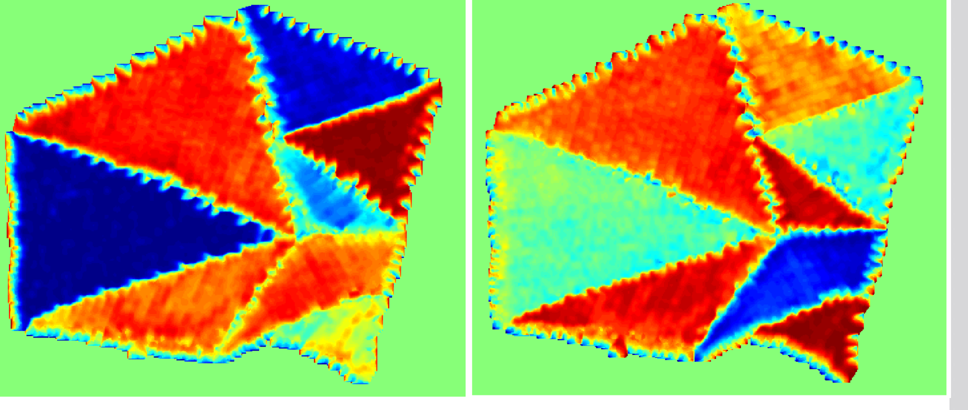


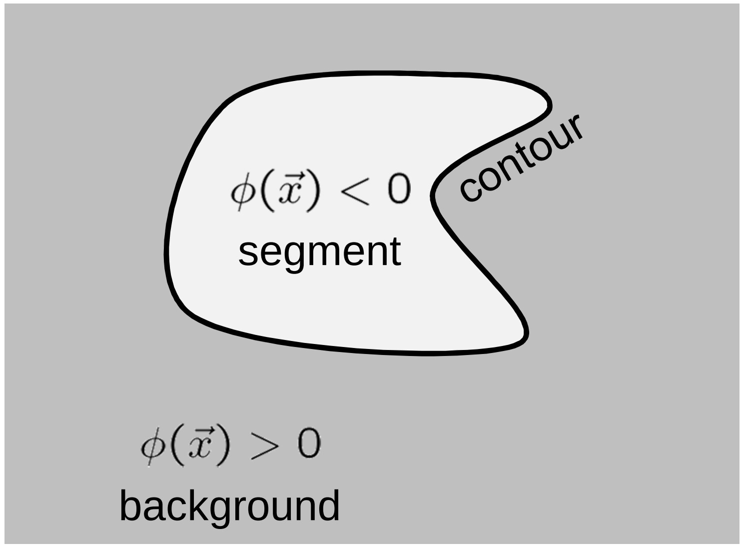
image features (illustrated as color images)



LEVEL SET METHODS

Level Set Representation

- two-class-segmentation can be represented by:
  - collection of all pixels that belong to segment
  - indicator function $\phi(\vec{x}) \begin{cases} < 0 & \text{if pixel } \vec{x} \text{ belongs to segment} \\ > 0 & \text{if pixel } \vec{x} \text{ belongs to background} \end{cases}$
  - contour
  - signed distance function



Level Set Representation cont.

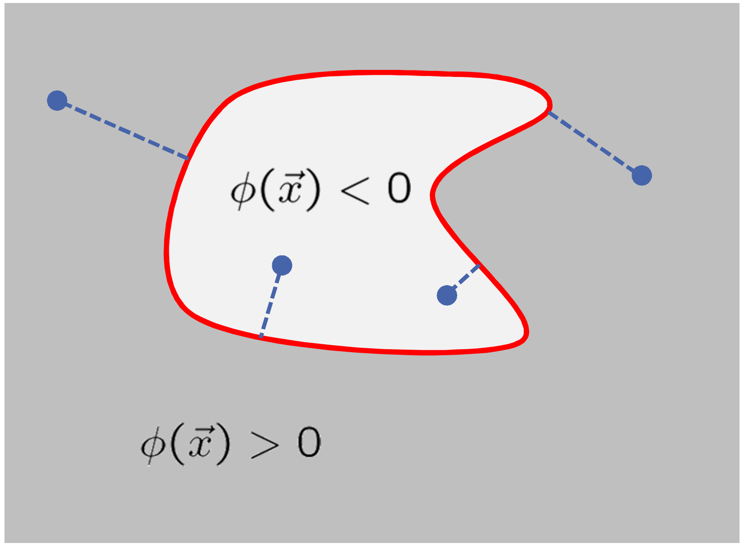
– signed distance function

$$\phi(\vec{x}) \begin{cases} < 0 & \text{if pixel } \vec{x} \text{ belongs to segment} \\ > 0 & \text{if pixel } \vec{x} \text{ belongs to background} \end{cases}$$

$$|\phi(\vec{x})| = \text{ distance of } \vec{x} \text{ from contour}$$

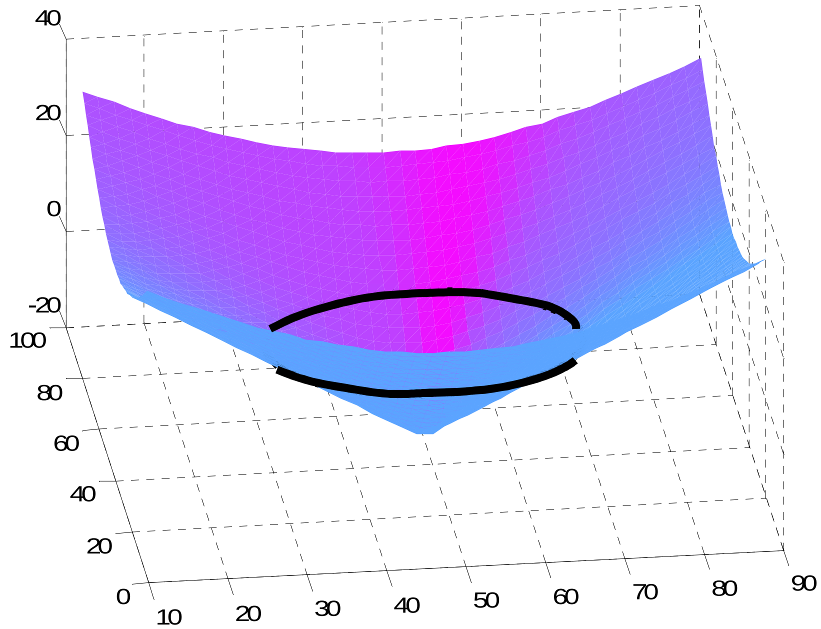
– contourpoints:

$$\phi(\vec{x}) = 0$$

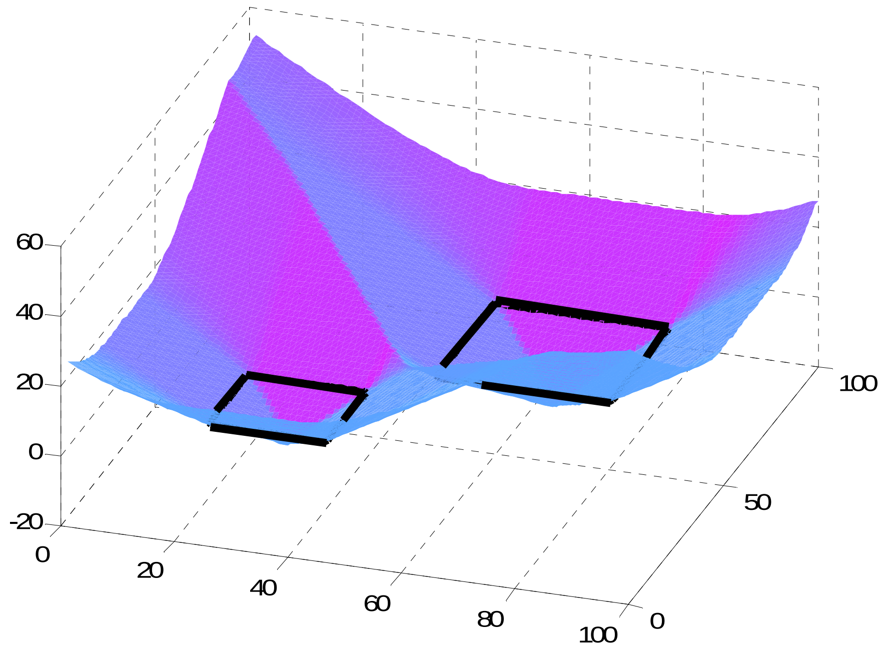


Level Set Representation cont.

– signed distance function



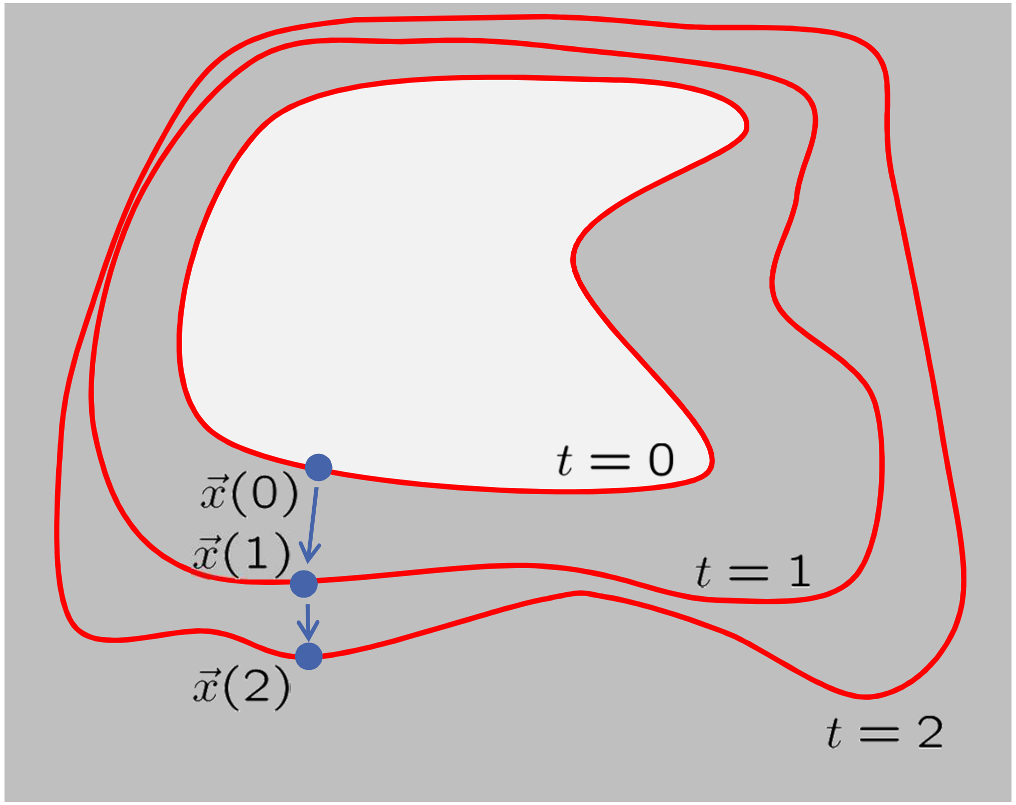
example: circlular contour



example: two rectangular contours

Level Set Evolution

- modeling temporal evolution of signed distance function $\phi(\vec{x}, t)$
  - tracking a point on the boundary over time $\vec{x}(t)$
  - obviously: $\phi(\vec{x}(t), t) = 0$ for all t



Level Set Evolution cont.

– from:

$$\phi(\vec{x}(t), t) = 0 \qquad \text{for all } t$$

– follows:

$$0 = \frac{d\phi(\vec{x}(t), t)}{dt} = \nabla\phi \cdot \frac{\partial \vec{x}}{\partial t} + \frac{\partial \phi}{\partial t}$$

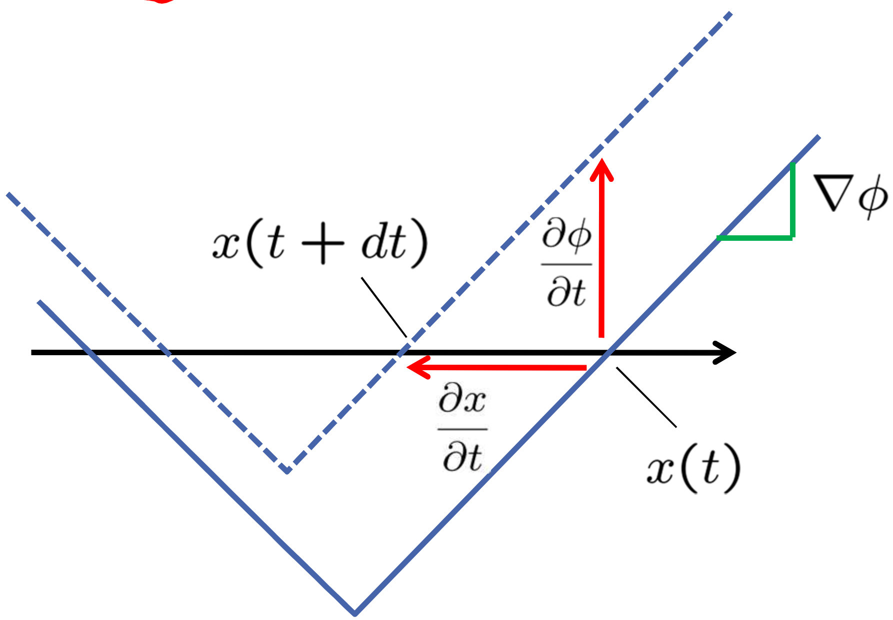
local structure of ϕ

movement of a contour point

evolution of ϕ

with:

$$\nabla\phi = \left(\frac{\partial\phi}{\partial x}, \frac{\partial\phi}{\partial y}\right)$$



Level Set Evolution cont.

– resolving w.r.t. $\frac{\partial \phi}{\partial t}$:

$$\frac{\partial \phi}{\partial t} = -\nabla \phi \cdot \frac{\partial \vec{x}}{\partial t}$$

- Basic idea of level set methods:
  - start with initial $\phi(\cdot, 0)$
  - assume reasonable $\frac{\partial \vec{x}}{\partial t}$
  - track $\phi(\cdot, t)$ over time

- Implementation using numerical integration, e.g. Euler‘s approach (tricky!)

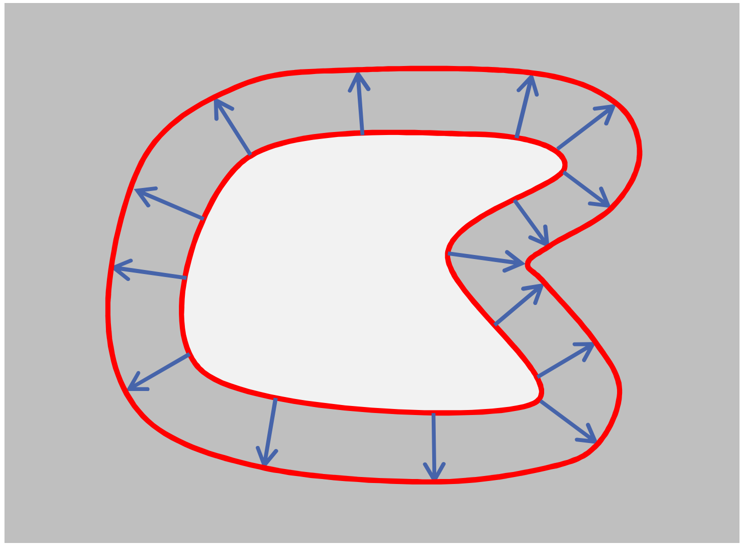
Expanding and Shrinking

- evolution orthogonal to contour

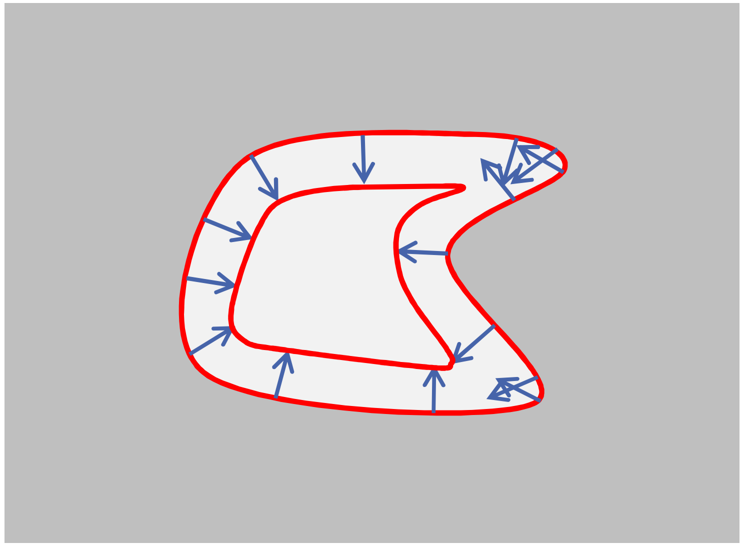
$$\frac{\partial \vec{x}}{\partial t} = \alpha \cdot \frac{\nabla \phi}{||\nabla \phi||}$$

$$\frac{\partial \phi}{\partial t} = -\nabla \phi \cdot \alpha \cdot \frac{\nabla \phi}{||\nabla \phi||}$$

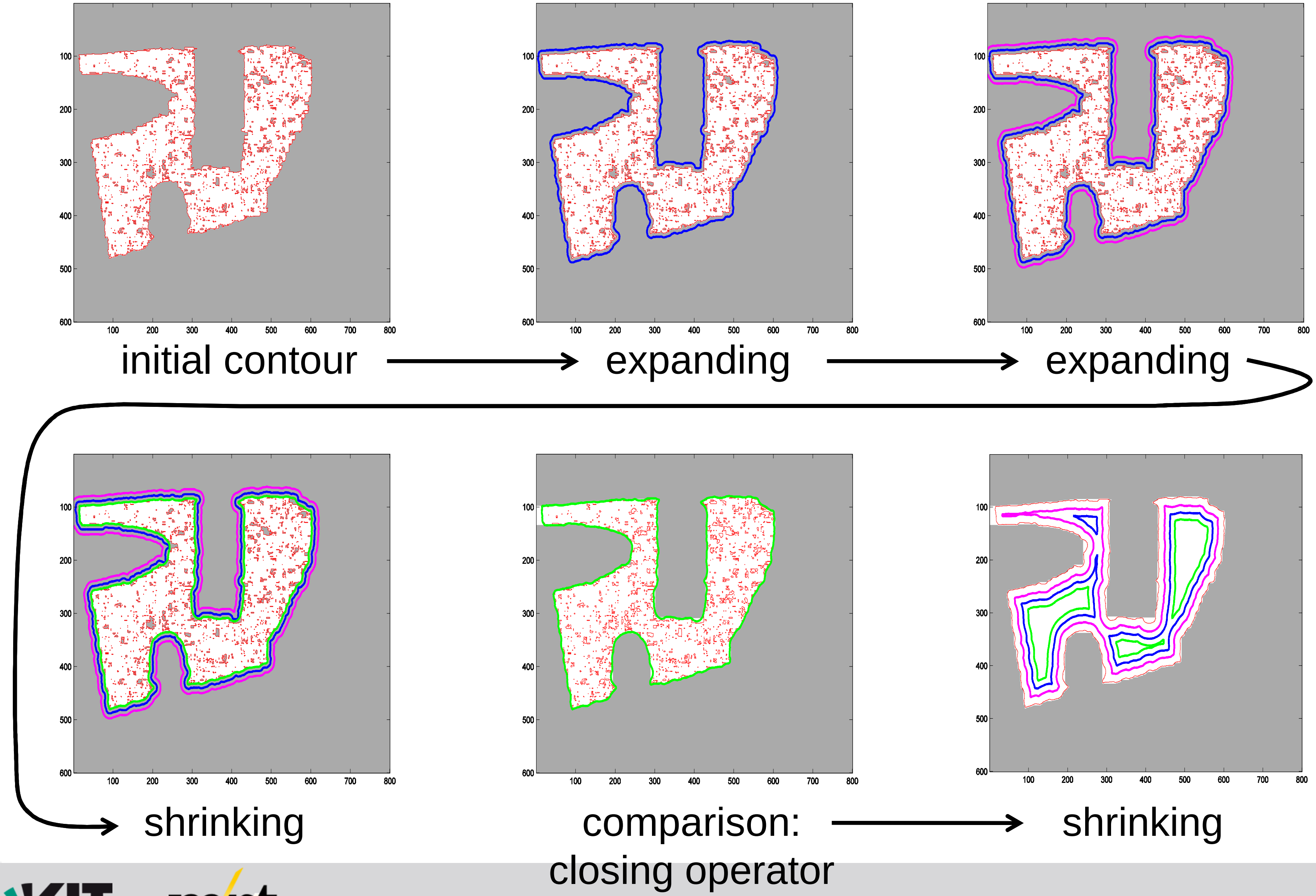
$$= -\alpha \frac{||\nabla \phi||^2}{||\nabla \phi||} = -\alpha ||\nabla \phi||$$



- 1. case $\alpha > 0$
  contour expands
- 2. case $\alpha < 0$
  contour shrinks



Expanding and Shrinking cont.

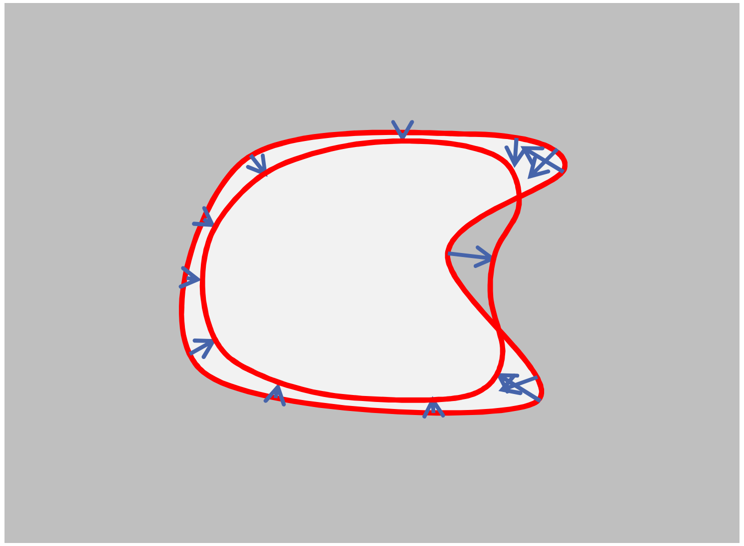


Expanding and Shrinking cont.

- level set evolution can be used to implement morphological operators:
  - dilation = expanding
  - erosion = shrinking
  - closing = shrinking after expanding
  - opening = expanding after shrinking

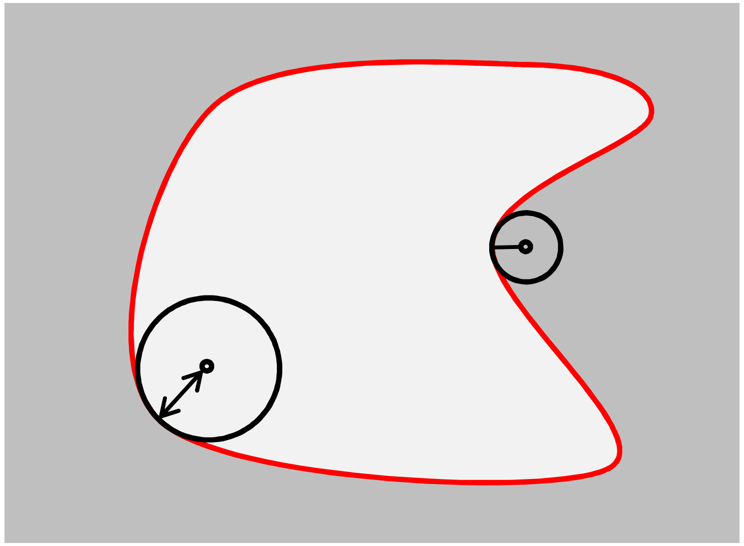
Contour Rectification

- making the contour smoother
  - expanding in concave areas
  - shrinking in convex areas
- evolving the level set
  - orthogonal to contour
  - depending on local curvature κ



Contour Rectification cont.

- curvature κ
  - in convex areas $\kappa = 1/r$ of circle that locally approximates contour
  - in concave areas: $\kappa = -1/r$ of circle that locally approximates contour
  - in general: $\kappa = \nabla \left(\frac{\nabla \phi}{||\nabla \phi||} \right)$



- level set update:

$$\frac{\partial \vec{x}}{\partial t} = -\beta \kappa \frac{\nabla \phi}{||\nabla \phi||}$$

$$\frac{\partial \phi}{\partial t} = \beta \kappa ||\nabla \phi||$$

Contour Rectification cont.

- Example:

Image Segmentation with Level Sets

- very simple idea for black/white images:
  - start with a very large contour
  - shrink contour at white pixels
  - don‘t shrink at black pixels

  $\rightarrow$ contour enwraps black areas

$$\frac{\partial \vec{x}}{\partial t} = \begin{cases} \gamma \cdot \frac{\nabla \phi}{||\nabla \phi||} & \text{if white pixel} \\ 0 & \text{if black pixel} \end{cases}$$

Image Segmentation with Level Sets cont.

- Example:

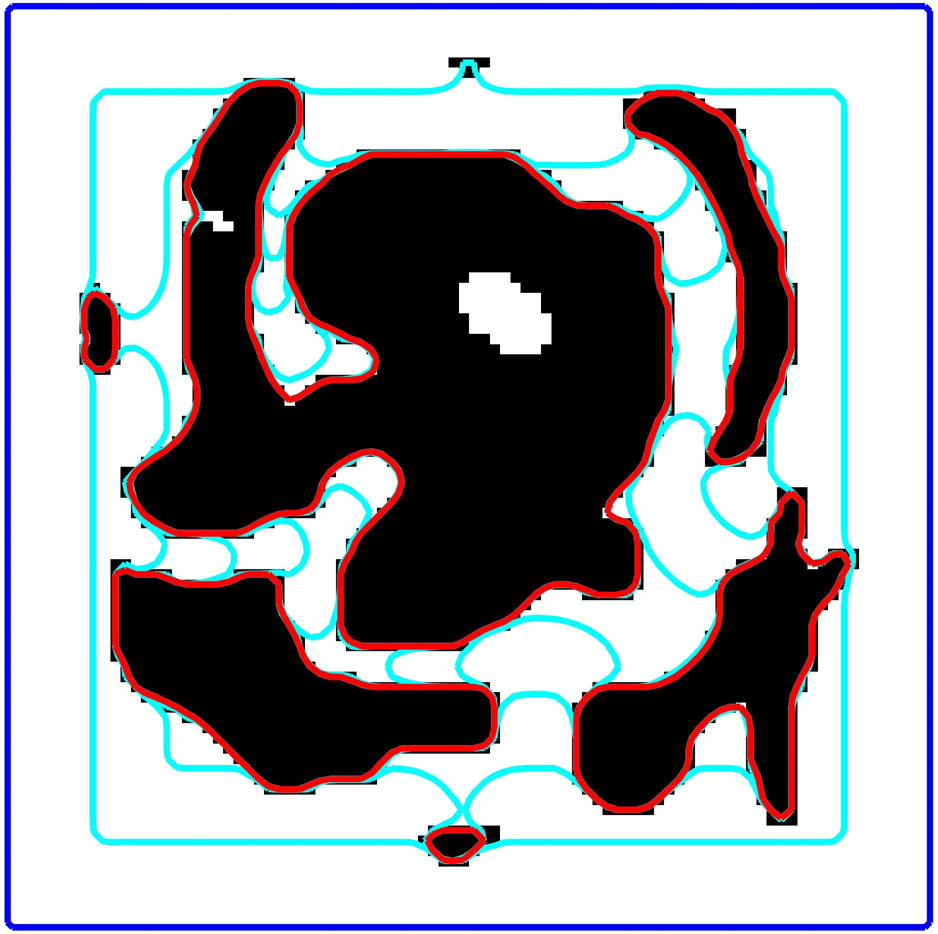


Image Segmentation with Level Sets cont.

- Example:

  combining segmentation
  with contour rectification

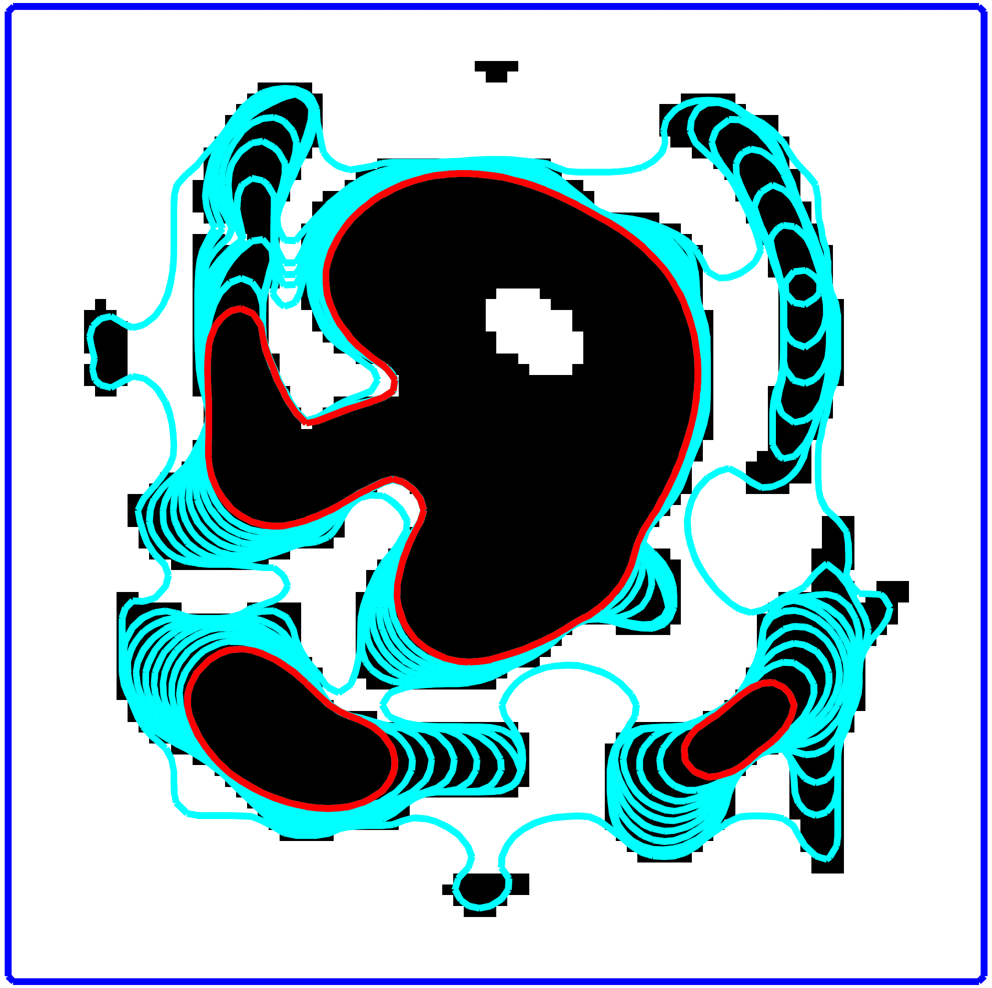


Image Segmentation with Level Sets cont.

- gradient based approach for image segmentation:
  – start with a very large contour
  – shrink contour at pixels with small gradient length
  – don‘t shrink at pixels with large gradient length (edge pixels)

  $\rightarrow$ contour enwraps areas bordered by edges

$$\frac{\partial \vec{x}}{\partial t} = -\epsilon(g) \cdot \frac{\nabla \phi}{||\nabla \phi||}$$

$$\epsilon(g) = \frac{\gamma}{\gamma + |Gauss * \nabla g|^p}$$

with appropriate $\gamma > 0, p \geq 1$

g denotes gray level image

Image Segmentation with Level Sets cont.

- Example:

Image Segmentation with Level Sets cont.

- Example:

Image Segmentation with Level Sets cont.

- Example:

  same as before, but with contour rectification

Image Segmentation with Level Sets cont.

- Example:

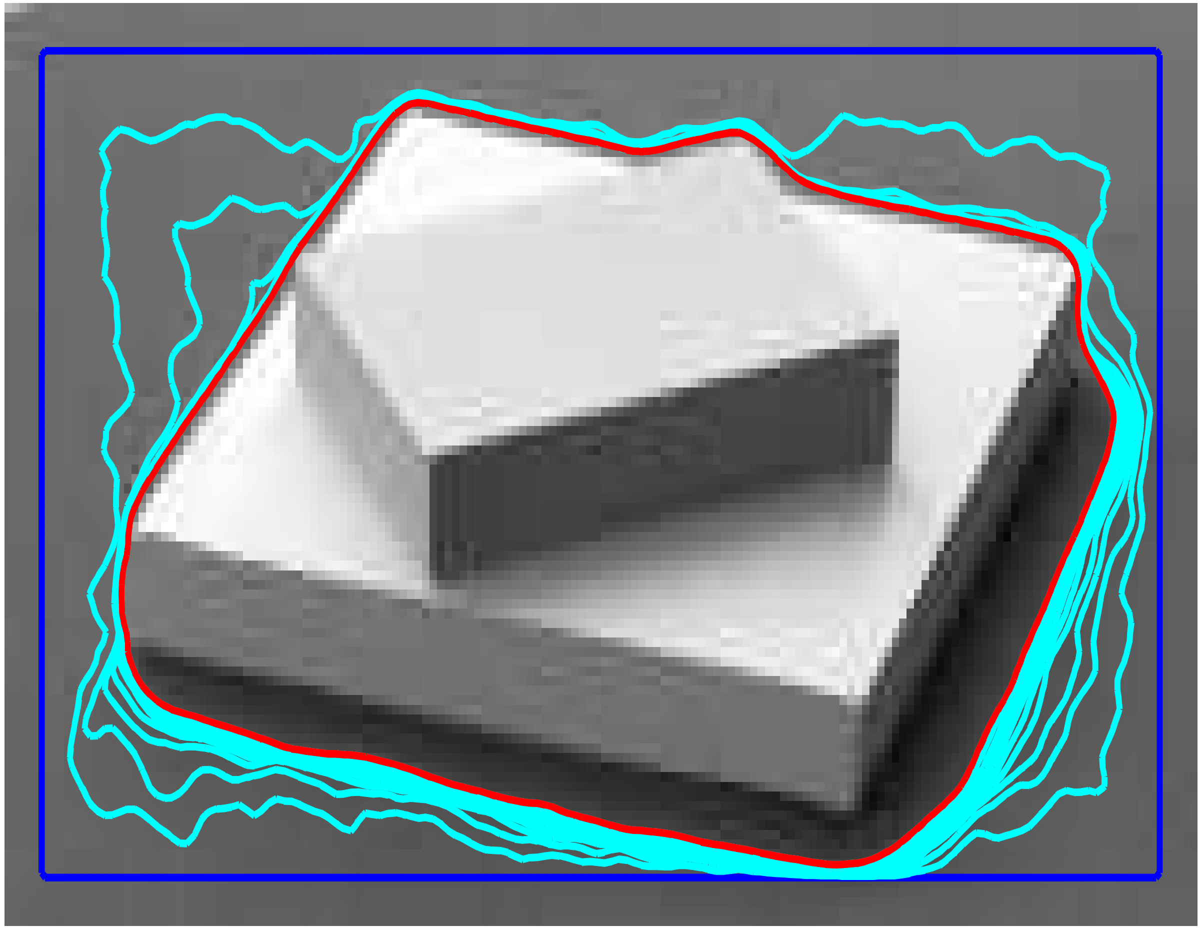


Image Segmentation with Level Sets cont.

- Mumford-Shah based segmentation
  - idea: pixels should be assigned to the segment with the most similar grey values (color values)

$\bar{g}_{foreground}$: average grey value (color) of pixels in foreground segment

$\bar{g}_{background}$: average grey value (color) of pixels in background segment

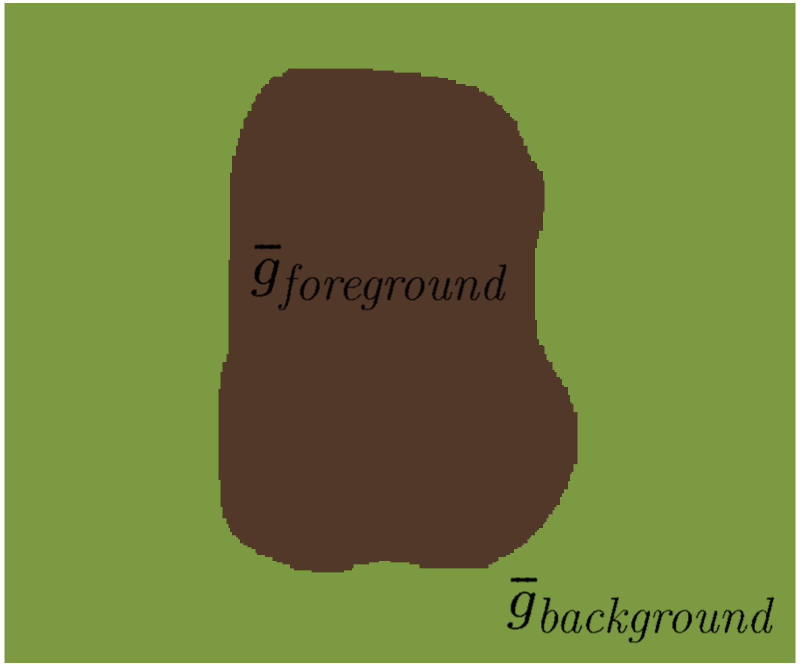


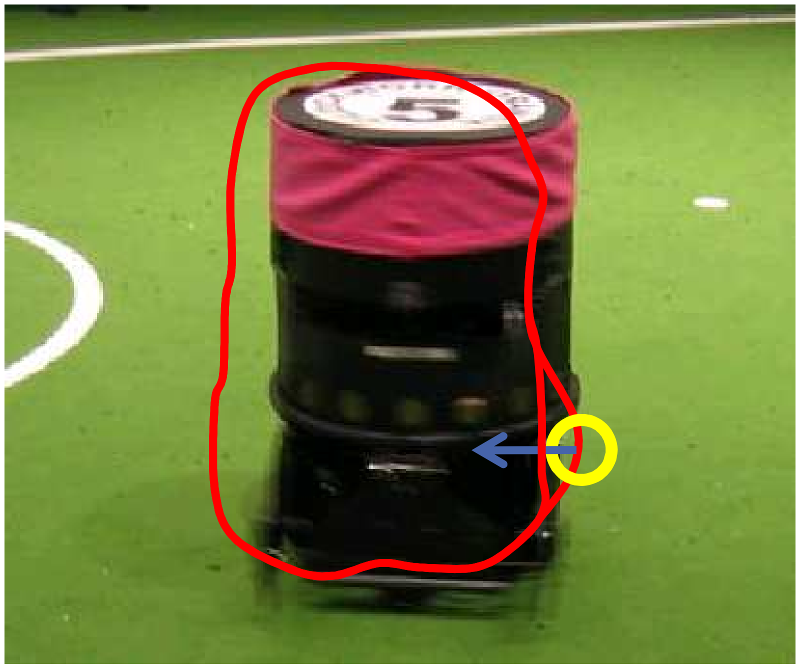
Image Segmentation with Level Sets cont.

– check for pixels on boundary with grey (color) value I

- pixel more similar to area outside

  $$(g - \bar{g}_{foreground})^2 > (g - \bar{g}_{background})^2$$

  → shrink contour



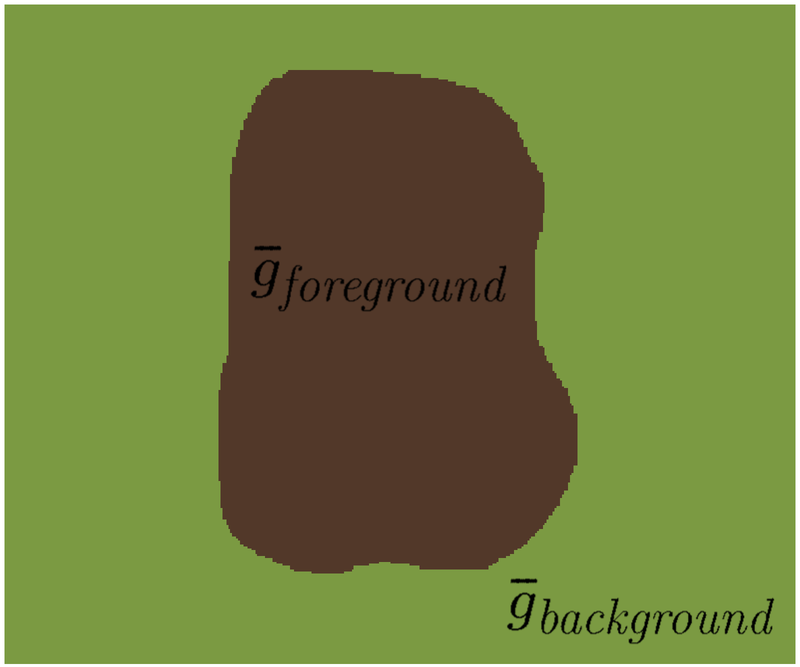


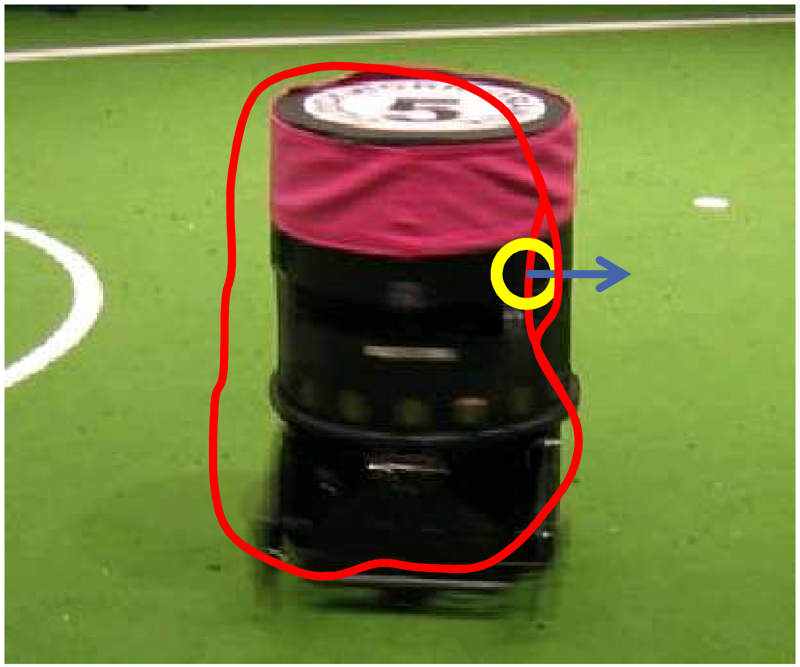
Image Segmentation with Level Sets cont.

– check for pixels on boundary with grey (color) value I

- pixel more similar to area inside

$$(g - \bar{g}_{foreground})^2 < (g - \bar{g}_{background})^2$$

$\rightarrow$ expand contour



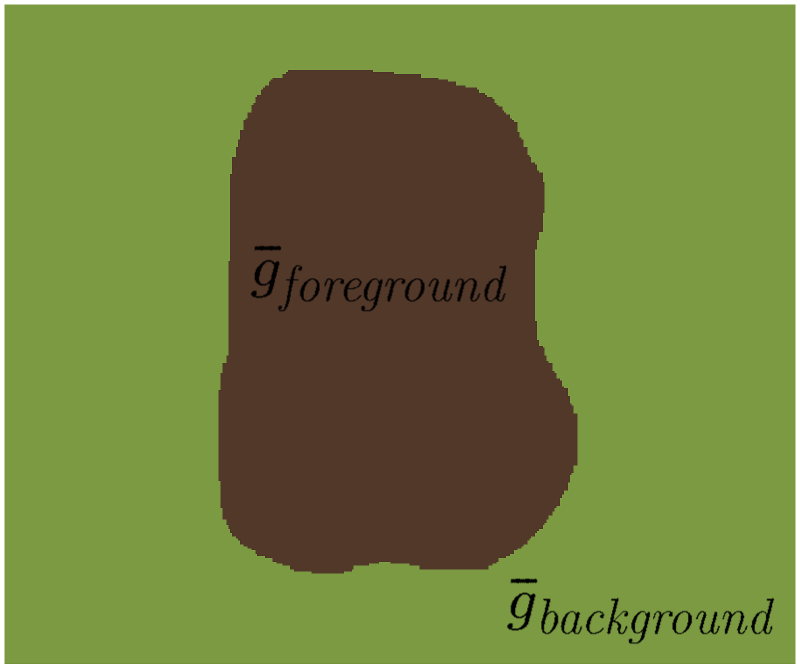


Image Segmentation with Level Sets cont.

- Mumford-Shah based segmentation:

$$\frac{\partial \vec{x}}{\partial t} = \frac{\nabla \phi}{||\nabla \phi||} \cdot \left(\; - \beta \kappa - \alpha - \lambda_1 (g - \bar{g}_{foreground})^2 + \lambda_2 (g - \bar{g}_{background})^2 \; \right)$$

contour rectification ($-\beta\kappa$)

overall preference for shrinking/expanding ($-\alpha$)

image segmentation ($-\lambda_1 (g - \bar{g}_{foreground})^2 + \lambda_2 (g - \bar{g}_{background})^2$)

  – $\alpha, \beta, \lambda_1, \lambda_2$ can be used to tune approach

Image Segmentation with Level Sets cont.

- Example:

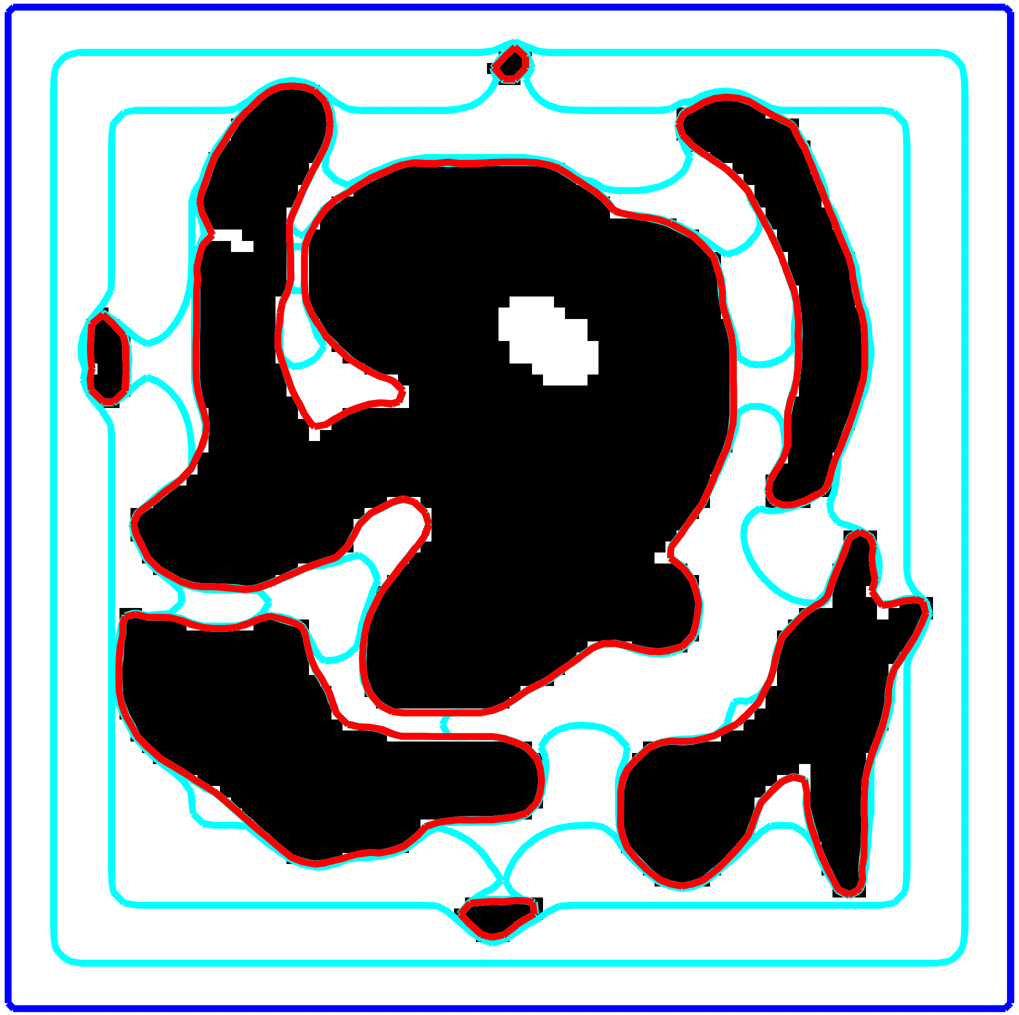
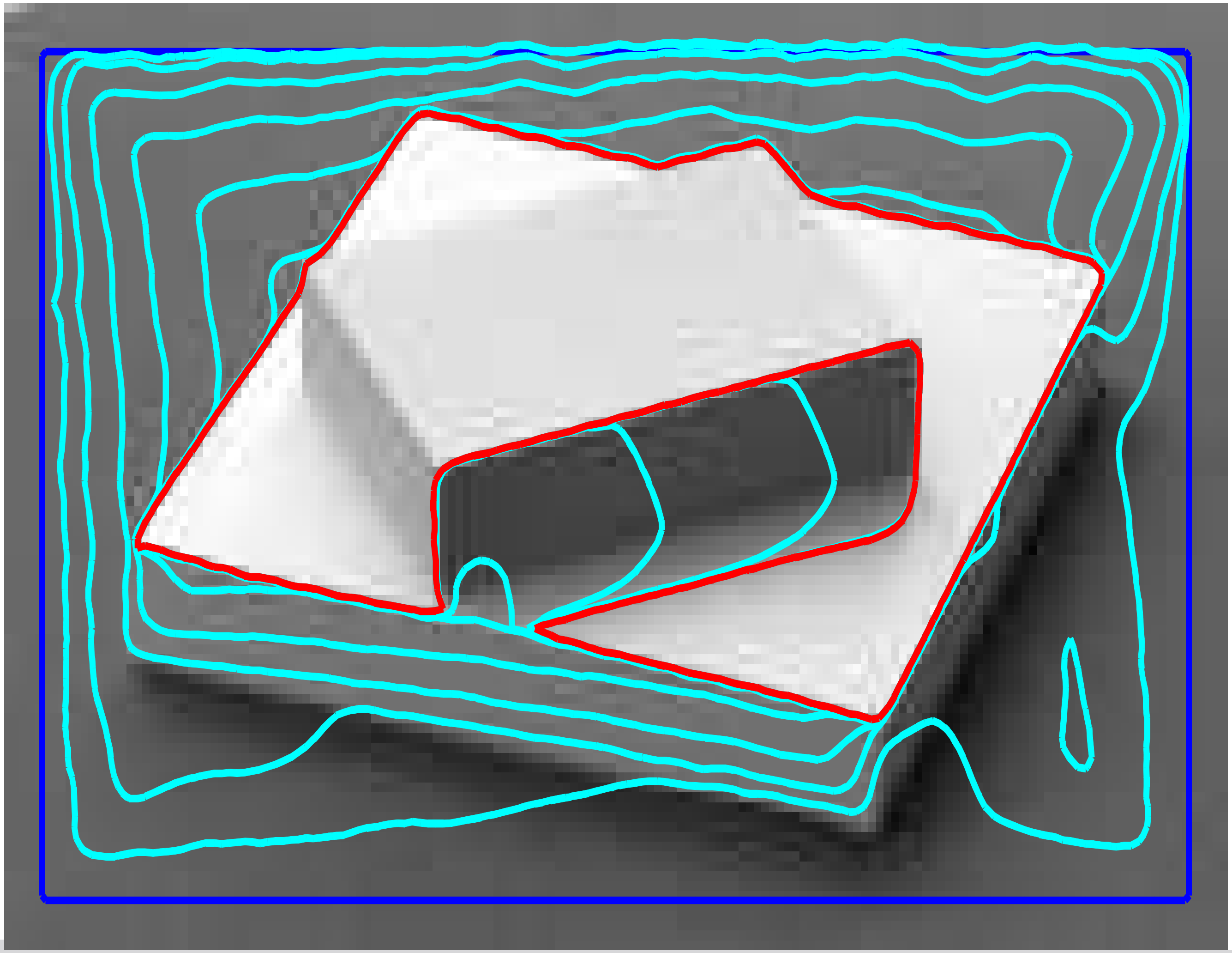


Image Segmentation with Level Sets cont.

- Example:

Image Segmentation with Level Sets cont.

- Example:



RANDOM FIELDS

Random Fields

– every pixel belongs to one segment. But to which one?

$$l(u,v) = ?$$

label is a priori unknown

label at pixel position, i.e. the number of the segment

- the segment label of each pixel is seen as a variable

– the feature vector of a pixel is related to its label

$$l(u,v) \leftrightsquigarrow f(u,v)$$

feature vector, known

label induces feature, feature allows conclusions about label

- feature vectors of pixels are also seen as variables, however, its value is observed
- the relationship is modeled by potential functions

$$\phi_f(l(u,v), f(u,v)) \begin{cases} \text{is small} & \text{if } f(u,v) \text{ supports label } l(u,v) \\ \text{is large} & \text{if } f(u,v) \text{ does not support label } l(u,v) \end{cases}$$

Random Fields

– labels of neighboring pixels are also related

$$l(u,v) \leftrightsquigarrow l(u+1,v)$$

$$l(u,v) \leftrightsquigarrow l(u,v+1)$$

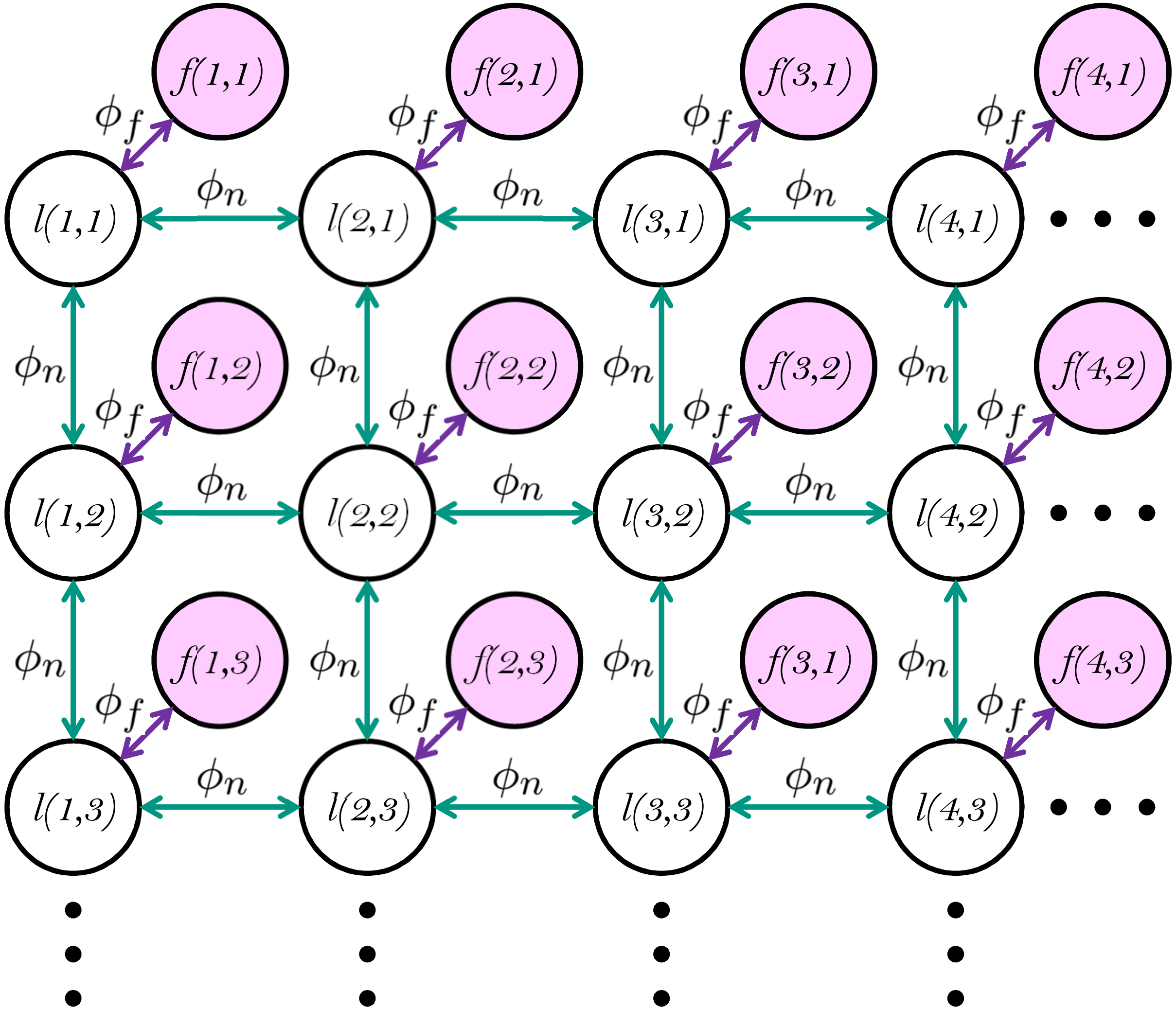
- the relationship is again modeled by potential functions

$$\phi_n(l(u,v), l(u+1,v))$$

$$\phi_n(l(u,v), l(u,v+1))$$

$$\phi_n(l(u,v), l(u+1,v)) \begin{cases} \text{is small} \\ \quad \text{if } l(u,v) \text{ and } l(u+1,v) \text{ are similar} \\ \text{is large} \\ \quad \text{if } l(u,v) \text{ and } l(u+1,v) \text{ are dissimilar} \end{cases}$$

Random Fields



Random Fields

- Goal:
  - find labels $l(u,v)$ so that the potential functions are minimized

$$\underset{l(\cdot,\cdot)}{minimize} \quad \alpha_f \cdot \sum_{u,v} \phi_f(l(u,v), f(u,v)) + \alpha_n \cdot \sum_{u,v} \phi_n(l(u,v), l(u+1,v)) + \alpha_n \cdot \sum_{u,v} \phi_n(l(u,v), l(u,v+1))$$

  - with weighting factors $\alpha_f, \alpha_n > 0$
  - solution of optimization problem
    - exact → hard (in general, exceptions exist)
    - approximative

Random Fields

- Example:
  - extract bright foreground object from dark background

    $l=0$ background

    $l=1$ foreground

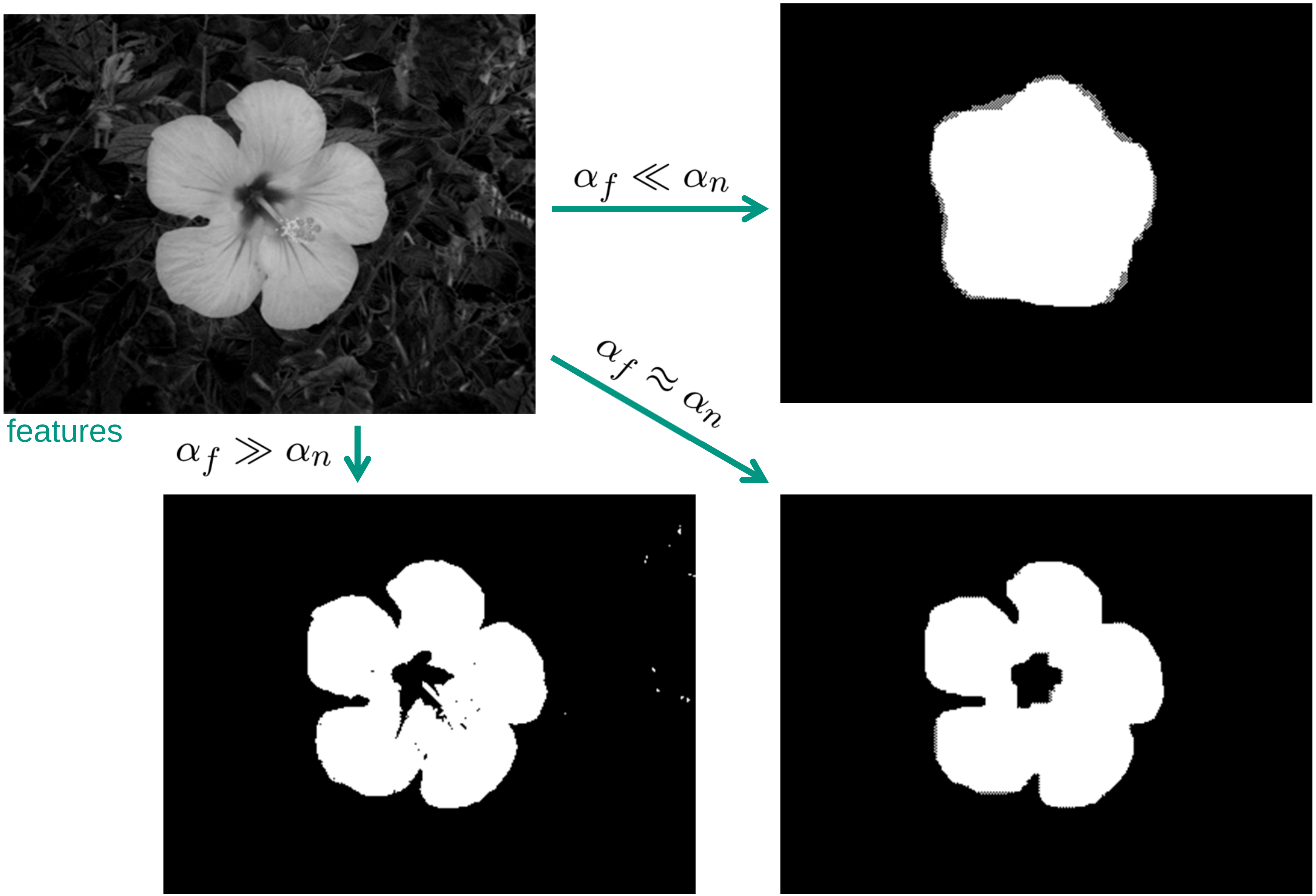
    f gray value $0 \leq f \leq 255$

$$\phi_f(l,f) = (l - \frac{1}{255} f)^2$$
$$\phi_n(l,l') = (l - l')^2$$

⇨ implements segmentation criteria:

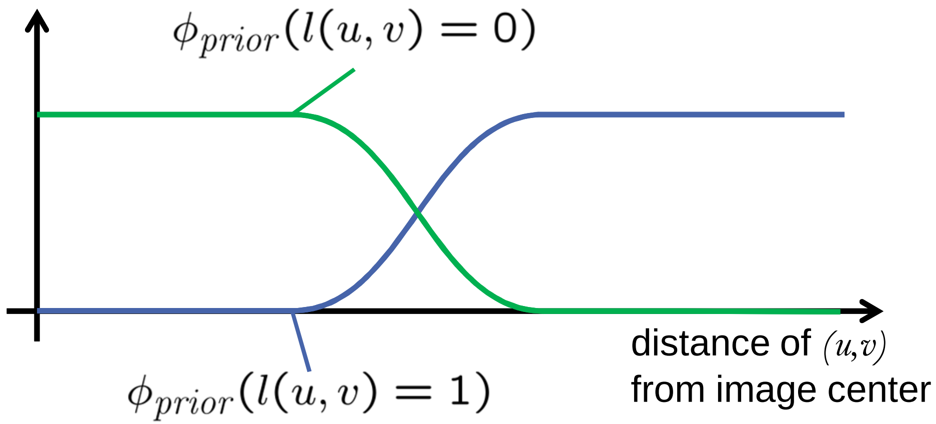
- predefined color criterion
- spatial criterion

Random Fields



Random Fields

- Advantage of random field modeling:
  - segmentation problem is formulated as optimization problem
  - potential functions allow to model many segmentation criteria, e.g.
    - seed points
      keep label function constant for seed points
    - general preferences for certain segment labels (a priori)
      → add unary potential function $\phi_{prior}(l)$
      e.g. to specify that the foreground object is expected to be in the center of the image



Random Fields

- prototype segment color. Pixels should be assigned to segment with most similar prototype feature
  → add prototype variables to random field, one for each segment
  → add potential functions that model similarity of prototype feature and pixel feature f

$$\phi_{prototype}(l, f, p) \begin{cases} \text{is small} & \text{if } f(u,v) \text{ and } p(l(u,v)) \text{ are similar} \\ \text{is large} & \text{if } f(u,v) \text{ and } p(l(u,v)) \text{ are dissimilar} \end{cases}$$

l: label at pixel position

f: feature(color) at pixel position

p: prototype features (colors) for all segments

⇨ implements homogeneity criterion

Random Fields

- Example:
  - subdivide foreground and background assuming that
    - foreground object is located in the center of the image
    - foreground object and background object have distinctive colors
    - uses pixel colors (e.g. in RGB) as features

$$\phi_{prior}(l(u,v)) = \begin{cases} \max\left\{\frac{|2u-width|}{width}, \frac{|2v-height|}{height}\right\} & \text{if } l(u,v)=1 \\ 1-\max\left\{\frac{|2u-width|}{width}, \frac{|2v-height|}{height}\right\} & \text{if } l(u,v)=0 \end{cases}$$

$$\phi_{prototype}(l,f,p) = ||f-p(l)||^2$$

$$\phi_n(l,l') = (l-l')^2$$

Random Fields

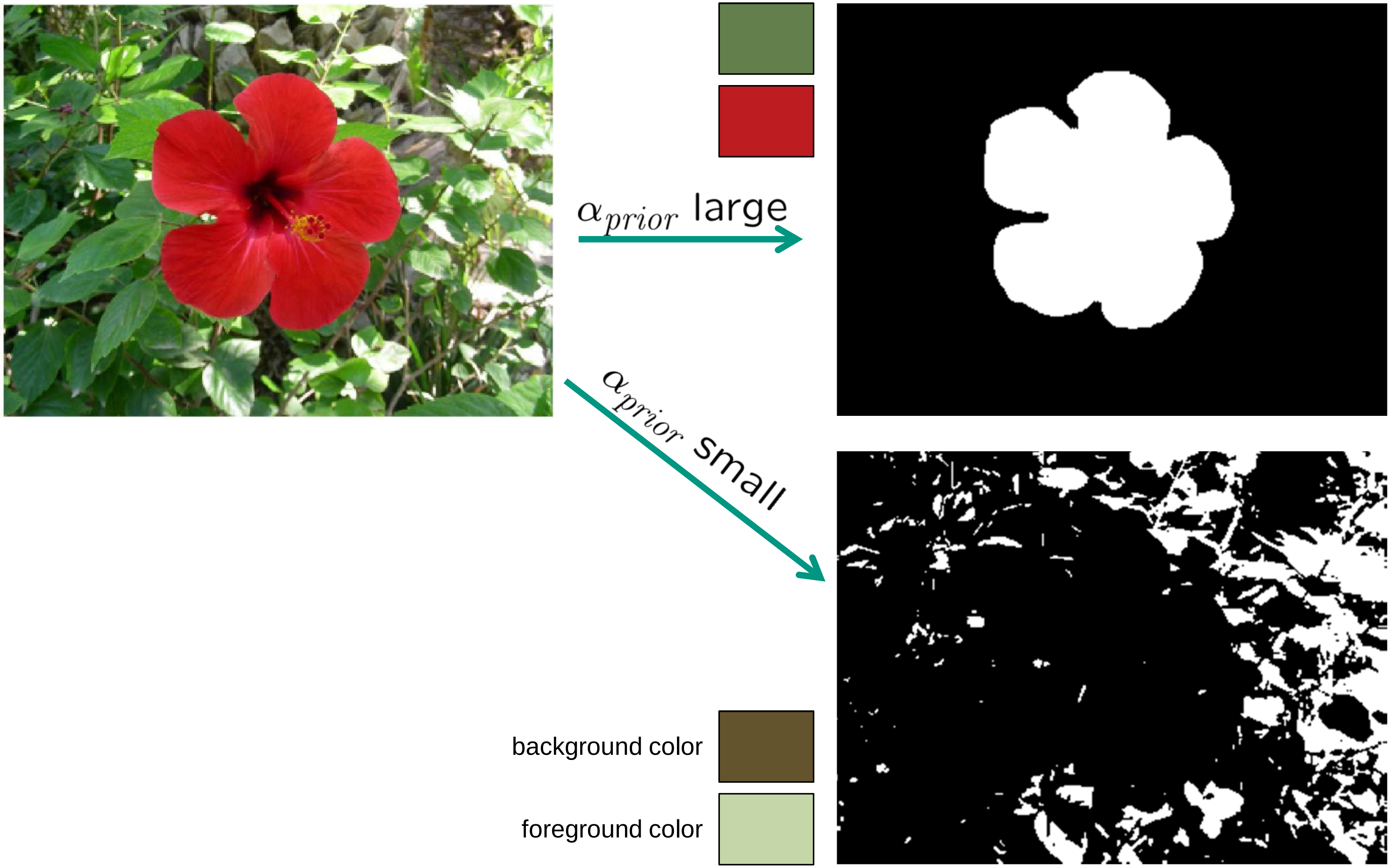
$$\phi_{prior}(l(u,v)) = \begin{cases} \max\left\{\frac{|2u-width|}{width}, \frac{|2v-height|}{height}\right\} & \text{if } l(u,v)=1 \\ 1-\max\left\{\frac{|2u-width|}{width}, \frac{|2v-height|}{height}\right\} & \text{if } l(u,v)=0 \end{cases}$$

$$\phi_{prototype}(l,f,p) = ||f-p(l)||^2$$

$$\phi_n(l,l') = (l-l')^2$$

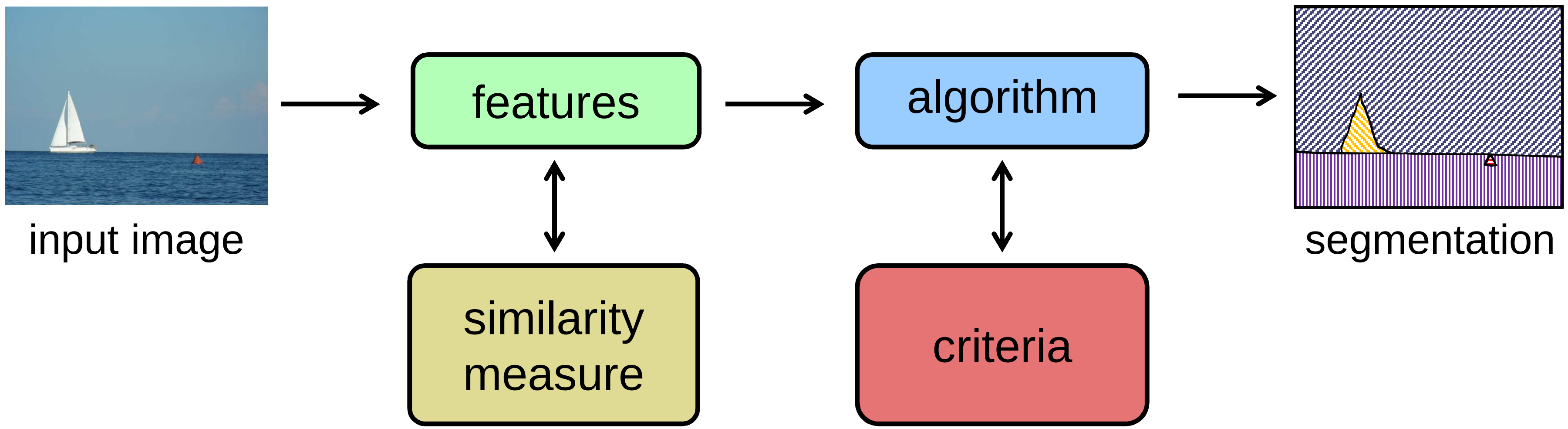
$$\begin{aligned} \underset{l(\cdot,\cdot),p(\cdot)}{minimize} \quad & \alpha_{prior} \cdot \sum_{u,v} \phi_{prior}(l(u,v)) \\ & + \alpha_f \cdot \sum_{u,v} \phi_{prototype}(l(u,v), f(u,v), p) \\ & + \alpha_n \cdot \sum_{u,v} \phi_n(l(u,v), l(u+1,v)) \\ & + \alpha_n \cdot \sum_{u,v} \phi_n(l(u,v), l(u,v+1)) \end{aligned}$$

Random Fields



SUMMARY: SEGMENTATION

Segmentation: the Complete Picture



features	similarity measure	criteria	algorithms
▪ color ▪ texture features ▪ depth ▪ motion ▪ …	▪ Euclidean dist. ▪ other metric ▪ …	▪ predefined values ▪ neighborhood ▪ homogeneity ▪ spatial ▪ size ▪ …	▪ region growing ▪ CCL ▪ mean-shift ▪ level sets ▪ random fields ▪ …

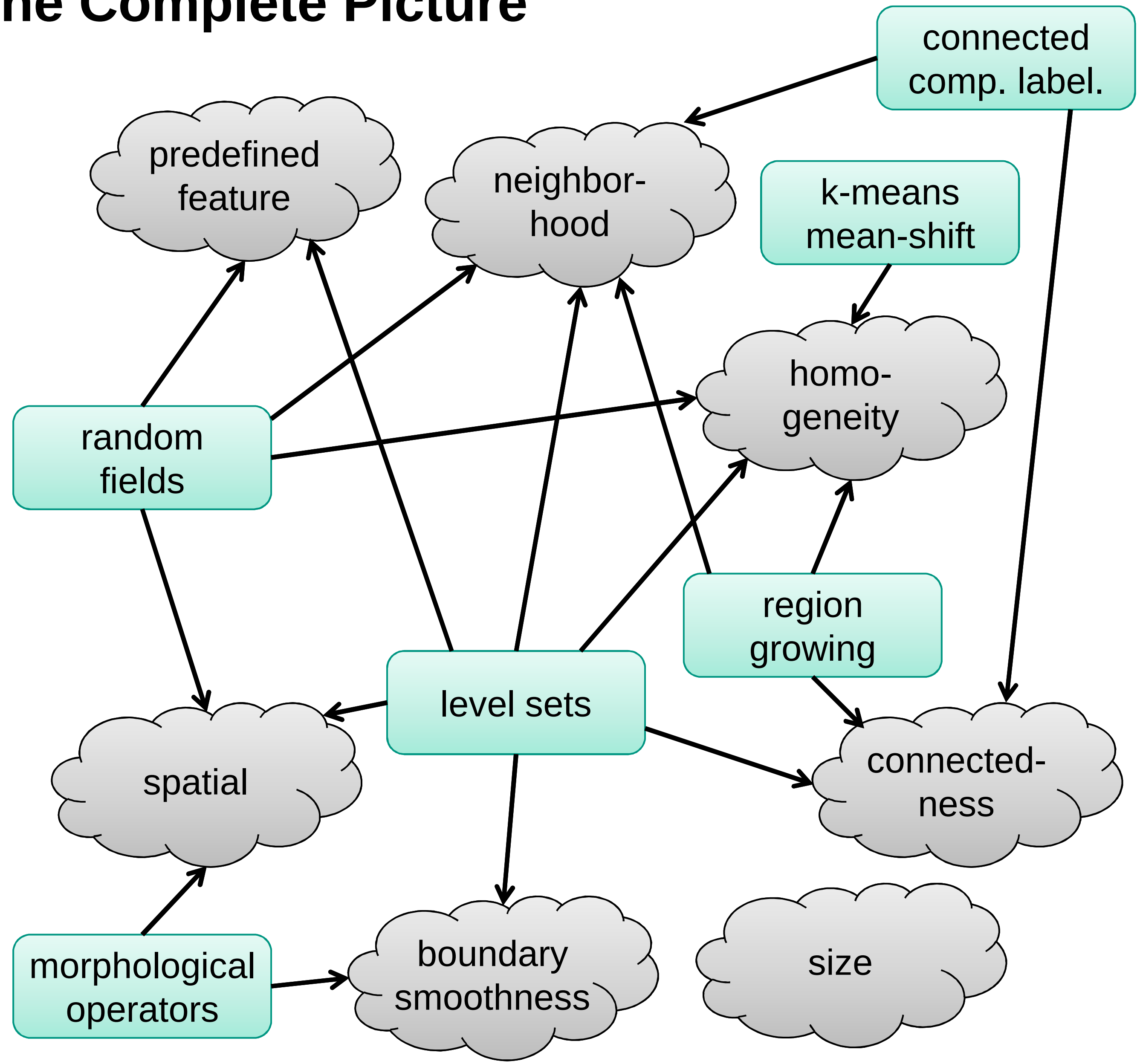
Segmentation: the Complete Picture

algorithms

- region growing
- CCL
- mean-shift
- level sets
- random fields
- …

criteria

- predefined values
- neighborhood
- homogeneity
- spatial
- size
- …



Segmentation: the Complete Picture

features

- color
- texture features
- depth
- motion
- …

similarity measure

- Euclidean dist.
- other metric
- …

- which features are salient and discriminative?
  - color
  - texture
  - depth
  - motion
  - …
- which representation is appropriate?
  - color space
  - various texture features
  - histograms
  - …
- how can we compare feature vectors?
  - similarity measures