Chapter 6

SEGMENTATION: PRINCIPLES AND BASIC TECHNIQUES

Abstract

- The purpose of image segmentation is to **generate pixel agglomerations** from an image that constitute parts of depicted objects.
- In medical imaging, segmentation often refers to the delineation of specific structures. Hence, it includes parts of classification as well. 2
- Segmentation strategies in medical imaging combine data knowledge with domain knowledge to arrive at the result.
- Data knowledge refers to assumptions about continuity, homogeneity, and local smoothness of image features within segments. Domain knowledge represents information about the objects to be delineated.

Concepts

› Data features: intensity and texture;

› The role of homogeneity, smoothness and continuity in segmentation, using object localization and appearance as domain knowledge;

› The role of interaction;

› Basic segmentation techniques: thresholding, region merging techniques, region growing, watershed trans-form, live wire.

Segmentation -Issues

Fig. 6.1 Finding a general solution for a segmentation task would be very difficult even if only the houses depicted in the four examples would need to be segmented correctly

- For analyzing a digital photograph, this segmentation task would group pixels to regions that may belong to (parts of) objects based on the attributes of these regions.
- Hence, segmentation of images is similar to creating phonemes in speech or detecting syllables in a written text as it creates basic semantic entities from images.
- However, it is difficult to apply domain knowledge about objects in an image to segmentation.
- Appearances of objects in some image—consider a picture of a landscape with a house in the foreground, some trees, and mountains in the background—may be very different within and between object classes

segmentation of medical images

- For the segmentation of medical images, the situation is somewhat less grave, as a medical image represents (ideally) the measurement of a diagnostically relevant entity that is measured in the same way everywhere in the body.
- Consider CT, for instance, where X-ray attenuation is measured on the normalized Hounsfield scale.
- Attenuation should not vary with location but only with density and atomic number.
- External influences such as shading or object-specific signal degradation still add an object- or location-dependent component to the measured and reconstructed signal.
- Furthermore, measured values are not unique for a specific object class.
- Hence, data-driven segmentation will almost always result in a collection of regions that in some cases will separate an object of interest into several segments and in other cases will fuse different objects into a single segment.

Segmentation Strategies

- There are several ways to deal with missing information without sacrificing the assumption that a low-level segmentation criterion is valid everywhere in the image:
- Foreground segmentation (Fig. 6.2) focuses on a single object in the image.
- **Segmentation criteria create a good partitioning of foreground objects,** whereas the quality of partitioning the background is irrelevant.
- Later analysis is carried out solely on foreground segments. The strategy requires some model knowledge to be applied after segmentation for separating foreground segments from the background.

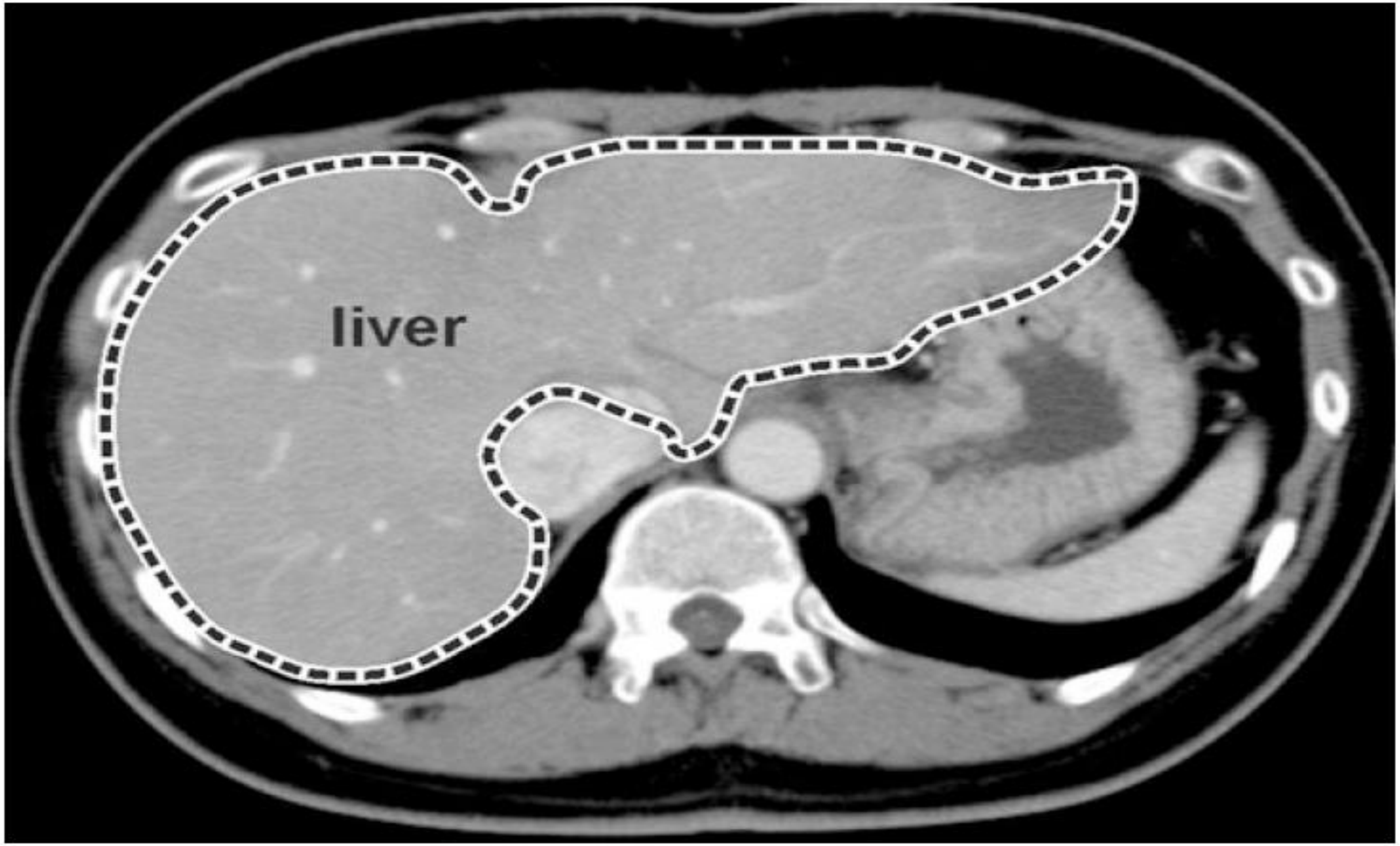


Fig. 6.2 If only the liver needs to be separated from the CT, segmentation would be successful irrespective of any errors in regions outside the liver. Foreground segmentation that only incorporates information as to what differentiates liver from all other tissues would be sufficient

Segmentation Strategies

- **Hierarchical segmentation** (Fig. 6.3) applies a multi-resolution concept for gradual refinement.
- A first segmentation creates segments that are smaller than the smallest object. It is assumed that a common criterion (in most cases a homogeneity criterion) can be found at this scale. The result is sometimes called **over-segmentation**.
- At the next level, some of these segments are merged into larger segments according to domain knowledge about object appearance.
- Successful application of this strategy requires that meaningful segments can be defined by a common criterion at a single but unknown scale.
- This scale is found by analyzing the levels of the segmentation hierarchy.

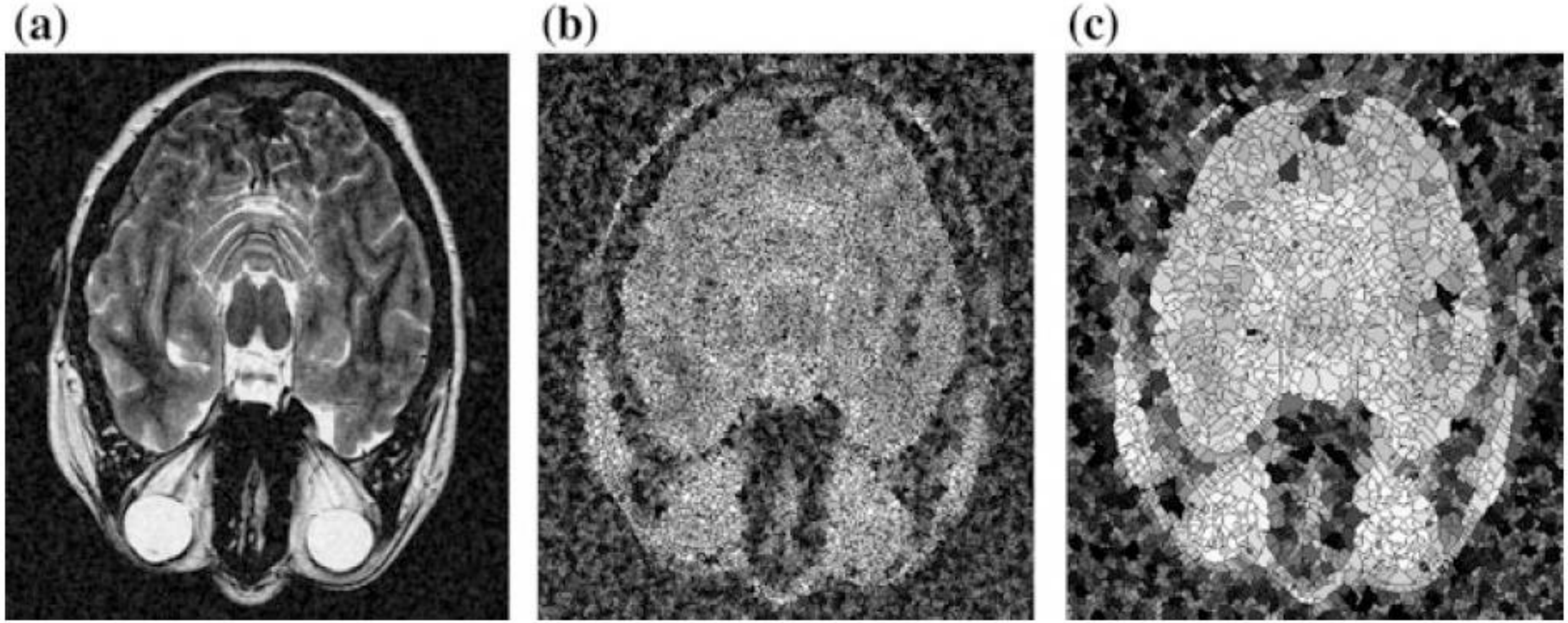


Fig. 6.3 In hierarchical segmentation, the first segmentation step provides little more than superpixels. Two examples from segmenting (**a**) can be seen in (**b**) and (**c**), where slightly different homogeneity constraints lead to different sizes. The next hierarchy level attempts to combine superpixels with higher semantic units

Segmentation Strategies

- Multilayer segmentation (Fig. 6.4) is another multi-resolution technique.
- It is assumed that a common segmentation criterion exists, but that its scale may vary throughout the image (like a structured texture of objects in a photograph of which the scale varies with distance of the object to the camera).
- Segmentation is carried out at different scales producing layers of segments.
- Later analysis will have to estimate local scales and patch segments according to it. It is more general than the previous strategy as the scale of a criterion often varies for different structures in an image.
- Analysis of segments is more difficult because an appropriate scale for every segment has to be established independently from other segments.

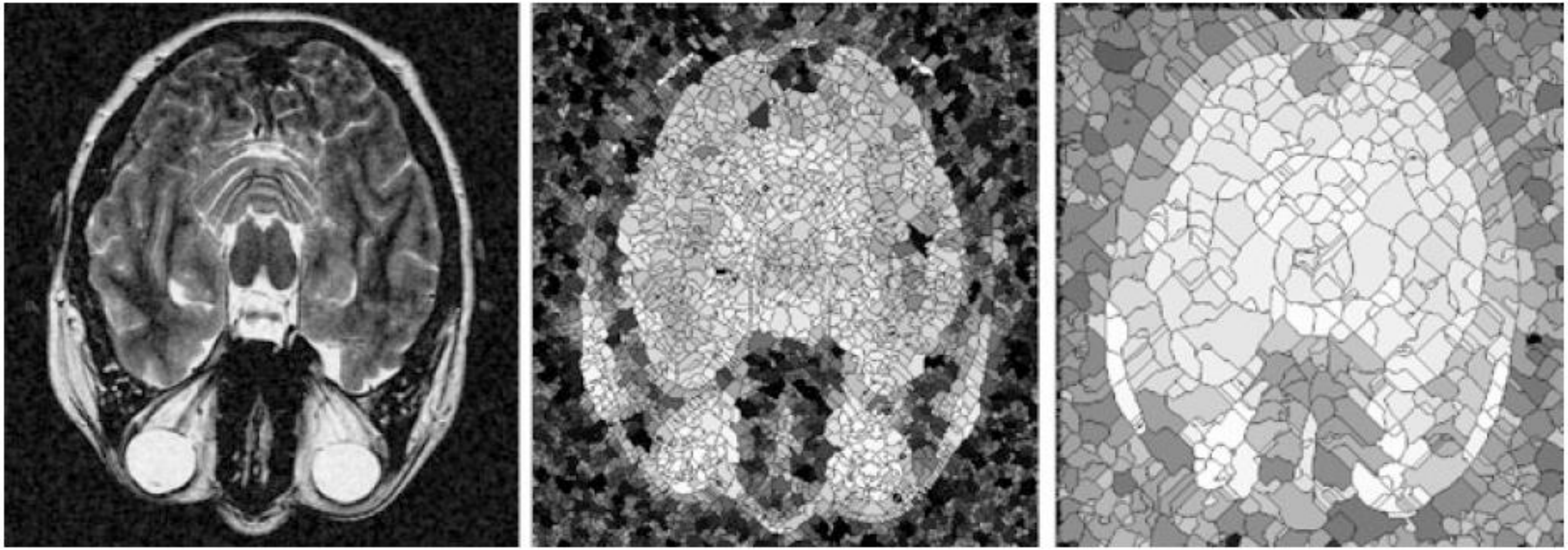


Fig. 6.4 In multilayer segmentation, segmentations at different levels of resolution are created and evaluated in parallel. In this example, the boundary between grey matter and CSF is captured quite well in the low-resolution segmentation, while the boundary between fat and bone is captured better in the high-resolution image

Medical Images- segmentation

- In medical imaging, different semantics stem from the intentional choice of the acquisition technique.
- The pixel value in a medical image is much more directly related to the diagnostic question than a pixel value of a photograph to the meaning of some outdoor scene.
- The acquisition technique has been chosen for the very reason that it is known to offer insight into some diagnostic question. This domain knowledge can be incorporated into the segmentation process. It becomes especially apparent for slice images.
- In some images, segmentation criterion on pixel values may be sufficient for assigning class membership to a segment. Hence, segmentation and classification may mix in medical image analysis.
- The search for occurrences of a specific structure by segmentation causes foreground segmentation to be more frequent in medical image analysis than in other image analysis tasks.
- computer-assisted analysis of medical images is virtually impossible without segmentation.

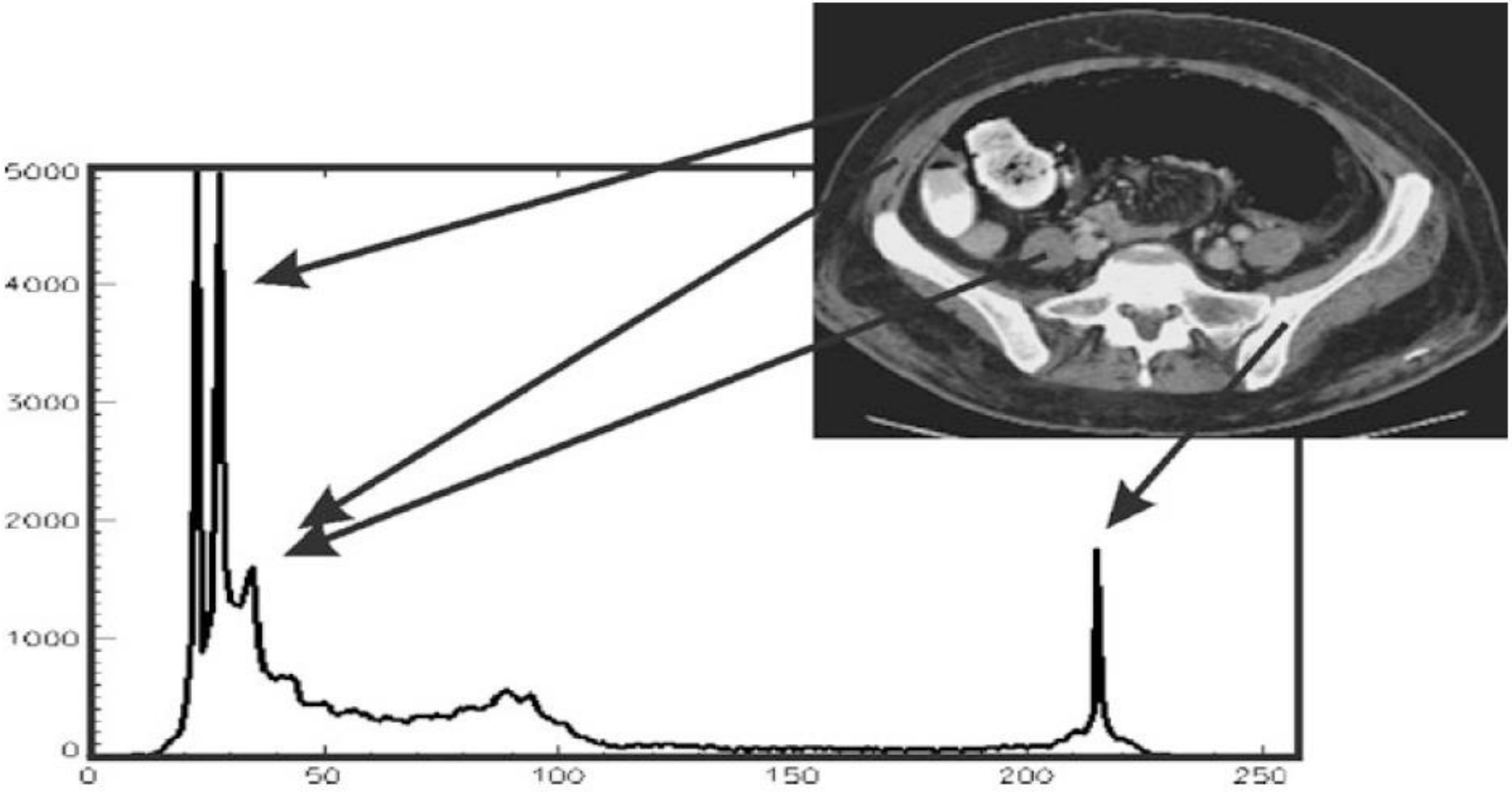


Fig. 6.5 In medical imaging, there is often a much more direct relationship between pixel intensity and semantics compared to photographic pictures (although it is by no means a unique mapping)

Data Knowledge

- **Continuity in space and continuity in time** are the two main data properties,used for segmentation.
- An observable object is assumed to stand out in an image by some homogeneous intensity or texture in a region.
- Segmentation based on spatial continuity partitions a 2d or 3d image such that homogeneity within segments is larger than between adjacent segments. It assumes that the **course of the segment boundary does not change abruptly.**
- Temporal continuity can be used in the same fashion by treating time as fourth dimension.
- Often, temporal continuity is exploited by computing a segmentation result at one time step and using it to constrain or initialize the segmentation at the next time step.

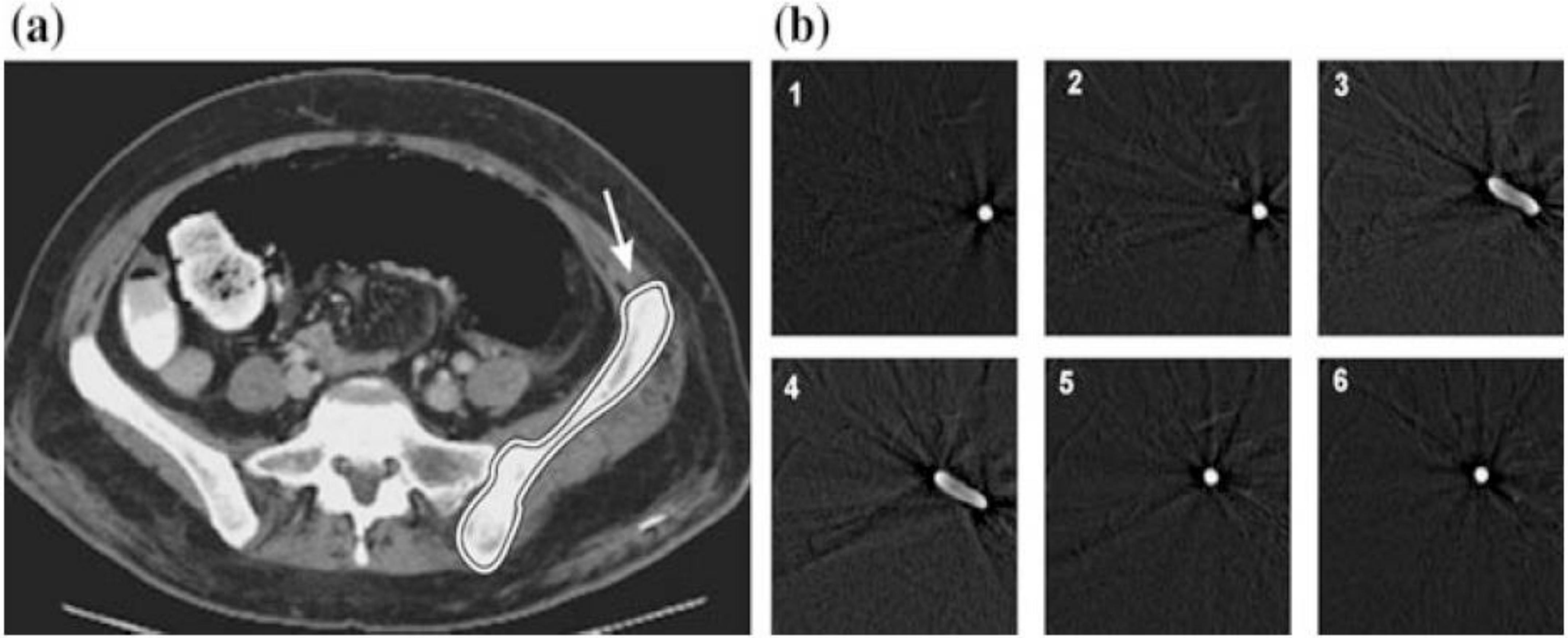


Fig. 6.6 Continuity in space is used, for instance, when the fairly smooth course of the boundary of the hip bone is segmented using a spline curve (**a**), or when predicting vessel locations in the sequence of slices in (**b**) by using the location from the previous slice for initialization

Data Knowledge

- Propagation of segmentation constraints along the time axis or a spatial axis makes the result dependent on the initial segmentation.
- A developer should make sure that this initialization is as good as possible. This may be achieved
- • by letting the user flip through slices or time steps for selecting the best starting point. Segmentation is then carried out from this initialization in both directions along the time or spatial axis.
- • by starting the segmentation from several initialization points and selecting the best-rated segmentation from this. It requires a quality measure for segmentation results.
- • by letting the process go several times back and forth through the data improving the segmentation until a stable state of segmentation is reached.
- Carrying out n-dimensional segmentation by imposing continuity constraints between adjacent segmentations in (n − 1)-dimensional space reduces subsequent segmentation to a registration task if a one-to-one correspondence exists between segments in adjacent segmentations.

Homogeneity of Intensity

- homogeneity of intensity which is given by the intensity variance within a segment. Other approximations such as computing the difference between the brightest and the darkest pixels of a segment can be used as well.
- Pixel or voxel intensities of a structure of interest often vary little throughout the segment.
- In consequence, intensity-based segmentation schemes are quite popular.
- However, a number of artefacts have to be accounted for. The best-known is noise.
- Segmentation in a noisy environment is more difficult than it seems, since noise reduction capabilities of the human visual system are quite effective.
- A human may see a visible difference between neighboring segments long before homogeneity-based segmentation would separate segments

Homogeneity of Intensity

- Noise is often modeled as Gaussian with zero mean value and a variance according to the SNR.
- Noise may be reduced during pre-processing, but this may cause small details to get removed (see Fig. 6.8).
- Noise reduction may be included into segmentation as well, e.g., **by applying a multi-resolution strategy.**
- A multi-resolution approach such as a **Gaussian pyramid** creates a sequence of images at different resolutions by repeated low-pass filtering and subsampling.
- Shading is another artefact that sometimes influences intensity-based segmentation.
- It usually stems from image acquisition. shading can be resolved when resorting to boundary criteria instead of region criteria.

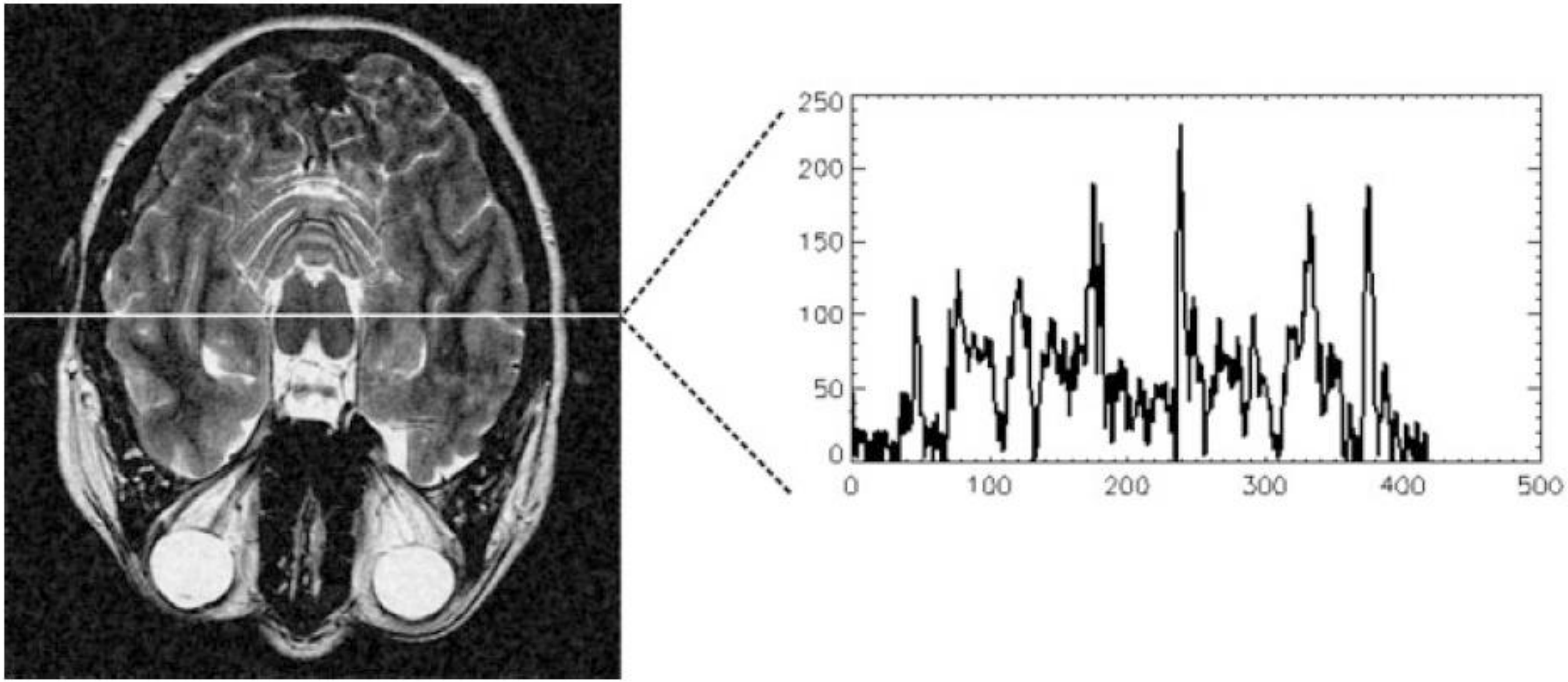


Fig. 6.7 Although contrast between tissues is good, the image contains a substantial amount of noise that can be seen in a plot of intensities of one line in the image

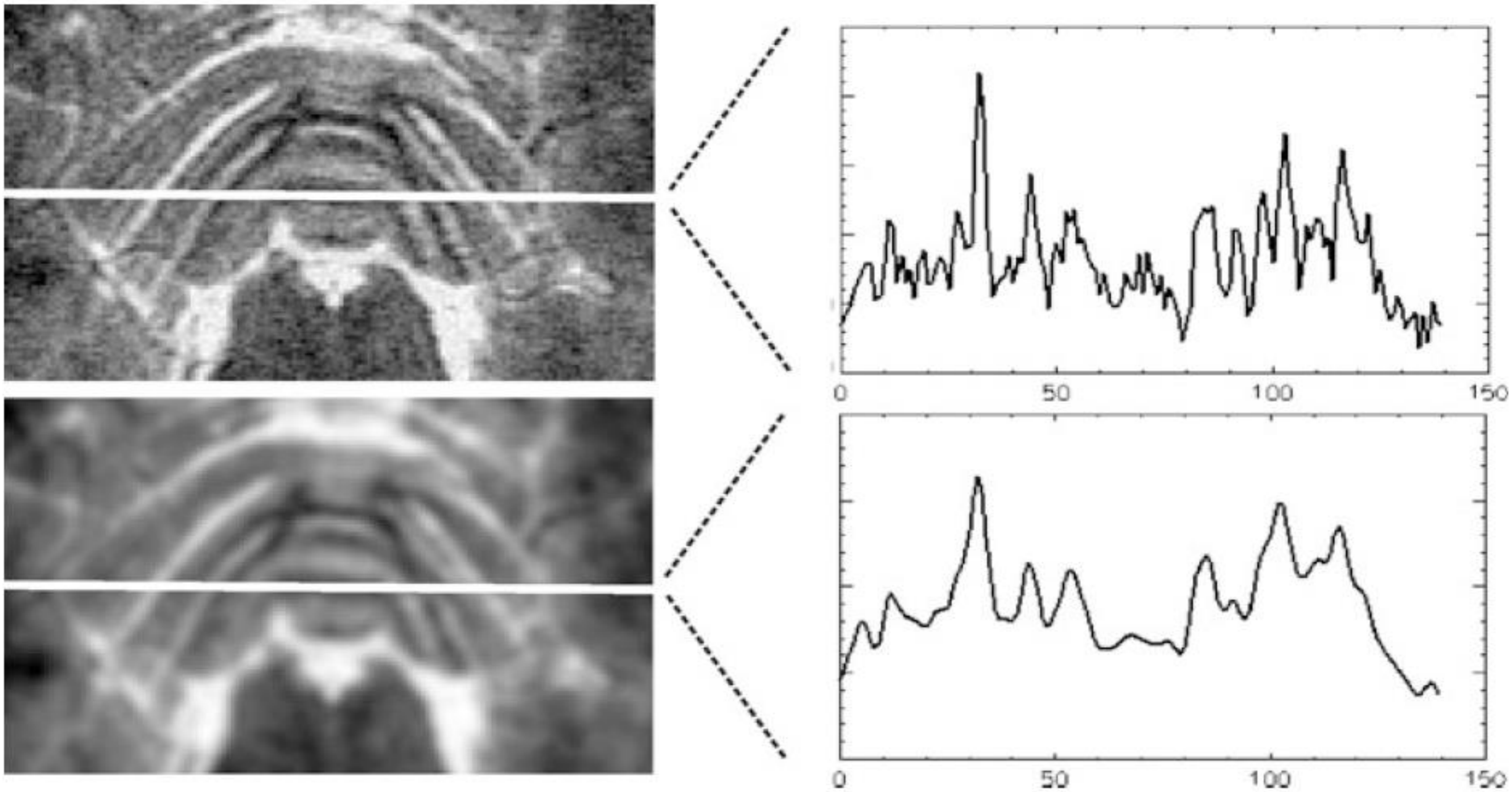


Fig. 6.8 Noise reduction prior to segmentation may cause loss of detail which is most critical if small structures are to be extracted by segmentation

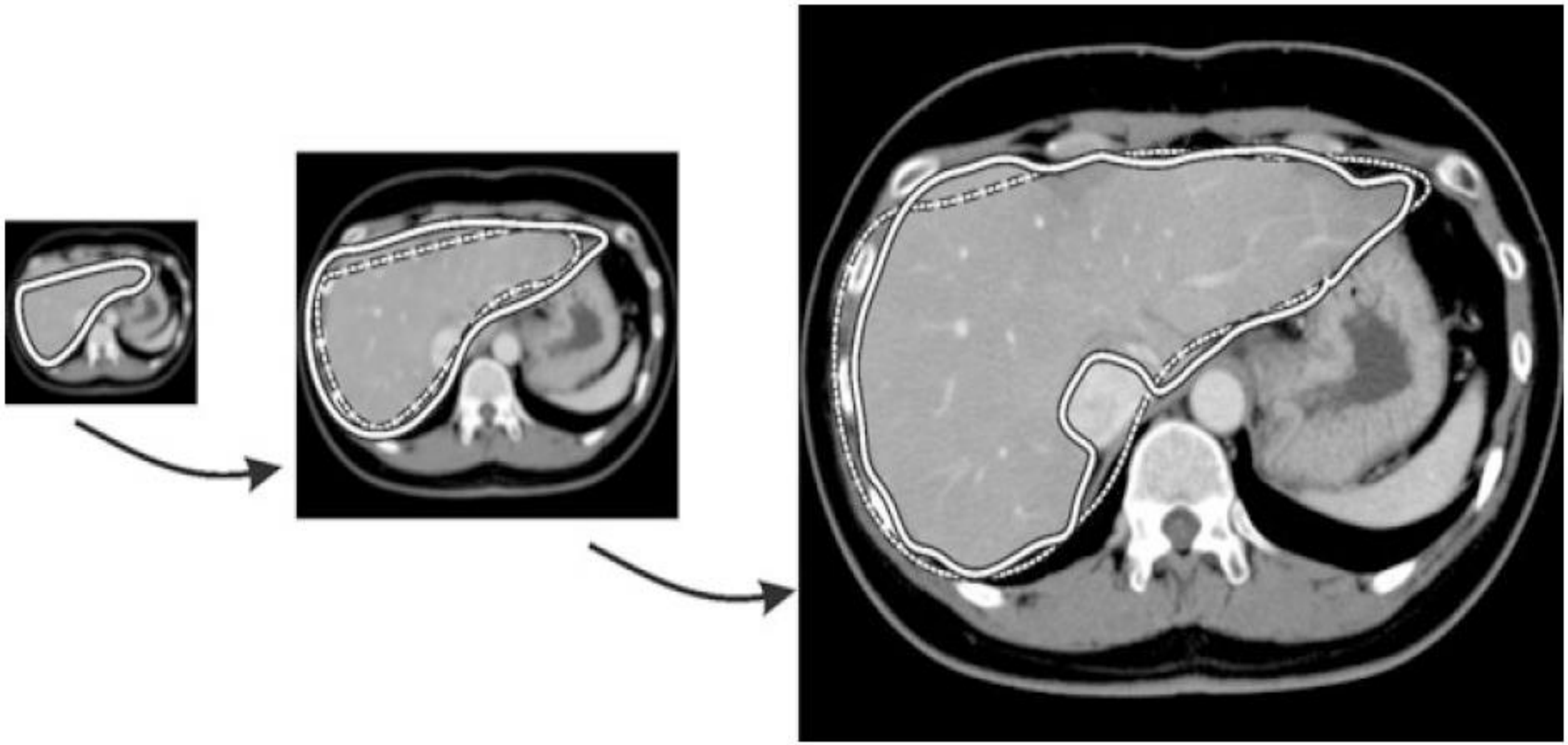


Fig. 6.9 Applying a multi-resolution strategy to segmentation: segmentation in a low-resolution image is used as initialization on the next higher resolution

Homogeneity of Texture

- Continuity may also refer to the texture of structures. Texture features, for a pixel can be computed from a region around this pixel. Their reliability depends on the size of this region. This is apparent for Haralick's GLCM features.
- Texture computation at **unknown segment boundaries becomes unreliable if pixels of more than one segment contribute to the texture measure.**
- **There are four strategies to deal with this problem as follows:**
- Texture measures are chosen that require only a small number of pixels for computing reliable features. Unreliability at segment boundaries is neglected or may even be used as characteristic for finding a boundary.
- Segmentation is carried out iteratively. At initialization, the neighborhood around a pixel of a given texture is assumed to contain only pixels of that texture. In a second step, regions for texture computation are refined using edge information from the first step.

Homogeneity of Texture

- Segmentation is carried out in a multi-resolution framework. Low-reliability results computed at a low resolution initialize the segmentation at higher resolution. It requires that textures can be computed at different levels of resolution and that resolution-dependent reliability can be computed.
- Texture-based segmentation is preceded by an initial segmentation step based on homogeneity.
- A strong homogeneity criterion is used that results in an over-segmentation. The resulting image consists of many segments containing only few pixels. The segments are called superpixels.
- Assuming that each superpixel lies in exactly one of the searched segments, a texture measure for each superpixel can be computed from all its pixels. Image-driven segmentation methods such as the watershed transform or normalized graph cuts may be used to produce the superpixels.
- Texture-based classification without segmentation is more widespread in medical image analysis than texture-based segmentation. In classification, a sample region with homogeneous texture is already computed. The problem of computing regions with homogeneous texture does not exist.

Domain Knowledge About the Objects

Domain knowledge consists of information as given below:

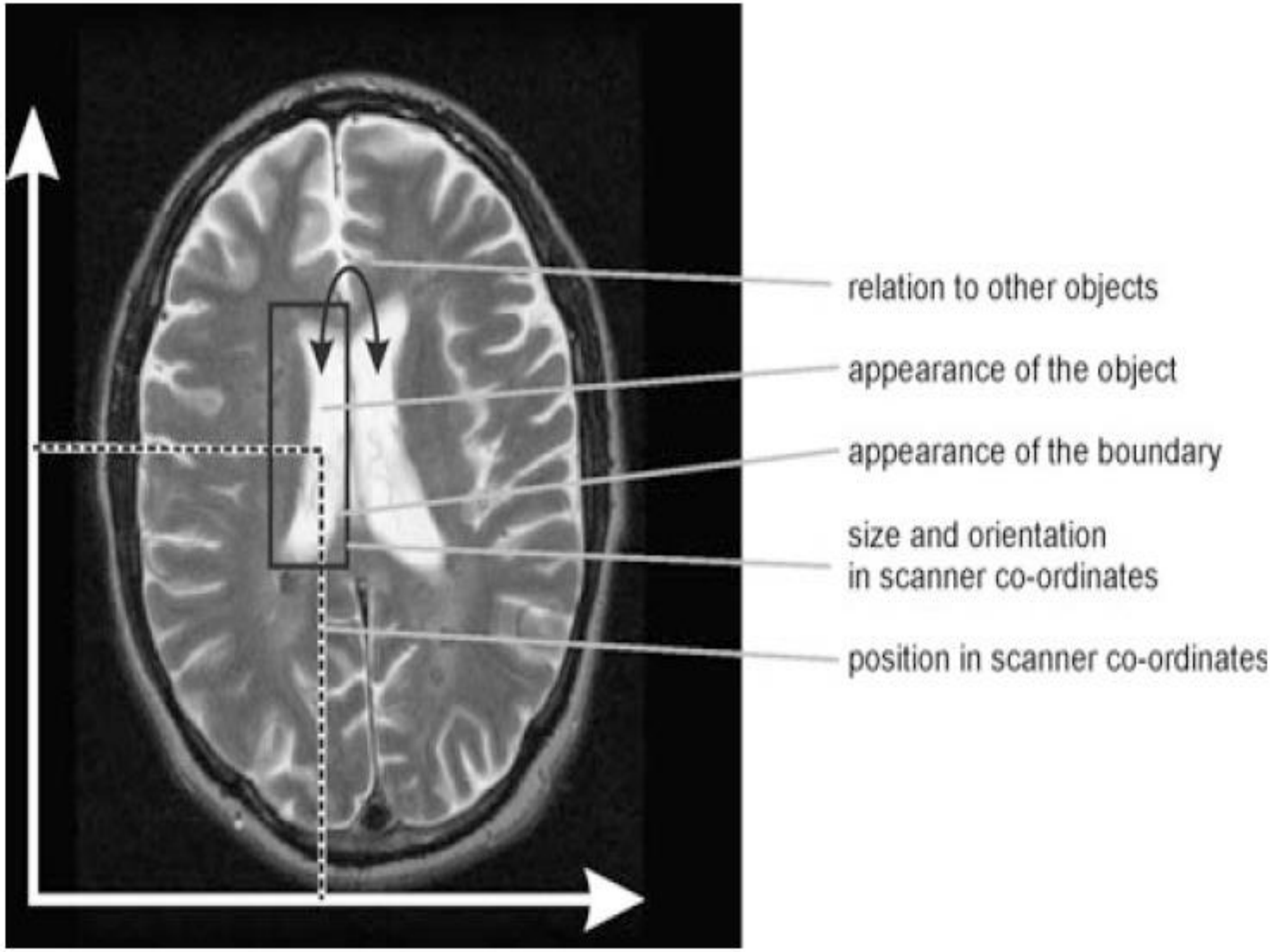
1. The appearance of boundaries between segments;

2. The location of an object within an image;

3. The orientation and size of the object with respect to the scanner coordinate system;

4. Spatial relationships (location, orientation or relative sizes) of the object with respect to other objects in the image; and

5. The shape and appearance of the object.



Different kinds of domain knowledge can be used to guide an analysis process

Domain Knowledge

- Most of the attributes relate to foreground segmentation where an object shall be separated from the background. Just what information is used depends on the specific segmentation task.
- In order to be useful, domain knowledge for describing a foreground object should be
- • **discriminative**, i.e., object and background must have different properties with respect to the feature;
- • **generalizable**, i.e., the property must be true for all possible instances of the object of interest in all possible images within the field of intended use; and
- • **efficiently computable** with sufficient reliability.
- Efficiency of computation is not mandatory but domain knowledge should not contain unnecessary information. If, for instance, bone segmentation in CT images using a simple threshold for discriminating bone from the less-dense background materials delivers sufficient accuracy, it is not efficient to require an additional shape model for describing a specific type of bone.

Representing Domain Knowledge

Each of the five types of domain knowledge listed above can be represented by

• a parameterized description such as the representation of a segment orientation by a vector in scanner space;

• a sampled description such as the representation of shape by a sequence of boundary points; or

• an implicit description such as the representation of a shape by a function on image domain describing its boundary

- A parameterized description reduces a property to a set of parameters. The parameters can usually be represented with arbitrary precision. Other aspects corresponding to the same property are excluded.
- Properties described by samples require a sufficiently high sampling rate. The almost oval shape in the example above could be described by a finite number of boundary points.
- Properties described implicitly as function of the image domain require a number of base functions on this domain which can be combined to describe the object boundary.

Variability of Model Attributes

- Variation is specified by a range of permissible property values in the property vector.
- Information about acceptable variance within a class may be obtained from expert information or from training. The reliability of expert information depends on the expert and on the kind of knowledge.
- Many implicit knowledge representations use simple assumptions about the local smoothness of object boundaries which can be readily assumed for most structures occurring in medical imaging.
- Apart from few parameters governing the influence of intensities or their derivatives on the model, no further information has to be introduced prior to applying a model-driven segmentation technique. The strategy may have limited success in the case of artefacts or an insufficient relationship between image information and object appearance.
- Very popular segmentation paradigm is based on implicit representation of local domain knowledge. An implicit representation, called **level set representation,** integrates many aspects of low-level knowledge about segments in a common concept

The Use of Interaction

- Interactive incorporation of domain knowledge has the advantage of being flexible because an expert user decides about necessary input at segmentation time.
- If the system responds immediately to interaction, knowledge incorporation at run-time also delivers cues about potential input errors.
- Interactive input may happen directly on the image or it may be an adjustment of segmentation parameters.
- The former is attractive to most users as it allows them to directly interact with the medium that they want to segment. However, interaction on the image can be tedious if
- • it is required for a prolonged time;
- • interaction devices are inappropriate; and
- • the relation between interaction and consequence for the result is not intuitive.

The Use of Interaction

- **Interaction in a segmentation algorithm may come in one of the five varieties**
- 1. In a priori parameterization, the user is requested to enter the parameter values of an adjustable segmentation algorithm. Once parameters are set—such as indicating the location of an object of interest or setting thresholds of the expected intensity range of the object—the segmentation algorithm proceeds automatically until it produces the result.
- 2. Through segmentation guidance, the user supports the segmentation until a satisfactory result is generated. An example would be the entering of boundary points in a user-guided delineation of an organ boundary.
- 3. Feedback happens after segmentation has been carried out. The user varies parameters or changes the way of guidance in order to improve the quality of the result. An example is the threshold variation in threshold segmentation. Feedback requires re-computation of the segmentation.
- 4. Correction changes the segmentation result according to user expectation. An example would be the removal of parts of a segment that do not belong to the object of interest. Correction usually implies positive confirmation.
- 5. Confirmation is the process by which the user accepts or rejects a result.

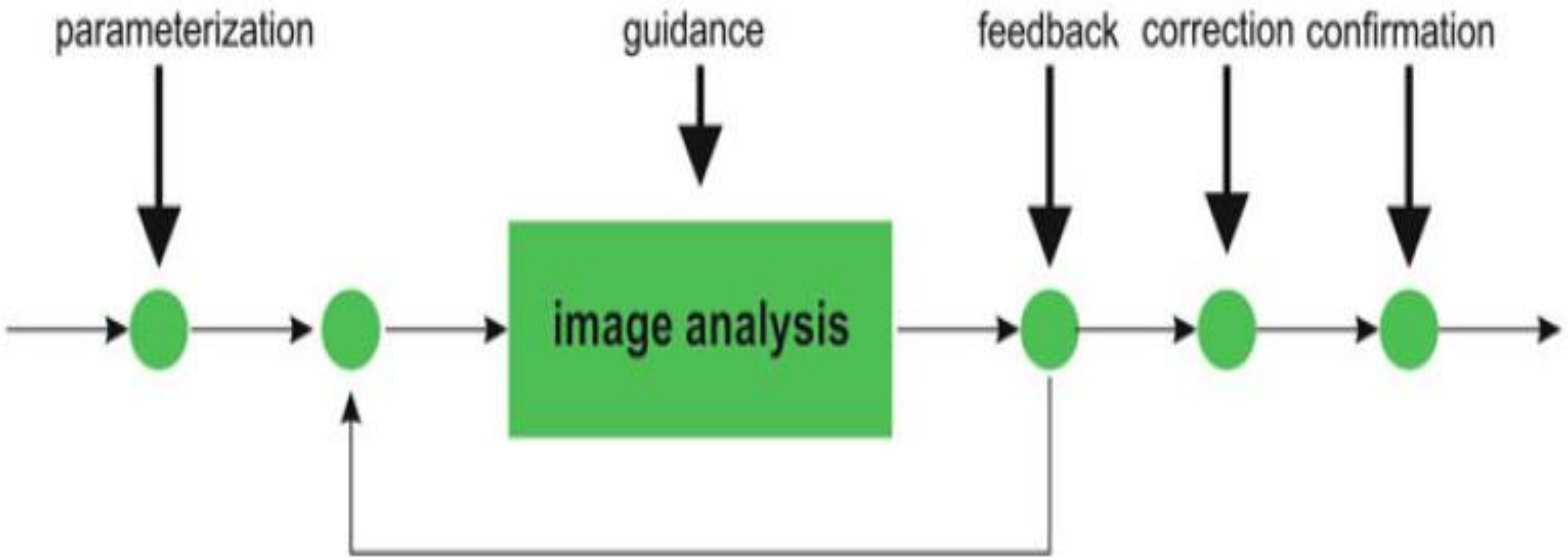


Fig. 6.11 Five different kinds of interaction that may happen during image analysis

Use of Interaction

- Parameterization is often required. Adapting parameters will be successful in applications which follow the underlying assumptions of the segmentation method and which can be characterized by a proper parameter setting.
- The limitation of parameterization is that interactively added knowledge can only specify but not extend or counteract knowledge implemented in the segmentation method.
- Using guiding interaction is more powerful but at the cost of reduced control about the result. A very general and very simple segmentation tool using guidance would draw a boundary of a foreground object according to interactive mouse input from the user.
- Guidance may also counteract an inappropriate segmentation model
- Feedback differs from guidance in that it does not interfere with the segmentation process itself but offers the user the chance to repeat the segmentation with refined parameters.
- Interaction through correction is another powerful tool because discrepancies between expected and computed results can be removed.

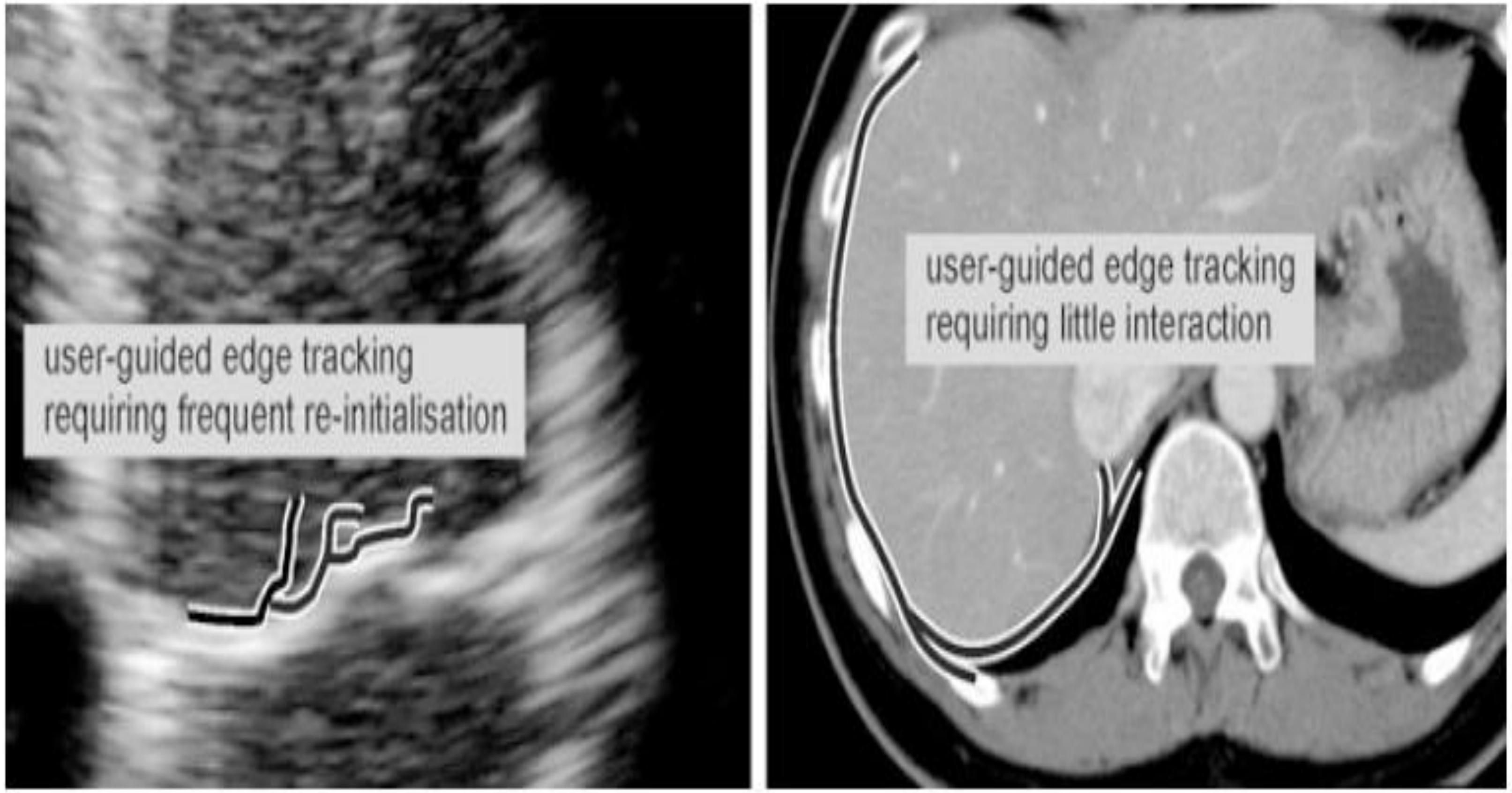


Fig. 6.12 It depends on the image (and information and artefacts contained in it) whether a certain interaction component is useful and efficient or not

- Use of correction should be limited to cases where inclusion of the missing domain knowledge is inefficient because costs exceed benefits.
- Correction that is required regularly for creating a valid segmentation indicates an inappropriate segmentation method.
- Interaction by confirmation does not extend the bandwidth of applications of a given segmentation method directly.
- It may be used, to adapt a segmentation method to some application.

Interactive Segmentation

- The algorithmically simplest way of segmentation is to completely rely on user guidance to outline the boundary of a foreground structure.
- Employing some input device such as a mouse, a trackball or an electronic stylus on a graphical tablet, the user traces the boundary on a rendition of a 2d scene.
- The method can be applied to arbitrary 2d scenes assuming that the user has all the necessary domain knowledge.
- The main problem of interactive segmentation is that it can neither be guaranteed that a user really possesses all the necessary information for a perfect segmentation of an image nor that this information is applied correctly during segmentation.
- Interactive segmentation as a validation tool hence requires some modeling of human error when segmenting an image.
- interaction is often supported by low-level techniques borrowed from image enhancement or data-driven segmentation.

Interactive Segmentation

Examples are as follows:

• Boundaries to be delineated are highlighted by displaying the intensity gradient instead of the original image. Edge contrast is increased by noise removal techniques such as edge-preserving smoothing.

• Just a small number of boundary points are provided by the user (see Fig. 6.13). They are connected by automatically generated line segments (straight lines or curves).

• User input is corrected automatically by offsetting the boundary orthogonal to its tangent towards the nearest highest gradient (see Fig. 6.13).

• The user is allowed to correct a delineated boundary. This is most efficient if the boundary does not consist of a sequence of neighboring pixels but of a sequence of points connected by curve segments. User correction of a single point then induces a corresponding correction of its two incident line segments.

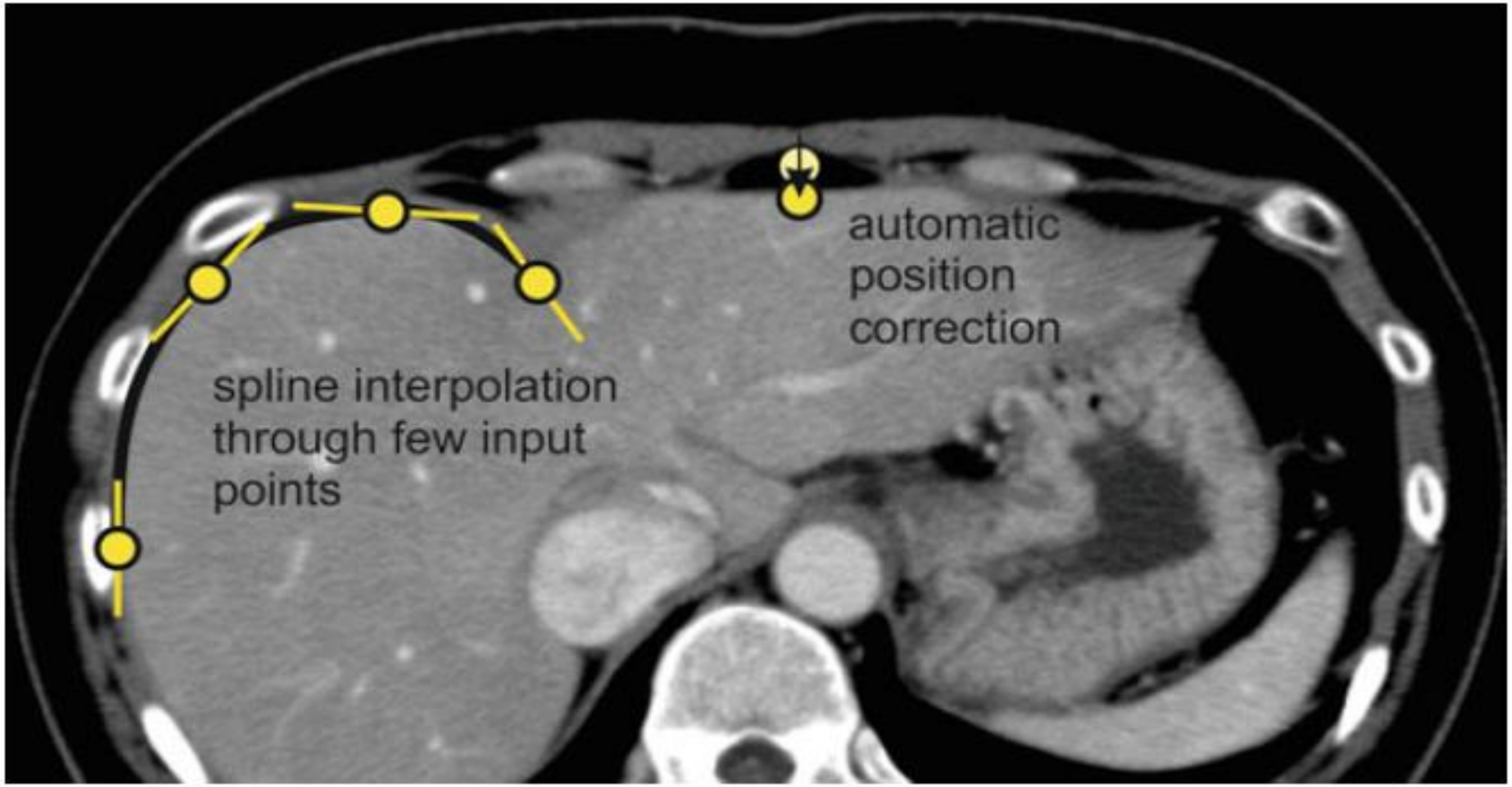


Fig. 6.13 Interactive delineation is supported if the user only has to click at few boundary points and if positions selected by user input are automatically corrected by displacing them toward the position with locally highest gradient

Segmentation by thresholding

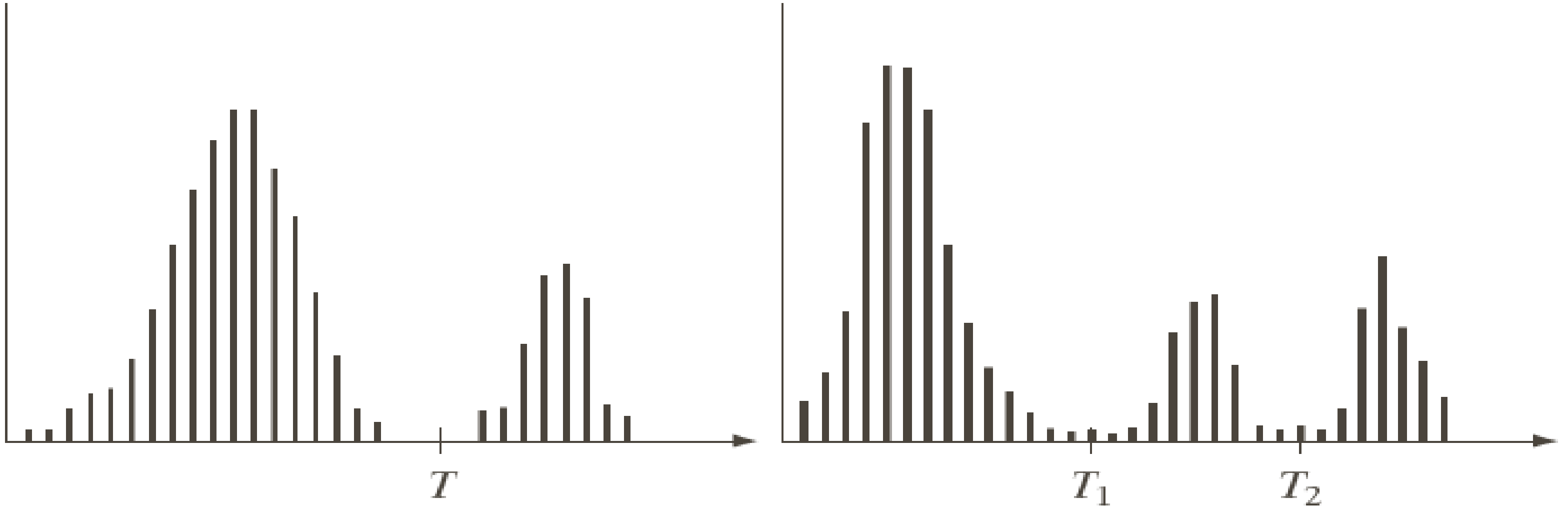
- Thresholding is the simplest segmentation method.
- The pixels are partitioned depending on their intensity value.
- Global thresholding, using an appropriate threshold T:

$$g(x, y) = \begin{cases} 1, & \text{if } f(x, y) > T \\ 0, & \text{if } f(x, y) \leq T \end{cases}$$

- Variable thresholding, if T can change over the image.
  - Local or regional thresholding, if T depends on a neighborhood of (x, y).
  - adaptive thresholding, if T is a function of (x, y).
- Multiple thresholding:

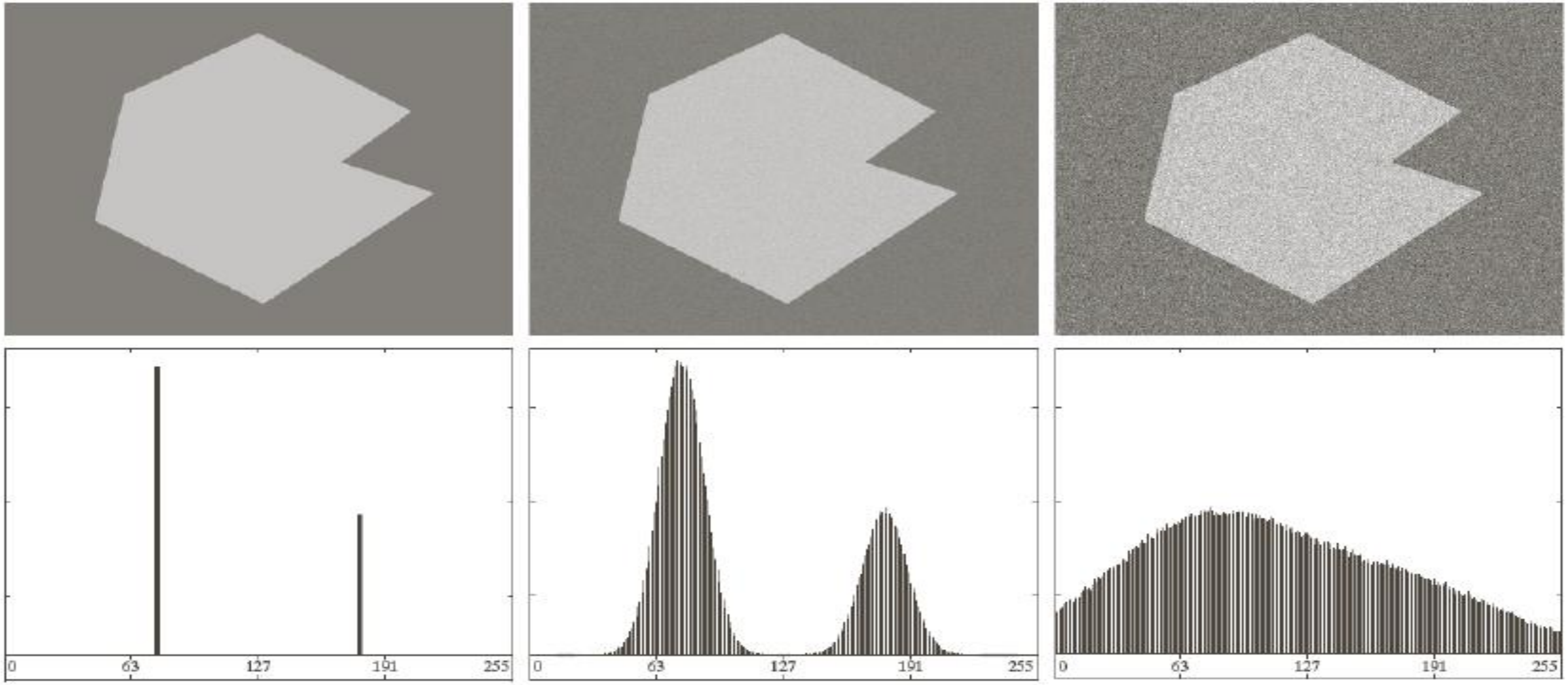
$$g(x, y) = \begin{cases} a, & \text{if } f(x, y) > T_2 \\ b, & \text{if } T_1 < f(x, y) \leq T_2 \\ c, & \text{if } f(x, y) \leq T_1 \end{cases}$$

Choosing the thresholds



- Peaks and valleys of the image histogram can help in choosing the appropriate value for the threshold(s).
- Some factors affects the suitability of the histogram for guiding the choice of the threshold:
  - the separation between peaks;
  - the noise content in the image;
  - the relative size of objects and background;
  - the uniformity of the illumination;
  - the uniformity of the reflectance.

Noise role in thresholding



No noise 10% noise 50% noise

Global thresholding

A simple algorithm:

1. Initial estimate of T
2. Segmentation using T:
   - G_1, pixels brighter than T;
   - G_2, pixels darker than (or equal to) T.
3. Computation of the average intensities m_1 and m_2 of G_1 and G_2.
4. New threshold value:

$$T_{\text{new}} = \frac{m_1 + m_2}{2}$$

5. If $|T - T_{\text{new}}| > \Delta T$, back to step 2, otherwise stop.

image segmentation using thresholding

Given a grayscale image represented by the following pixel values:

120 & 125 & 130 & 135 & 140 \\

110 & 115 & 120 & 125 & 130 \\

100 & 105 & 110 & 115 & 120 \\

90 & 95 & 100 & 105 & 110 \\

80 & 85 & 90 & 95 & 100 \\

Perform image segmentation using thresholding technique. Assume that the threshold value is 115. Segment the image into two regions: one for pixel values below the threshold and the other for pixel values above or equal to the threshold.

Solution

Now, we apply thresholding:

- Pixels with values below the threshold (115) will be assigned one value (e.g., 0).

- Pixels with values equal to or above the threshold will be assigned another value (e.g., 255).

Here's the segmented image based on the thresholding process:

$$
\begin{matrix}
255 & 255 & 255 & 255 & 255 \\
0 & 0 & 255 & 255 & 255 \\
0 & 0 & 0 & 255 & 255 \\
0 & 0 & 0 & 0 & 255 \\
0 & 0 & 0 & 0 & 0 \\
\end{matrix}
$$

image segmentation using Otsu's thresholding technique

Otsu's thresholding technique is a method used for automatic image thresholding, **where the threshold value is determined by maximizing the inter-class variance of pixel intensities**.

Consider a grayscale image represented by the following matrix:

[[120, 130, 140, 120, 110],

[125, 135, 145, 125, 115],

[115, 125, 135, 125, 120],

[110, 120, 130, 120, 110],

[105, 115, 125, 115, 105]]

calculate Otsu's threshold for this image.

Summary of Otsu's algorithm

(1) **Compute normalized histogram of the image,** $p_i = \dfrac{n_i}{MN}, \; i = 0, \ldots, L-1$

(2) **Compute cumulative sums,** $P_1(k) = \sum_{i=0}^{k} p_i, \; k = 0, \ldots, L-1$

(3) **Compute cumulative means,** $m(k) = \sum_{i=0}^{k} i\, p_i, \; k = 0, \ldots, L-1$

(4) **Compute global intensity mean,** $m_G = \sum_{i=0}^{L-1} i\, p_i$

(5) **Compute between-class variance,** $\sigma_B^2(k) = \dfrac{[m_G P_1(k) - m(k)]^2}{P_1(k)[1 - P_1(k)]}, \; k = 0, .., L{-}1$

(6) **Obtain the Otsu threshold,** k^***, that is the value of** k **for which** $\sigma_B^2(k^*)$ **is a maximum** $-$ **if this maximum is not unique, obtain** k^* **by avaraging the values of** k **that correspond to the various maxima detected**

(7) **Obtain the separability measure** $\eta(k^*) = \dfrac{\sigma_B^2(k^*)}{\sigma_G^2}$

Homogeneity-Based Segmentation

- **Segmentation based on local intensity homogeneity** does not require an absolute threshold but a local variance criterion that is valid for all pixels within a segment.
- The goal is to separate an image into the smallest number of segments, so that for each of the segments this criterion is fulfilled.
- Examples for homogeneity criteria are the variance of pixel values, maximum deviation between pixel intensities, or the probability that all pixels belong to the same probability distribution.
- Two **basic segmentation algorithms for this are region merging and the split-and-merge algorithm**.

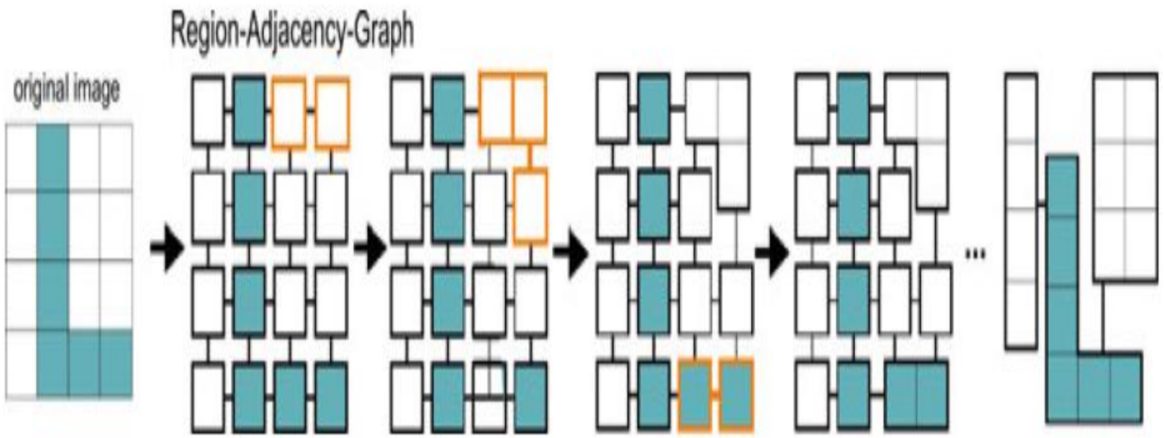


Fig. 6.19 Schematic view at the region merging process. At each iteration, the two most similar regions are merged until such merging would violate the similarity criterion for pixels belonging to the same region

Region merging

The following are the steps for computing segmentation by region merging:

• Initially, each pixel is considered to be its own region.

• Map regions to a **region adjacency graph (RAG)** in which nodes represent regions and adjacent regions are connected by an edge.

• Compute the homogeneity value for each edge for a region that consists of the two regions connected by the edge.

• As long as there exists at least one edge of which the homogeneity value fulfils the homogeneity criterion

– Merge the two most similar regions

– Update the RAG accordingly

Region growing is a popular technique in image processing for segmentation, where pixels with similar properties are grouped together to form regions. Here's a numerical example of region growing for image segmentation along with answers:

Let's consider a grayscale image represented by the following matrix:

[[120, 130, 140, 120, 110]
[125, 135, 145, 125, 115]
[115, 125, 135, 125, 120]
[110, 120, 130, 120, 110]
[105, 115, 125, 115, 105]

Let's perform region growing starting from the seed point (2, 2) with a threshold of 10.

- **Initialization**:
  - Seed point: (2, 2) with intensity value 135.
  - Threshold: 10.
- **Region Growing Algorithm**:
  - Start with the seed point (2, 2).
  - Neighboring pixels within threshold (10): (1, 2), (3, 2), (2, 1), (2, 3).
  - Pixels (1, 2) and (3, 2) meet the criteria (intensity difference < 10), add them to the region.
  - Neighboring pixels within threshold of (1, 2) and (3, 2): (1, 1), (1, 3), (3, 1), (3, 3).
  - Pixels (1, 1), (1, 3), (3, 1), (3, 3) meet the criteria, add them to the region.
  - No more neighboring pixels meet the criteria, stop.
- **Result**:
  - Segmented region (marked with 'X'):

[[0, 0, 0, 0, 0]
[0, X, X, 0, 0]
[X, X, X, X, 0]
[0, X, X, 0, 0]
[0, 0, 0, 0, 0]

In this result, the 'X' marked pixels belong to the segmented region based on the region growing algorithm starting from the seed point (2, 2) with a threshold of 10.

split-and-merge algorithm

- split-and-merge algorithm starts with the complete image being a single region and keeps splitting the image until each region fulfils the homogeneity criterion. The split part has the following steps
- • Initially, the complete image is a single region
- • As long as a region exists that does not fulfil the homogeneity criterion
- – Split this region in four quarters (for a 2d image) or eight subvolumes (for a 3d volume).

– Document the split in an appropriate data structure (quadtree or octtree).

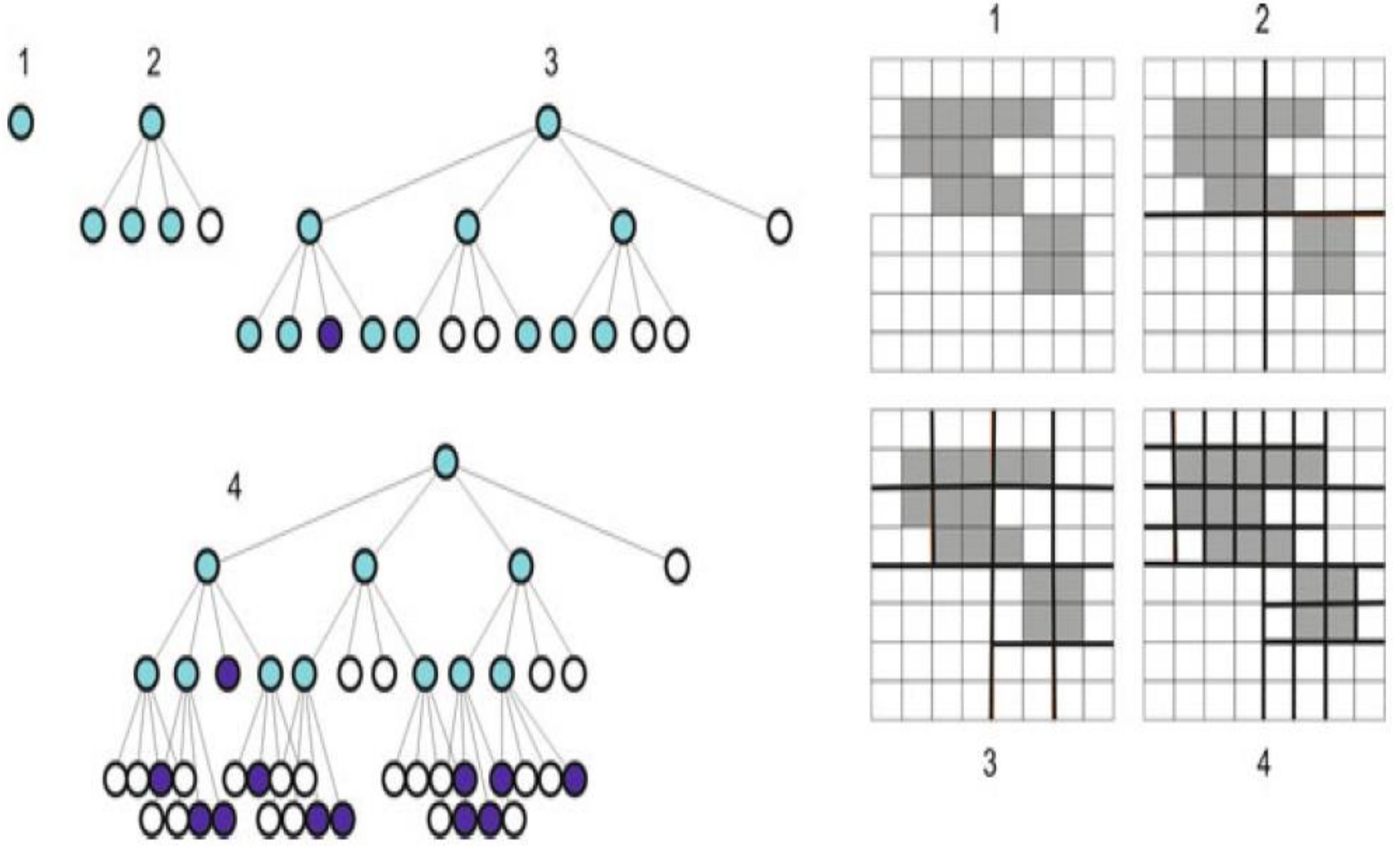


Fig. 6.20 During the first phase of the split-and-merge algorithm, regions are split into subregions until each subregion fulfils the homogeneity criterion. The split procedure is documented in a quadtree

simplified version of the algorithm, where we split a region into quadrants if the intensity range within the region exceeds a certain threshold, and we merge adjacent regions if their intensity difference is less than a certain threshold.

Given the 4*4 grayscale image matrix:

Image = [
  [150, 130, 120, 140],
  [140, 160, 120, 130],
  [120, 125, 135, 145],
  [110, 115, 130, 140]
]

Let's define the following thresholds for splitting and merging:

- Splitting & Merging threshold: 20 (if the intensity range within a region exceeds 20, we split the region).

Step 1: Initial Region (4x4)

- Intensity Range: Max - Min = 160 - 110 = 50 (greater than threshold)
- Split into four 2x2 regions

Regions:

[150, 130] [120, 140]

[140, 160] [120, 130]

[120, 125] [135, 145]

[110, 115] [130, 140]

Step 2: Splitting

- Evaluate each 2x2 region

The Watershed Transform: Computing Zero Crossings

The watershed transform (WST) is a popular way to use edge information as criterion to separate segments.

The watershed transform to compute the segments is defined as follows:

- The scene is treated as a landscape in which function values (i.e., the gradient length) represent height;
- Each local minimum in this landscape is a basin; and
- Watersheds in this landscape are boundaries in the terrain which separate regions that drain into different basins.

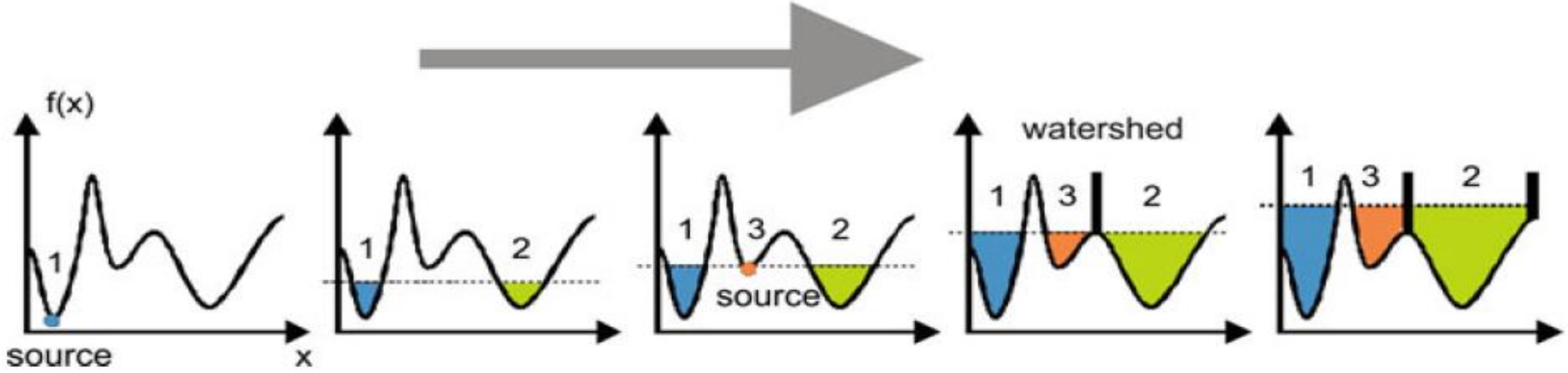


Fig. 6.21 Watershed transform can be carried out by flooding the scene from sources at local minima in the image

set the initial flood level for an image f to $l = \min_{\mathbf{v}}(f(\mathbf{v}))$

while $l < \max_{v}(f(\mathbf{v}))$ **do**

Detect all pixel $\mathbf{v}_l$ that are newly flooded at level l

if a pixel $\mathbf{v}_l$ is connected to pixels which all have a segment label L **then**

segment L is extended by $\mathbf{v}_l$.

if a pixel $\mathbf{v}_l$ is not connected to any pixel that has a segment label **then**

this is the first pixel of a new segment: label it L_{new}.

if a pixel $\mathbf{v}_l$ is connected to at least two pixels with different labels **then**

label the pixel W (for watershed)

$l = l+1$

end_while

Fig. 6.22 Sketch of the flooding algorithm for the watershed transform

marker-based WST

- The watershed transform can be combined with user interaction by providing a picking component.
- Over-segmentation from standard WST arises because the underlying model for segments (each local minimum in the map of gradient lengths is a segment) does not describe what is wanted, i.e., the separation of organs in a medical image.
- The marker-based WST (mWST) adds information about objects to be segmented by replacing local minima as source for flooding by pre-specified marker positions

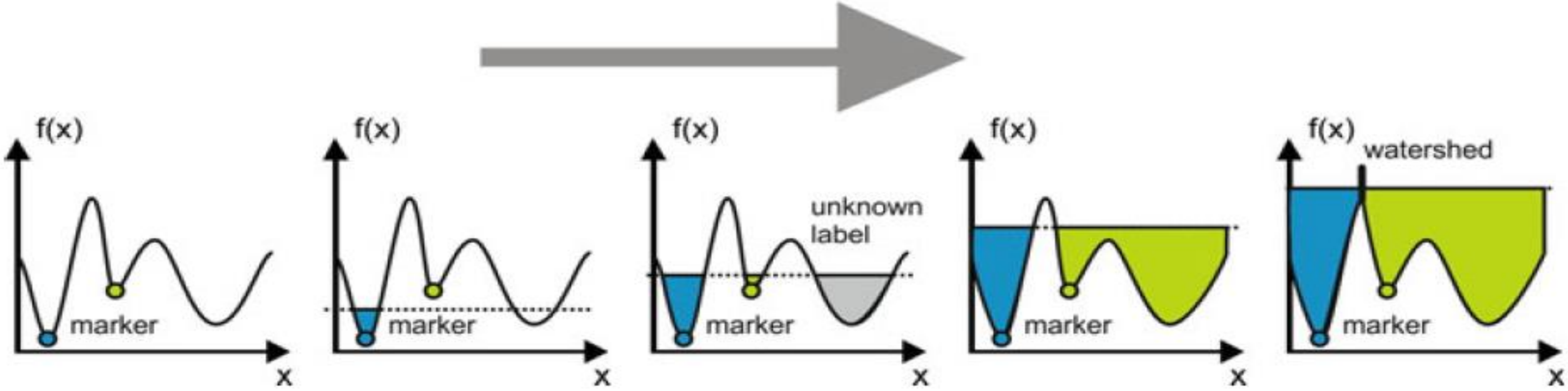


Fig. 6.23 Marker-based WST proceeds in a similar fashion than the original WST, except for the fact that flooding occurs only from marker positions. Regions that are not connected to a marker-labeled region receive a provisional label "unknown"

Seeded Regions

- A variant to make the region growing process independent of parameters except for the seeds is seeded region growing that turns region growing into an mWST-like segmentation procedure .
- In seeded region growing, the user specifies a number of seeds that separate the image in as many segments as there are seeds. Initially, each seed forms its own segment and labels of all other pixels are unknown. Unlabeled neighbors of all labeled segments are ordered by some appropriate homogeneity criteria (e.g., intensity difference). The most similar unlabeled pixel is then selected to be labeled. If this pixel is adjacent to labeled pixels which all have the same label, it receives this label. Otherwise, it receives the label of the segment to which it is most similar

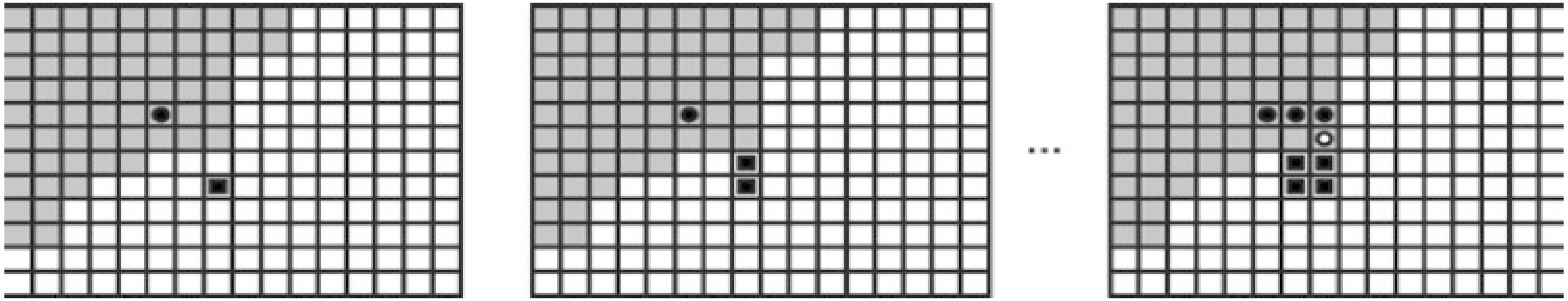


Fig. 6.27 In seeded region growing, each region receives a seed. Since always the most similar pixel is added to one of the regions, homogeneous sets of pixels will have been added to the regions before a pixel at the boundary of two regions is selected (e.g., the *white circle*). Pixels neighbored to two or more regions are added to the one region to which they are the most similar

Thank You