Image Segmentation
Part II

Figures are provided by the Pearson Education

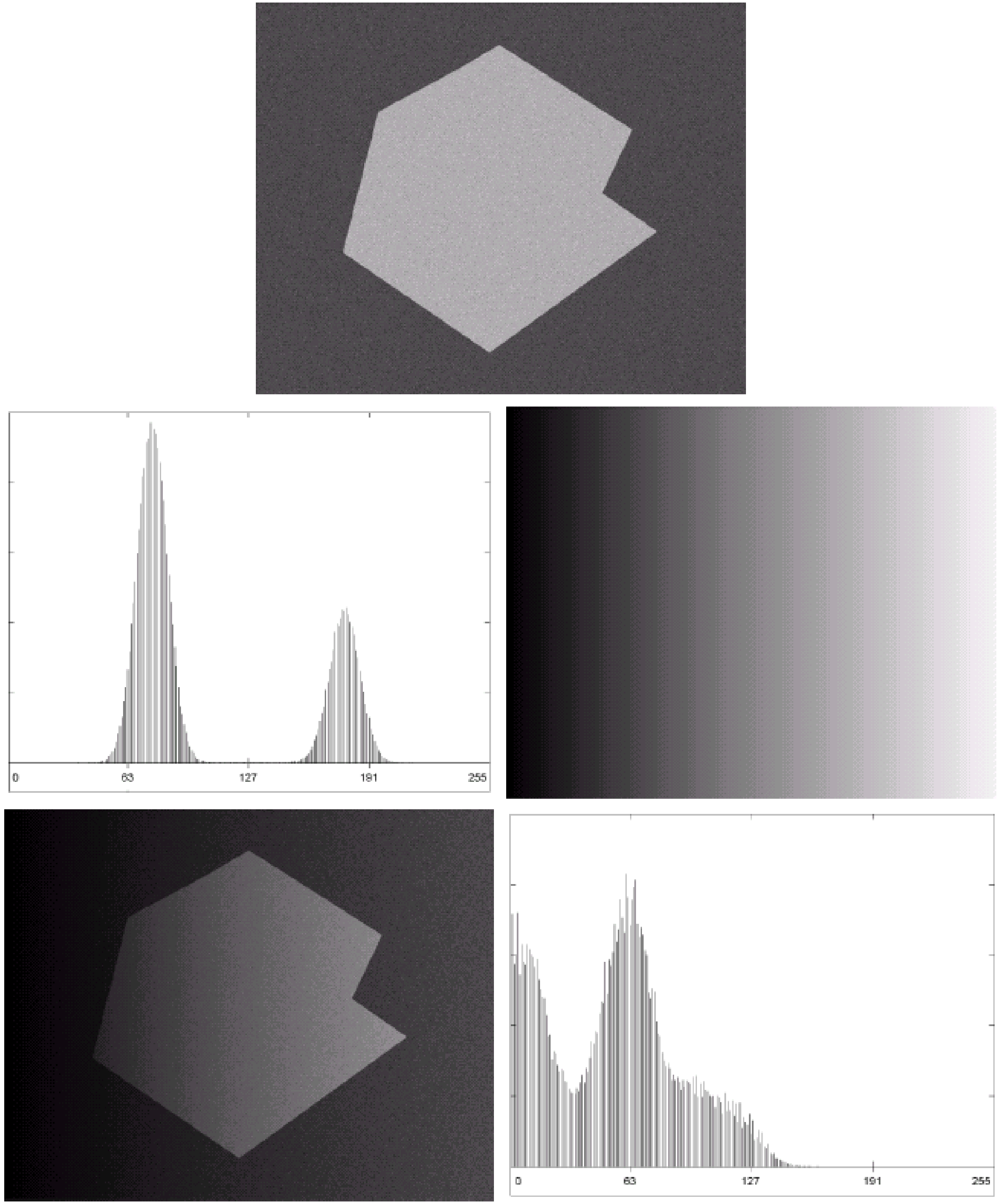
Local/adaptive intensity based segmentation

The Effect of Illumination

1. Assume that an image is modelled as the product of illumination and reflectance functions.

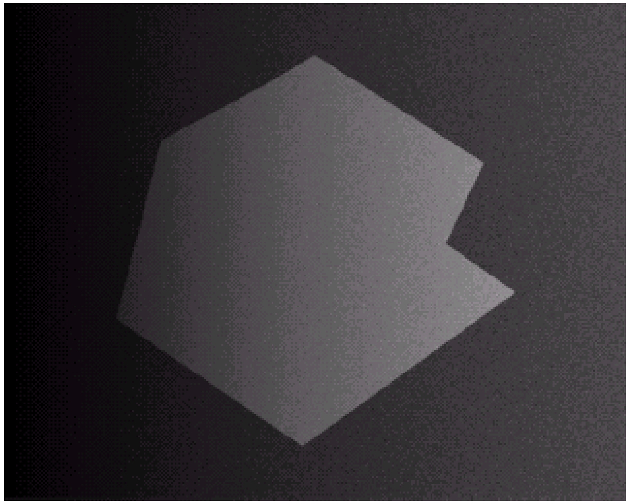
$$f\left(x,y\right)=i\left(x,y\right)r\left(x,y\right)$$

2. If the illumination i is non-uniform or heterogeneous, then the quality of segmentation can be adversely affected.
3. Reason: the intensity values in object and background regions are changing as the pixel position changes. In this case, any threshold cannot clearly separate the distributions of background and object regions.

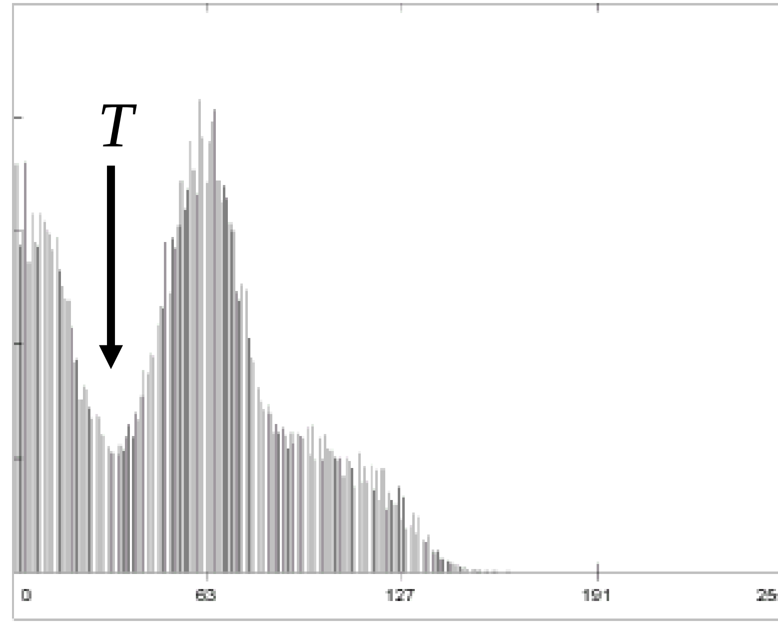


a
b c
d e

FIGURE 10.27 (a) Computer generated reflectance function. (b) Histogram of reflectance function. (c) Computer generated illumination function. (d) Product of (a) and (c). (e) Histogram of product image.



An image with
non-uniform or heterogeneous
illumination function



Histogram and
threshold T

Globally thresholded
image

Adaptive Thresholding

1. Idea: dividing an image into subimages and then applying different thresholds to segment regions individually.
2. Advantage: the effect of non-uniform illumination is reduced because the area of subimages is smaller.
3. It is a local thresholding method because threshold depends on image locations.
4. For each subimage, its histogram can be either
   a. *bimodal* if the total variance in the subimage is larger than a variance threshold, T_v, or
   b. *unimodal* if the total variance is smaller than a variance threshold, T_v.

Adaptive Thresholding

5. If the histogram is bimodal, then threshold can be found by using the methods described in the *Global Thresholding* Section.
6. If the histogram is unimodal, then
   a. all pixels in the subimage are labelled based on the subimage mean if the subimage size is small; otherwise
   b. the subimage is further partitioned into sub-subimages.

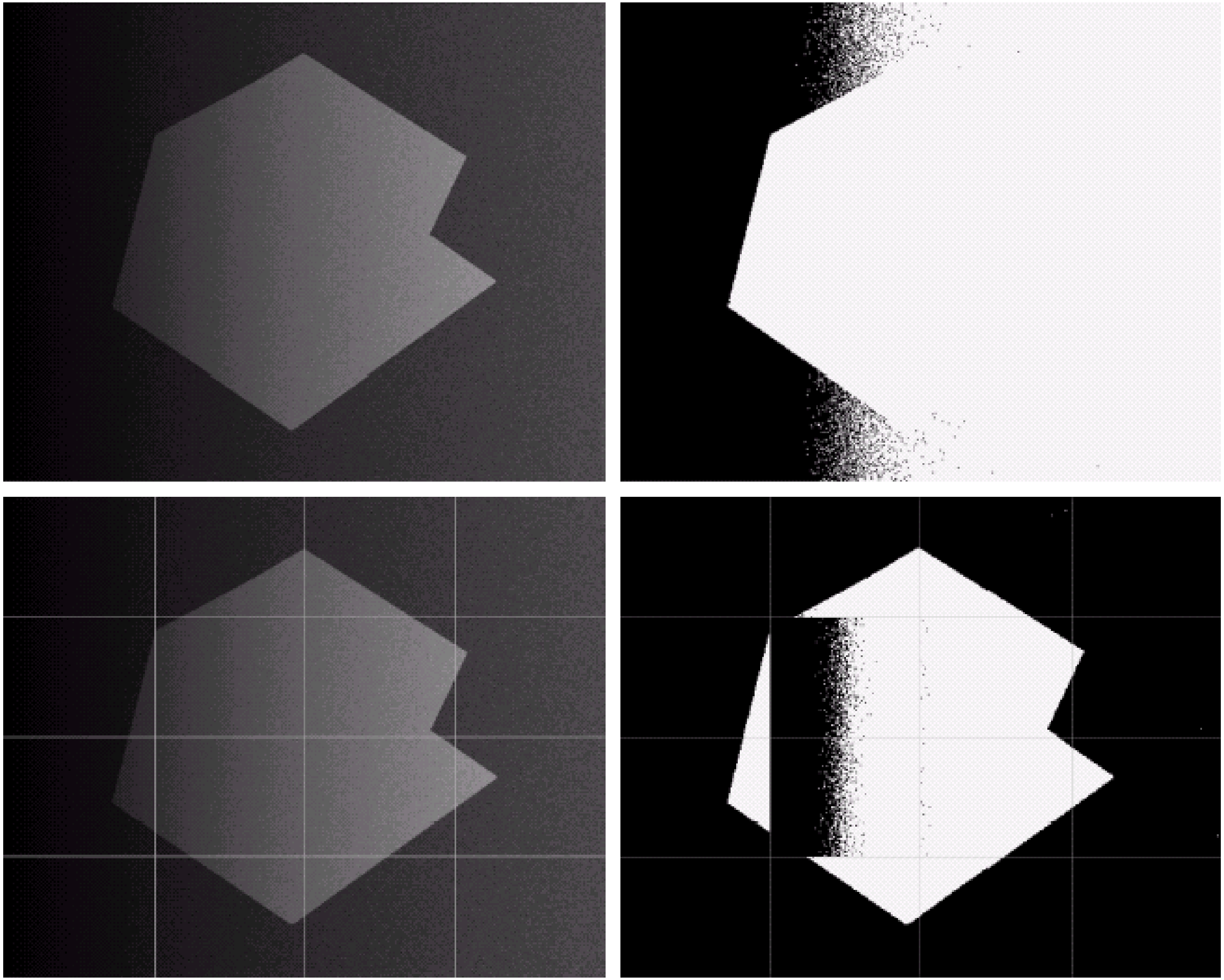


FIGURE 10.30 (a) Original image. (b) Result of global thresholding. (c) Image subdivided into individual subimages. (d) Result of adaptive thresholding.

To improve segmentation quality, we can further partition a subimage into smaller *'sub-sub-images'*, and then apply different thresholds in each smaller regions.

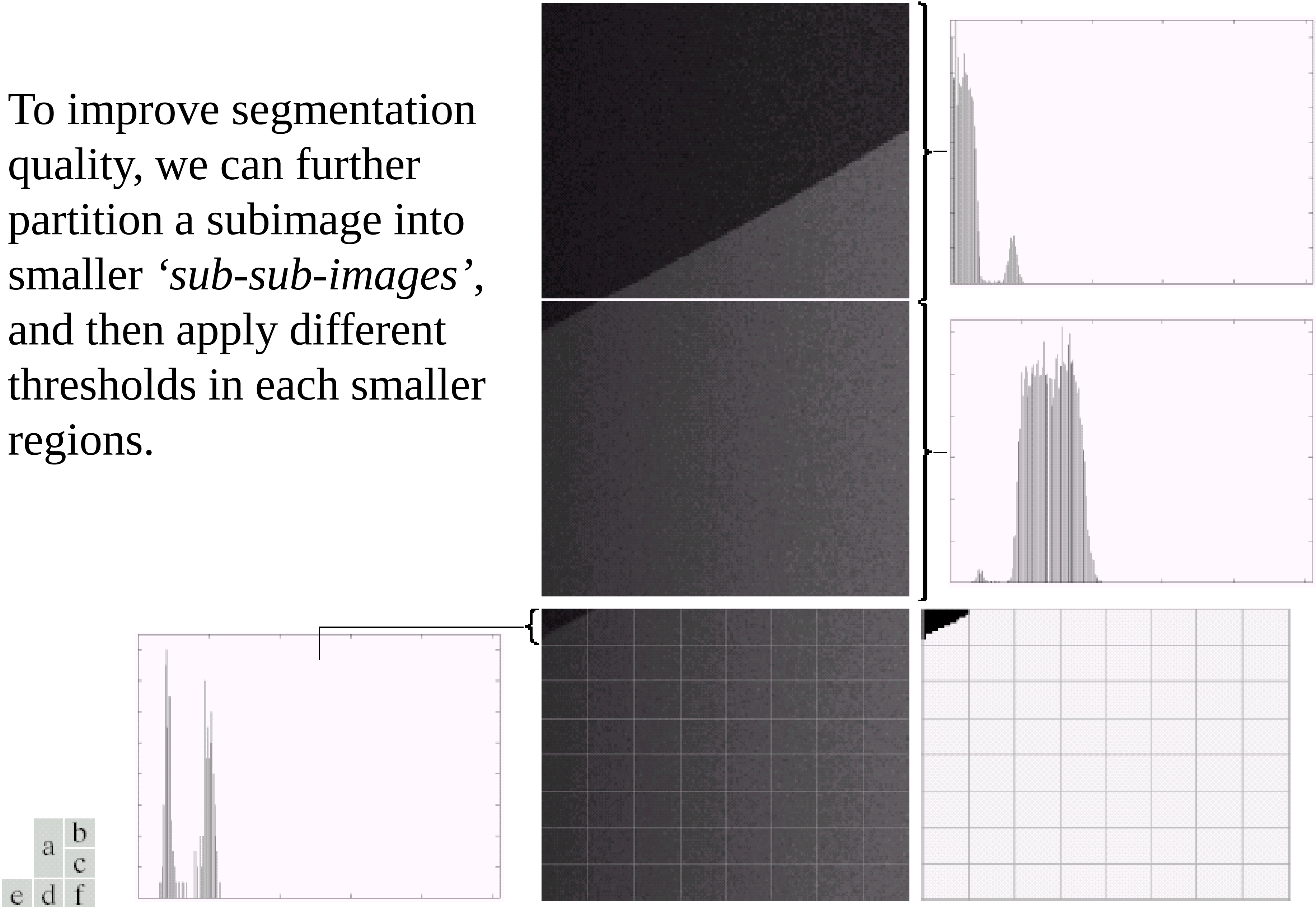


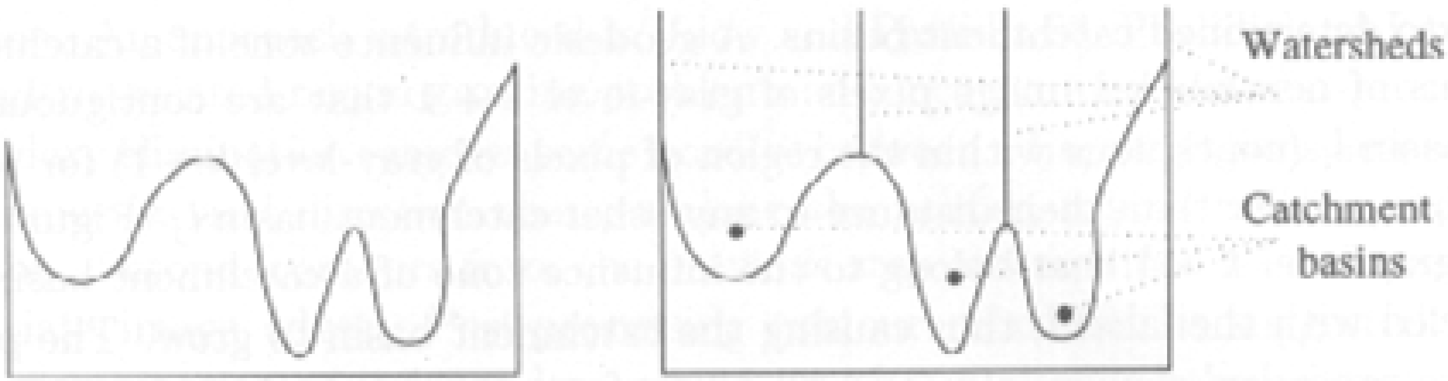
FIGURE 10.31 (a) Properly and improperly segmented subimages from Fig. 10.30. (b)–(c) Corresponding histograms. (d) Further subdivision of the improperly segmented subimage. (e) Histogram of small subimage at top, left. (f) Result of adaptively segmenting (d).

Watershed segmentation

http://en.wikipedia.org/wiki/Watershed_(image_processing)
Or, search "Watershed Segmentation" in the Internet for more information.

Segmentation by Morphological Watersheds

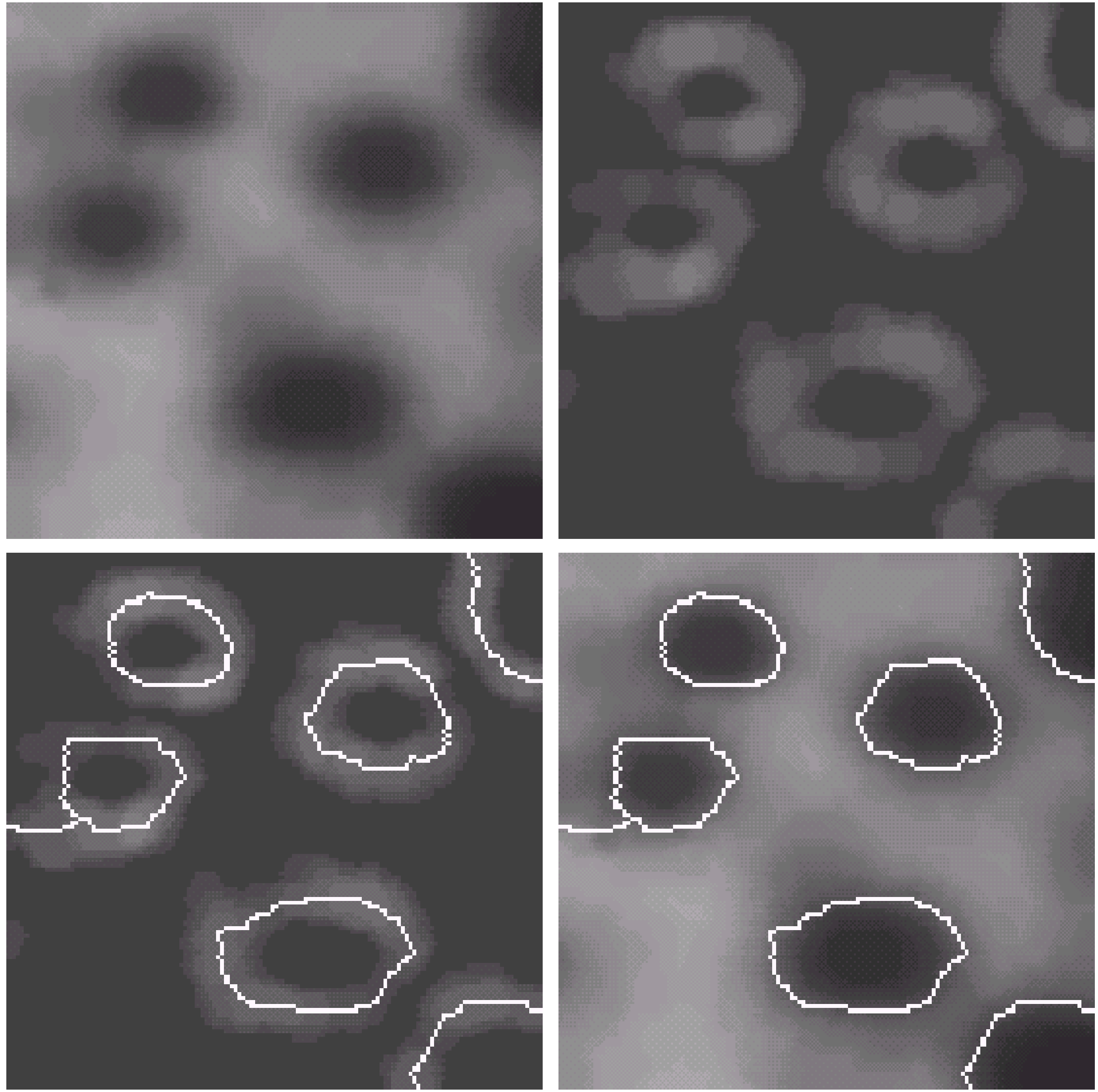
1. There are 3 types of points (see next slide):
   a. Points belonging to a regional minimum;
   b. Points at which a drop of water would fall with certainty to a single minimum (called *catchment basin* of that minimum);
   c. Points at which water would be equally likely to fall to more than one such minimum (called *crest line* on the topographic surface, *divide lines* or *watershed lines*).
2. Segmentation = finding watershed lines (see Figure 10.46d, Figure 10.44h).



(a) (b)

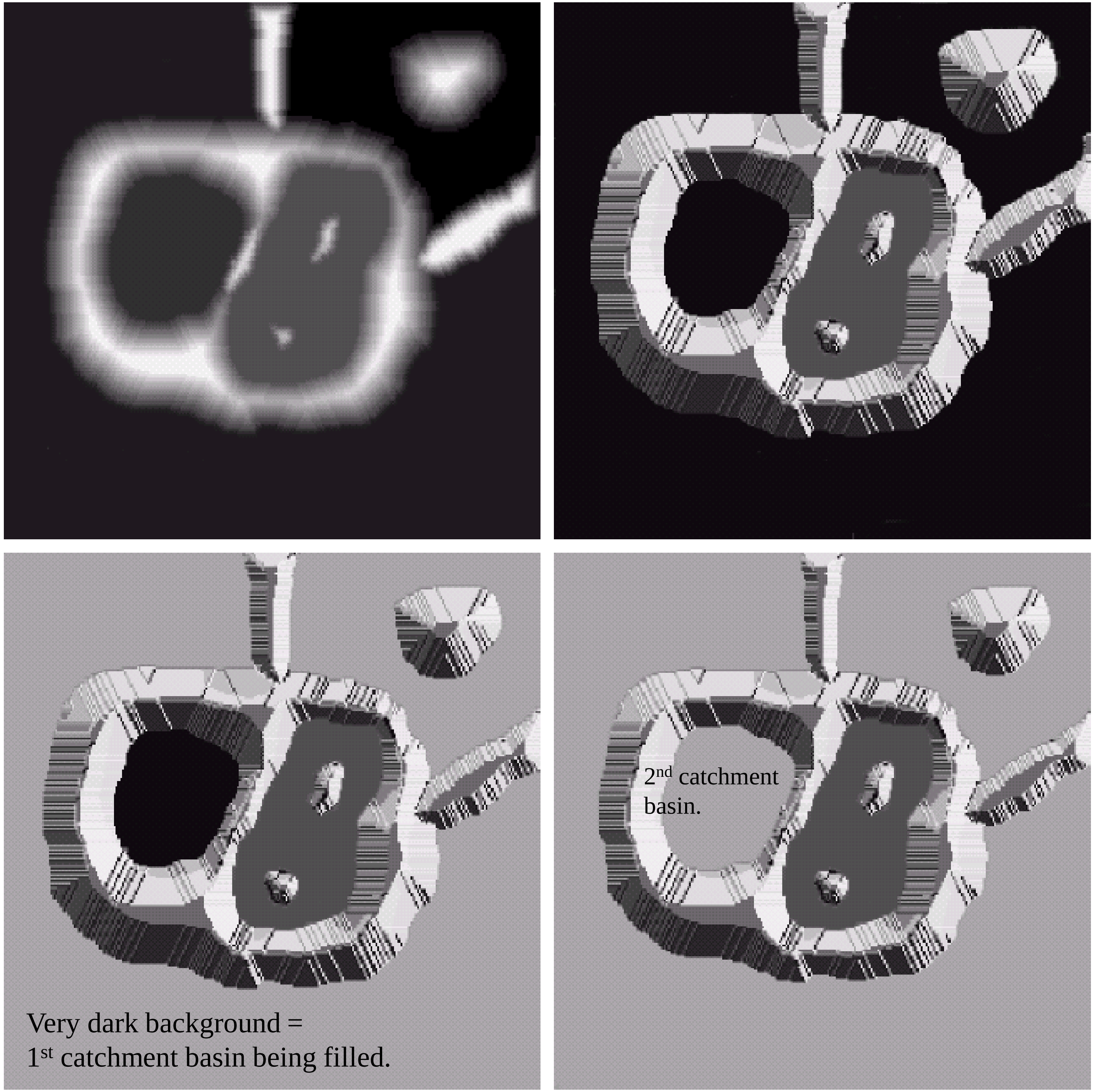
Figure 5.49: *One-dimensional example of watershed segmentation: (a) gray-level profile of image data; (b) watershed segmentation—local minima of gray-level (altitude) yield catchment basins, local maxima define the watershed lines.*

Image Processing, Analysis, and Machine Vision, by Sonka, Hlavac and Boyle, 1999.



a b
c d

FIGURE 10.46 (a) Image of blobs. (b) Image gradient. (c) Watershed lines. (d) Watershed lines superimposed on original image. (Courtesy of Dr. S. Beucher, CMM/Ecole des Mines de Paris.)



a b
c d

FIGURE 10.44
(a) Original image.
(b) Topographic view. (c)–(d) Two stages of flooding.

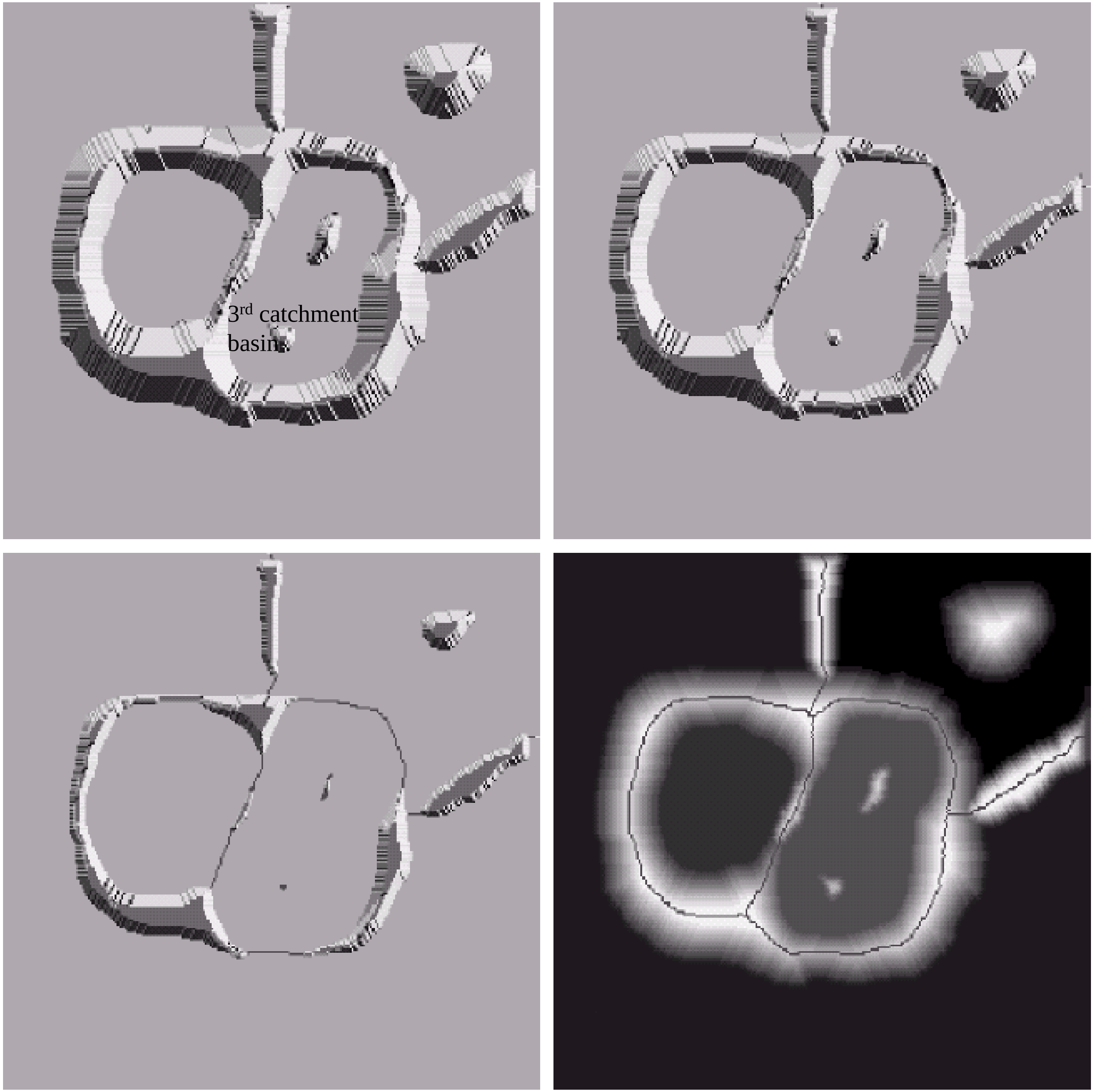


FIGURE 10.44 *(Continued)* (e) Result of further flooding. (f) Beginning of merging of water from two catchment basins (a short dam was built between them). (g) Longer dams. (h) Final watershed (segmentation) lines. (Courtesy of Dr. S. Beucher, CMM/Ecole des Mines de Paris.)

Grey lines = Watershed lines = Boundaries.

Basic concepts

1. Figure 10.44a shows an input image (edge map).
2. Figure 10.44b shows the corresponding topographic surface, on which the height = grey-level values.
3. A hole is punched in each regional minimum.
4. The entire topographic surface is flooded from below by letting water rise through the holes at a uniform rate. Assume that the perimeter of the image is surrounded by the highest dam.
5. Figure 10.44c shows the first catchment basin (very dark background) is being filled. Figures 10.44d and 10.44e show second and third regions being filled.

Basic concepts

6. When the rising water in distinct catchment basins is about to merge (see Figure 10.44f, water in left catchment basin overflowed into right catchment basin), a dam is built/extended to prevent merging.
7. The flooding will eventually reach a stage when only the top of the dams are visible above the water line, or the maximum level of flooding is reached.
8. These final dam boundaries (dark, one-pixel-thick and continuous paths) = divide lines of the catchment basins = object boundaries. (See Figure 10.44h.)

Basic concepts

9. Watershed segmentation is often applied to the gradient of an image, rather than to the image itself. Regional minima of the catchment basins = small values of the gradient in the image. As such, they are inside the objects of interest.

Dam construction

1. It is based on binary images and morphological dilations.
2. Figure 10.45a shows 2 catchment basins at flooding step n-1.
3. Let M_1 and M_2 be the sets of coordinates of points in two regional minima (minimum points).
4. Let $C_{n-1}(M_1)$ and $C_{n-1}(M_2)$ be the sets of coordinates of points in two catchment basins associated with the corresponding minima M_1 and M_2. Let $C[n-1]$ be the union of these two sets.
5. Figure 10.45b shows the next flooding step n. The water has spilled from one basin to the other and a dam must be built.
6. Let q be the connected component. Note that $q \cap C[n-1]$ gives the two components in Figure 10.45a. In general, $q \cap C[n-1]$ can be either empty (new component) or non-empty (one component or two components).

Flooding step n-1.

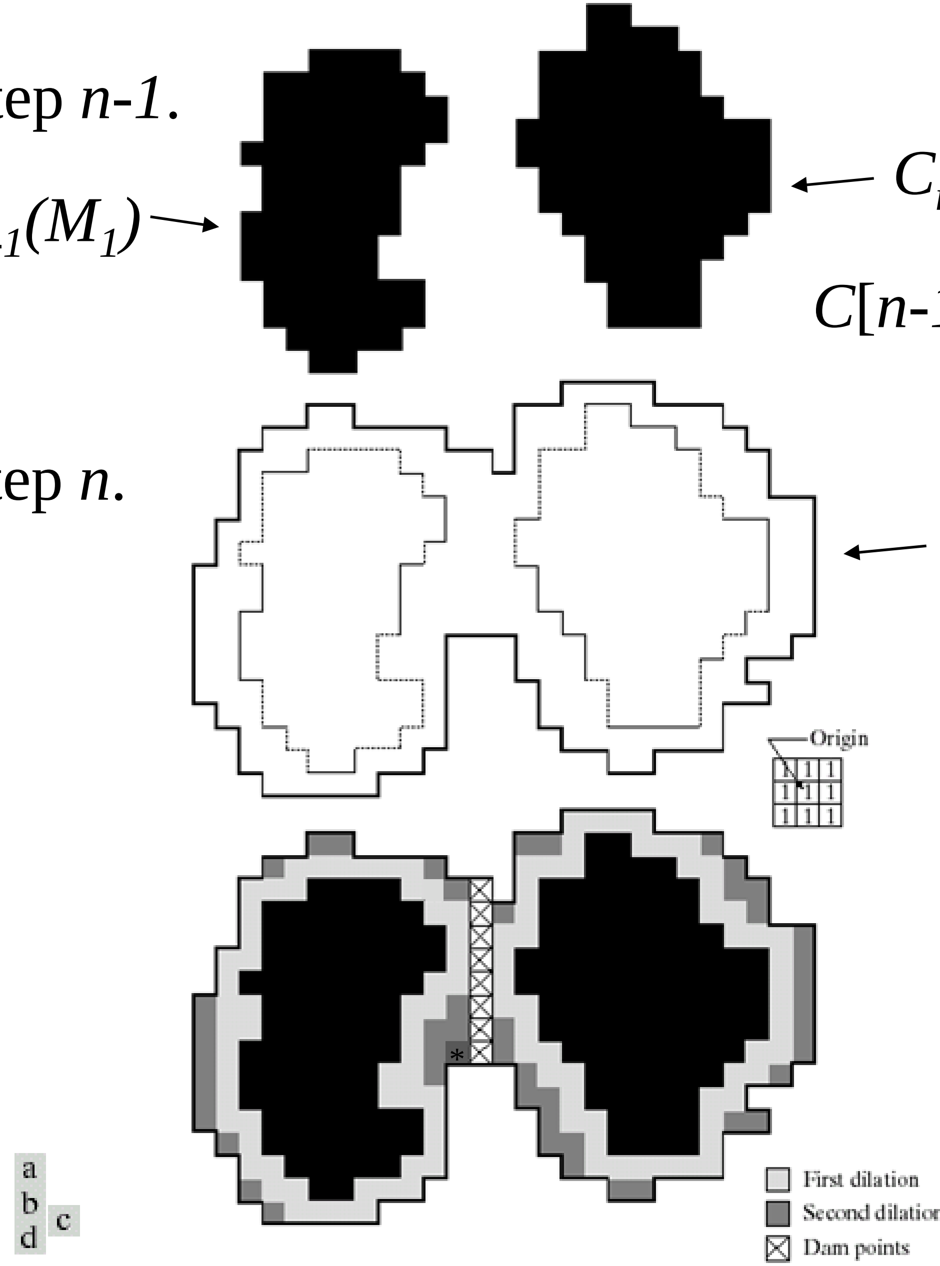
$C_{n-1}(M_1)$

$C_{n-1}(M_2)$

$C[n\text{-}1]=C_{n-1}(M_1)\cup C_{n-1}(M_2)$

Flooding step n.

q



* *Dark grey is the third dilation*

FIGURE 10.45 (a) Two partially flooded catchment basins at stage $n-1$ of flooding. (b) Flooding at stage n, showing that water has spilled between basins (for clarity, water is shown in white rather than black). (c) Structuring element used for dilation. (d) Result of dilation and dam construction.

Dam construction

7. Assume that each of the connected components in Figure 10.45a is dilated subject to a condition.
   a. <u>Dilation has to be constrained to *q*</u> and <u>dilation does not perform on the existing dam points</u>.
8. Figure 10.45d shows the results of the 1st dilation (light grey). Note that every point satisfies condition (a).
9. In the 2nd dilation, all points satisfying condition (a) are in medium grey colour. All points satisfying (1) condition (a) and (2) causing the sets being dilated to merge are cross-hatched.
10. The construction terminates when all points in *q* are coloured or marked.

Watershed Segmentation Algorithm

Definitions:

1. Let $M_1, M_2, \ldots, M_R$ be sets representing the coordinates of the points in the regional minima of an image $g(x,y)$, which is a gradient image of the original image.
2. Let min = minimum value of $g(x,y)$, and max = maximum value.
3. Let $T[n]$ be the set of coordinates (s,t) for which $g(s,t) < n$.

$$T[n] = \{(s,t) \mid g(s,t) < n\}$$

4. The topological surface will be flooded in integer flood increments, from $n=min+1$ to $n=max+1$.

Watershed Segmentation Algorithm

Definitions:

5. At any step n of the flooding process, assume that all points in $g(x,y)$ below n are marked black. Otherwise, marked white.
6. Let $C_n(M_i)$ be the set of coordinates of points in the catchment basin associated with minimum M_i that are flooded at step n.
7. Let $C[n]$ be the union of the flooded catchment basin portions at step n.

$$C[n] = \bigcup_{i=1}^{R} C_n\left(M_i\right)$$

8. It can be shown that the number of elements in $C_n(M_i)$ and $T[n]$ either increases or remains the same as n increases.

Watershed Segmentation Algorithm

Definitions:

9. Let $Q[n]$ denote the set of connected components in $T[n]$, and q be any connected component in Q, i.e., $q \in Q[n]$.

Watershed Segmentation Algorithm

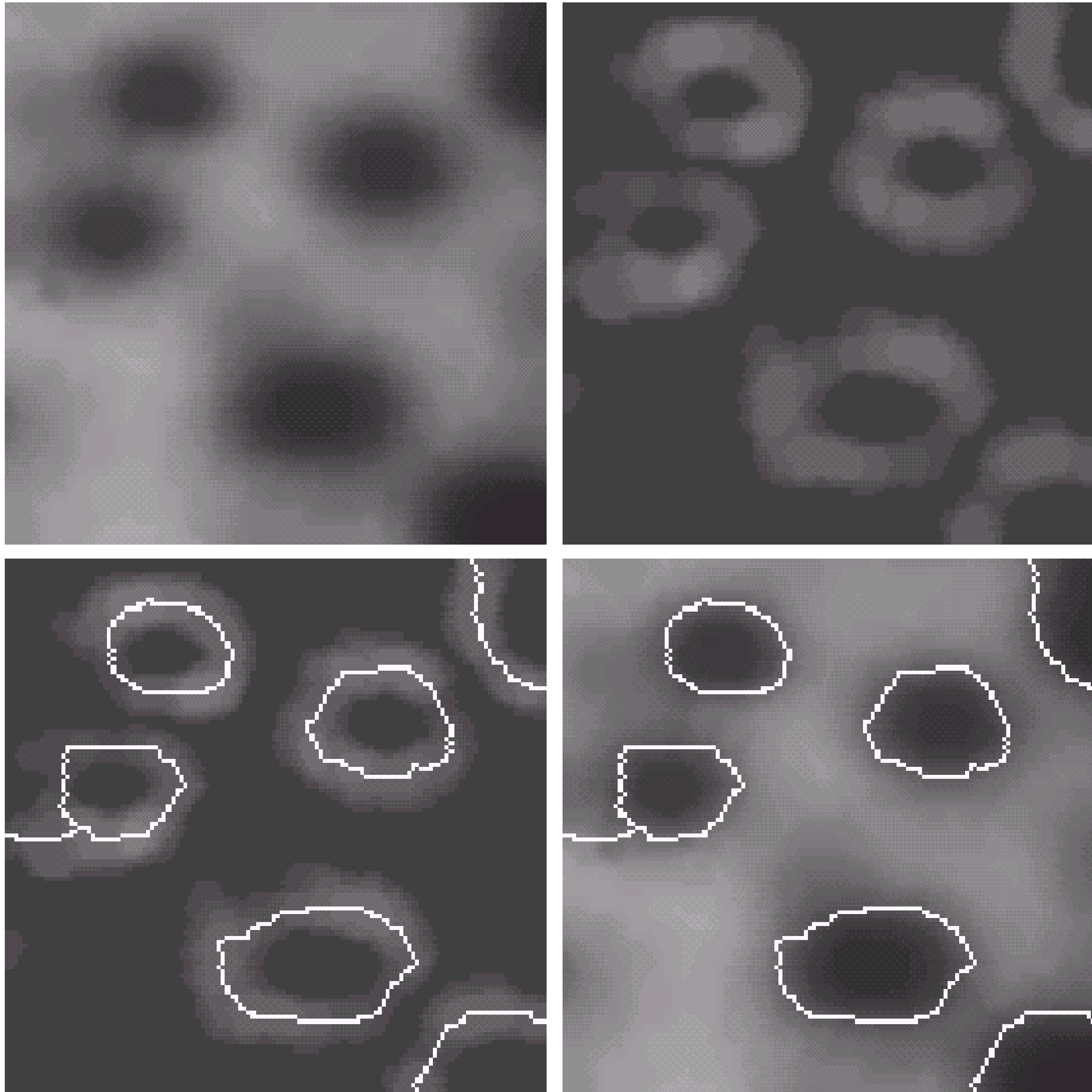
1. At step 0, the algorithm is initialised with $C[min+1] = T[min+1]$, and C contains a set of connected components.
2. At step n, we assume that $C[n\text{-}1]$ has been constructed. The goal is to construct $C[n]$ based on $C[n\text{-}1]$ and $Q[n]$.
3. For each connected component $q \in Q[n]$, there are three possible outcomes:
   a. $q \cap C[n\text{-}1]$ is empty.
   b. $q \cap C[n\text{-}1]$ contains one connected component of $C[n\text{-}1]$.
   c. $q \cap C[n\text{-}1]$ contains more than one connected components of $C[n\text{-}1]$.
4. Actions depend on the outcomes listed in (3).

Watershed Segmentation Algorithm

5. If outcome (a) happens, then a new minimum is encountered and the new connected component q is added into $C[n\text{-}1]$ to form $C[n]$.
6. If outcome (b) happens, then the connected component q lies within catchment basin of some regional minimum. The corresponding $C_{n-1}(M_i)$ is updated to $C_n(M_i)$.
7. If outcome (c) happens, then all, or part, of a ridge separating two or more catchment basins is encountered. Further flooding would cause the water level in these catchment basins to merge further. Thus a dam must be built within q to prevent overflow between the catchment basins.

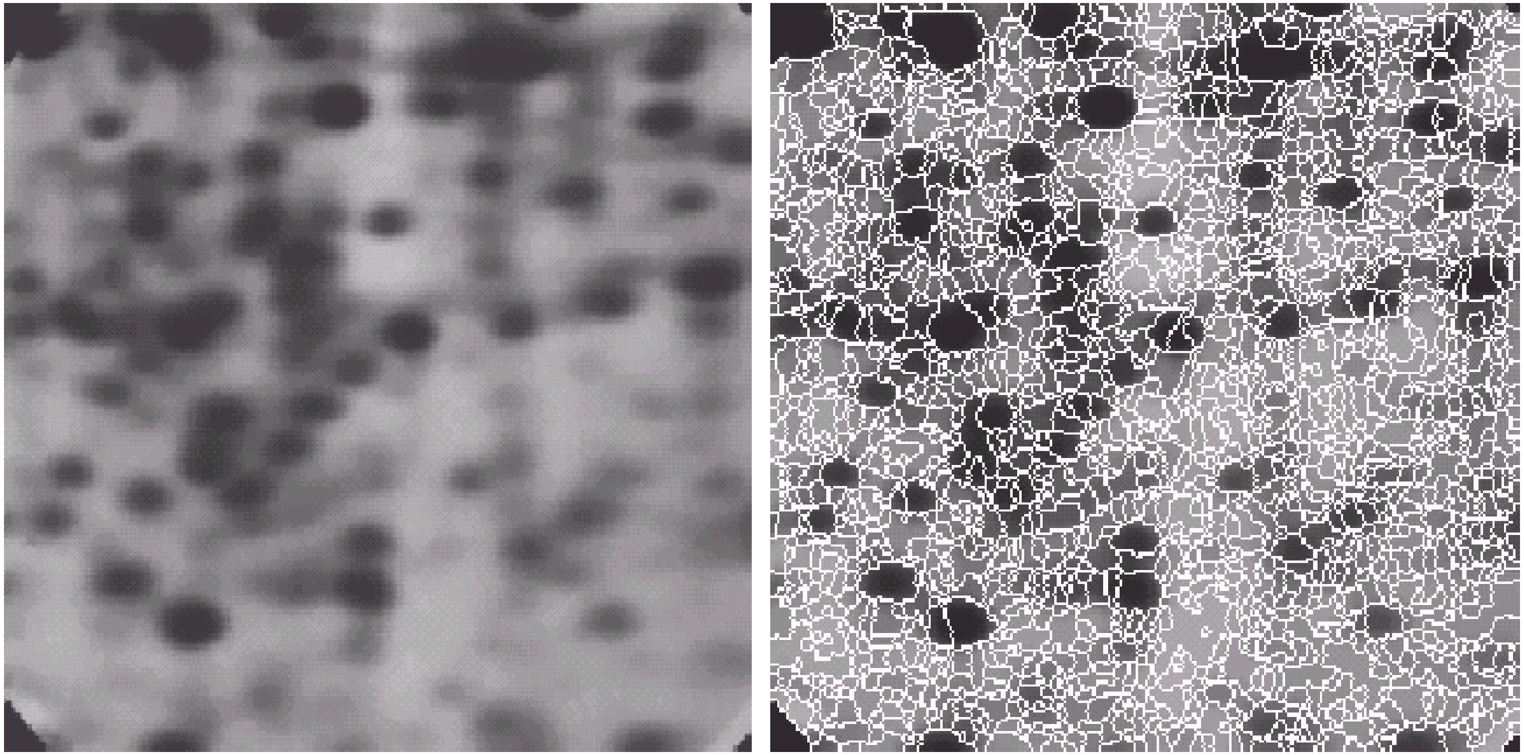
Watershed Segmentation Algorithm

8. Dam construction: dilating $q \cap C[n\text{-}1]$ with a 3x3 structuring element of 1's and constraining the dilation to q.
9. The algorithm terminates when $n = max + 1$.



a b
c d

FIGURE 10.46 (a) Image of blobs. (b) Image gradient. (c) Watershed lines. (d) Watershed lines superimposed on original image. (Courtesy of Dr. S. Beucher, CMM/Ecole des Mines de Paris.)



a b

FIGURE 10.47 (a) Electrophoresis image. (b) Result of applying the watershed segmentation algorithm to the gradient image. Oversegmentation is evident. (Courtesy of Dr. S. Beucher, CMM/Ecole des Mines de Paris.)

The algorithm may lead to over-segmentation due to noise and other local irregularities of the gradient, which can create large number of potential regional minima.

Use of motion in segmentation

The Use of Motion in Segmentation

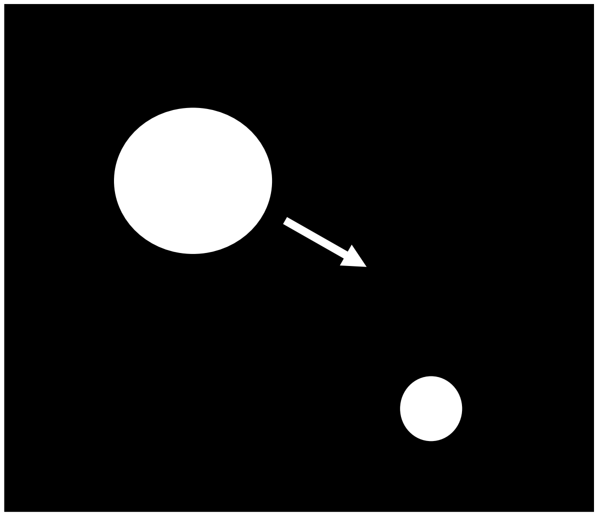
1. Motion is a powerful cue for extracting objects of interest from a background of irrelevant details.
2. In imaging applications, motion arises from a relative displacement between the sensing system and the scene being viewed.
3. Based on estimated displacements, a moving object can be detected, and its speed and direction can be estimated.
4. Two basic techniques:
   a. Basic approach based on direct differences
   b. Accumulative differences

Basic approach based on direct differences

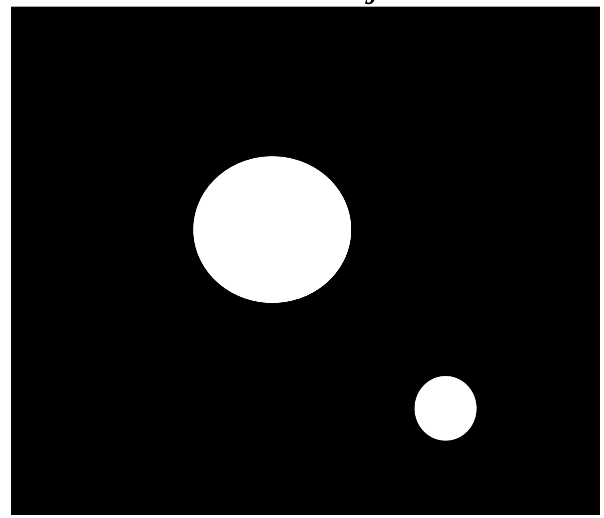
1. Idea: Two images, which are acquired at different times, are compared pixel by pixel. Object motions can be detected by locating the ‘large’ intensity differences between two images.
2. Let $f(x,y,t_i)$ be a reference image frame taken at time t_i.
3. Let $f(x,y,t_j)$ be a subsequent image frame taken at time t_j. It is an image of the same scene and has a moving object in it.
4. Suppose that the subsequent image is subtracted from the reference image. The difference image cancels the stationary elements, and leaves only nonzero entries that correspond to the non-stationary image components.

Basic approach based on direct differences

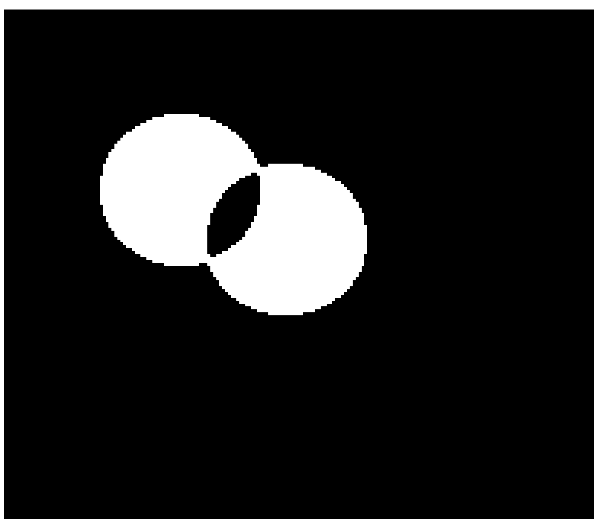
$f(x,y,t_i)$



$f(x,y,t_j)$



d_{ij}



Assumptions:

(1) The rigid object motion.

(2) In-plane motion.

Basic approach based on direct differences

5. A difference image between two images is given by (T is a specified threshold.)

$$d_{ij}(x,y)=\begin{cases}1 & \text{if } \left|f\left(x,y,t_i\right)-f\left(x,y,t_j\right)\right|>T \\ 0 & \text{otherwise}\end{cases}$$

6. The difference image d_{ij} has the size of f.
7. If the specified threshold T is not set correctly, then image noise can affect the quality of difference image d_{ij}. Solution: remove all 4- or 8-connected regions of 1's, which have less than a predetermined number of 1's. (Island Removal)
8. The difference image d_{ij} can be noise sensitive and it gives limited information about the motion, e.g., motion information (direction/speed) is not easy to estimate.

Accumulative difference approach

1. Idea: differences between the reference and subsequent image frames are accumulated. As such, noise sensitivity can be decreased, and motion direction and speed can be estimated.
2. Let $f(x,y,t_1)$, $f(x,y,t_2)$,..., $f(x,y,t_n)$ be a sequence of image frames, and $f(x,y,t_1)$ be the reference frame.
3. An accumulative difference image (ADI) is formed by comparing the reference image with every subsequent image in the sequence.
4. A counter for each pixel location in the ADI is incremented every time a difference occurs at that pixel location between the reference and an image in the sequence.

Accumulative difference approach

5. Three types of ADIs: absolute, positive and negative ADIs.
6. Absolute ADI, *A*

$$A_k(x,y) = \begin{cases} A_{k-1}(x,y)+1 & \text{if } \left|R(x,y) - f(x,y,k)\right| > T \\ A_{k-1}(x,y) & \text{otherwise} \end{cases}$$

where $k = t_k$, $R(x,y) = f(x,y,1)$ and k represents time.

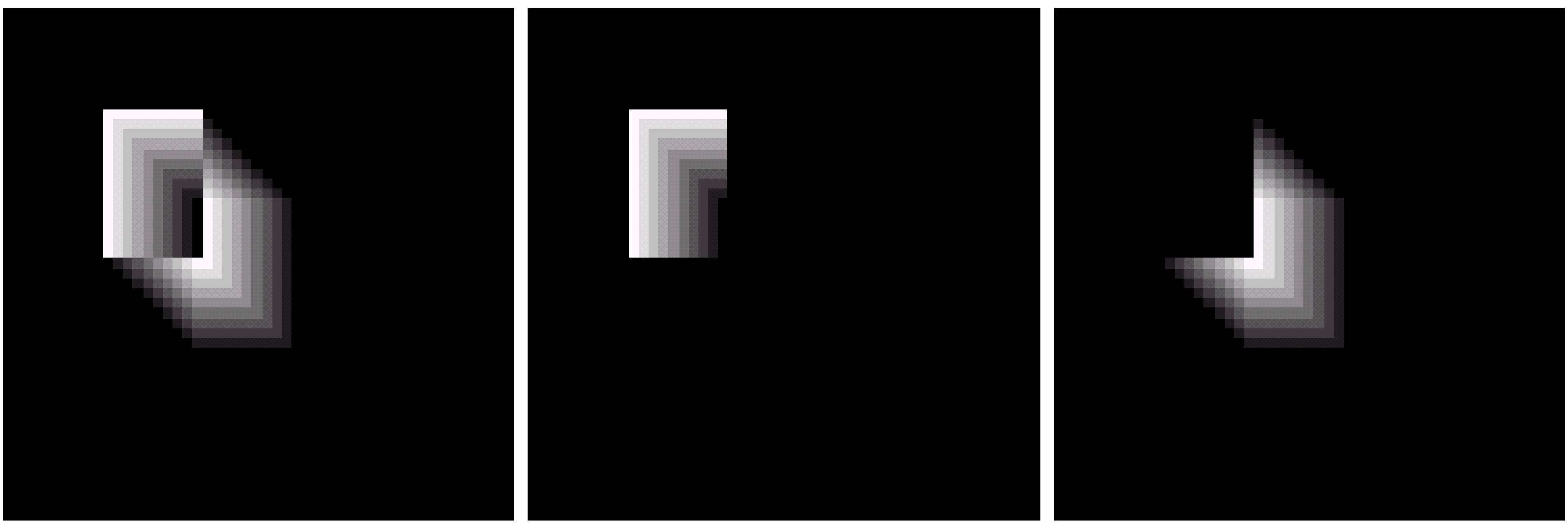
7. Positive ADI, *P*

$$P_k(x,y) = \begin{cases} P_{k-1}(x,y)+1 & \text{if } \left[R(x,y) - f(x,y,k)\right] > T \\ P_{k-1}(x,y) & \text{otherwise} \end{cases}$$

Accumulative difference approach

8. Negative ADI, N

$$N_k(x,y)=\begin{cases} N_{k-1}(x,y)+1 & \text{if } \left[R(x,y)-f(x,y,k)\right]<-T \\ N_{k-1}(x,y) & \text{otherwise} \end{cases}$$



a b c

FIGURE 10.49 ADIs of a rectangular object moving in a southeasterly direction. (a) Absolute ADI. (b) Positive ADI. (c) Negative ADI.

Accumulative difference approach

9. The figure shows a rectangular bright object moving toward the southeast direction in the dim background.
10. Key observations:
    a. The nonzero area of the positive ADI is equal to the size of the moving object
    b. The location of the positive ADI corresponds to the location of the moving object in the reference frame.
    c. The number of non-zero entries in the positive ADI stops increasing when the moving object is displaced completely with respect to the same object in the reference frame.

Accumulative difference approach

10. Key observations:
    d. The absolute ADI contains the regions of the positive and negative ADI.
    e. The motion information of the moving object can be determined from the entries in the absolute and negative ADIs.

Accumulative difference approach

11. Example: building a reference image
    a. Size of the non-stationary components can be detected from the positive ADI.
    b. When a non-stationary component has moved completely out its position in the reference frame, the corresponding background in the present frame can be duplicated.

a b c

FIGURE 10.50 Building a static reference image. (a) and (b) Two frames in a sequence. (c) Eastbound automobile subtracted from (a) and the background restored from the corresponding area in (b). (Jain and Jain.)