



Chapter 10 Image Segmentation

FIGURE 10.1 A
general 3×3
mask.

w_1	w_2	w_3
w_4	w_5	w_6
w_7	w_8	w_9

We can regard a 3×3 mask as either a filter mask
or a correlation mask.



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single black point
we want to find

point in
response R

-1	-1	-1
-1	8	-1
-1	-1	-1

a
b c d

FIGURE 10.2

(a) Point detection mask.
(b) X-ray image of a turbine blade with a porosity.
(c) Result of point detection.
(d) Result of using Eq. (10.1-2).
(Original image courtesy of X-TEK Systems Ltd.)



↑
result of thresholding

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Consider (a) as a mask for a point, i.e., correlation.

$$R = \sum_{i=1}^9 w_i z_i$$

If $|R| \geq T$ we have found a point.

The mask here is also that of a Laplacian operator but we can also consider it as a point correlator.



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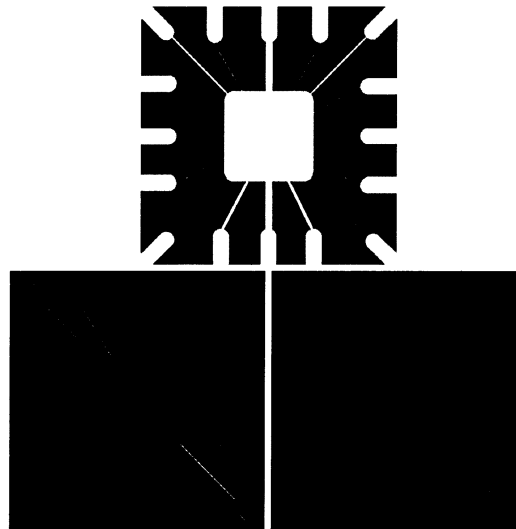
FIGURE 10.3 Line masks

-1	-1	-1	-1	-1	2	-1	2	-1	2	-1	-1
2	2	2	-1	2	-1	-1	2	-1	-1	2	-1
-1	-1	-1	2	-1	-1	-1	2	-1	-1	-1	2
Horizontal			+45°			Vertical			-45°		

These are examples of correlation (also derivative) masks for single pixel width lines



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a
b c
FIGURE 10.4
Illustration of line
detection.
(a) Binary wire-
bond mask.
(b) Absolute
value of result
after processing
with -45° line
detector.
(c) Result of
thresholding
image (b).

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(b) shows the result of using a -45° line detector mask on the wire bond mask for an integrated circuit.

2	-1	-1
-1	2	-1
-1	-1	2

(c) shows the result of thresholding (b).

A good rule of thumb for these masks is to use

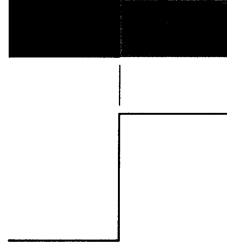
$T = \text{maximum pixel value in original image (a)}$

The isolated points in (c) could be eliminated using morphological processing.



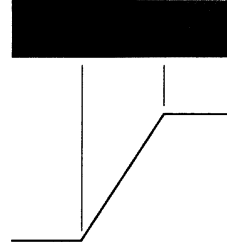
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Model of an ideal digital edge



Gray-level profile
of a horizontal line
through the image

Model of a ramp digital edge



Gray-level profile
of a horizontal line
through the image

a b

FIGURE 10.5
(a) Model of an
ideal digital edge.
(b) Model of a
ramp edge. The
slope of the ramp
is proportional to
the degree of
blurring in the
edge.

sharp edge

blurred edge

models of gray scale images.
The slope is proportional to the amount of blurring.

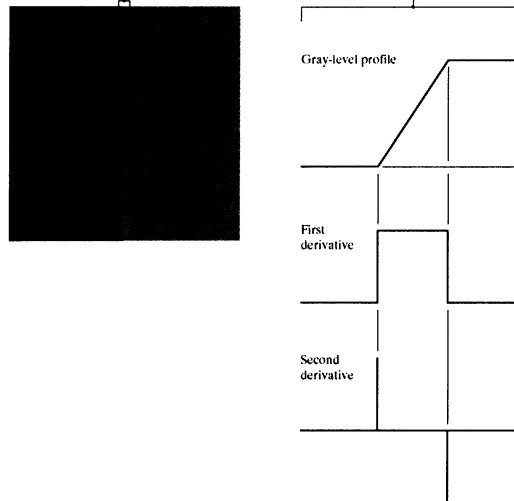


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a b

FIGURE 10.6

(a) Two regions separated by a vertical edge.
(b) Detail near the edge, showing a gray-level profile, and the first and second derivatives of the profile.



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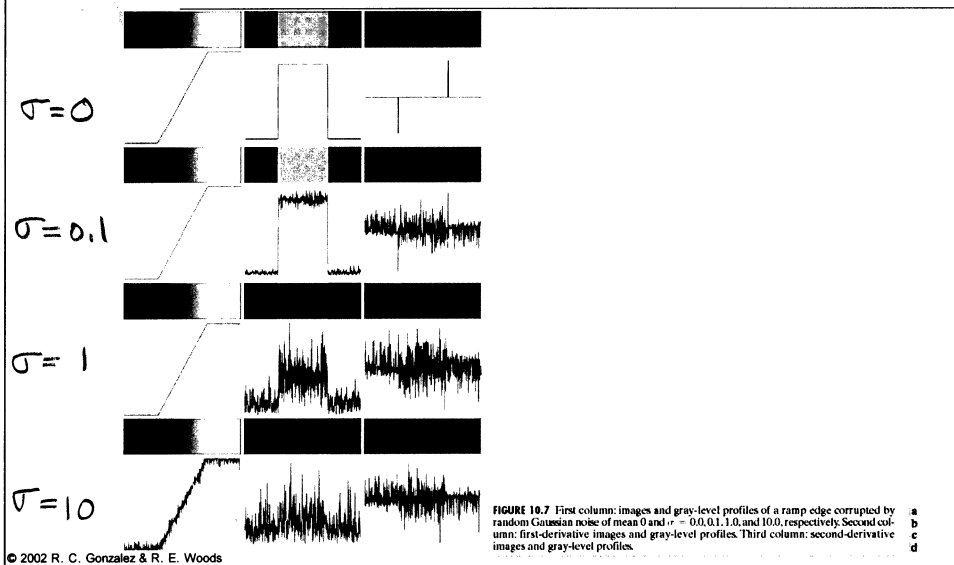
"blurred" gray scale edge

the magnitude of the first derivative can be used to detect the presence of an edge

the second derivative's zero crossing property is also appropriate for detecting the presence of an edge, i.e., a line drawn between the two extrema must cross through zero near the center of the edge



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gray level edges first derivative second derivative



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a
b c
d e
f g

FIGURE 10.8
A 3×3 region of
an image (the z 's
are gray-level
values) and
various masks
used to compute
the gradient at
point labeled z_5 .

z_1	z_2	z_3
z_4	z_5	z_6
z_7	z_8	z_9

-1	0	0	-1
0	1	1	0

Roberts

-1	-1	-1	-1	0	1
0	0	0	-1	0	1
1	1	1	-1	0	1

Prewitt

-1	-2	-1	-1	0	1
0	0	0	-2	0	2
1	2	1	-1	0	1

Sobel

most
commonly
used
gradient
masks

superior noise
characteristics
to Prewitt

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Gradient

$$\underline{\nabla f} = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix}$$

$$|\nabla f| = \sqrt{G_x^2 + G_y^2}$$

$$\alpha(x, y) = \tan^{-1} \left(\frac{G_y}{G_x} \right)$$

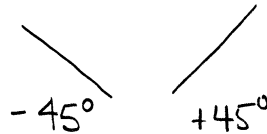
The above operators are attempts to implement
first-order partial derivatives



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0	1	1	-1	-1	0
-1	0	1	-1	0	1
-1	-1	0	0	1	1
Prewitt					
0	1	2	-2	-1	0
-1	0	1	-1	0	1
-2	-1	0	0	1	2
Sobel					

FIGURE 10.9 Prewitt and Sobel masks for detecting diagonal edges.

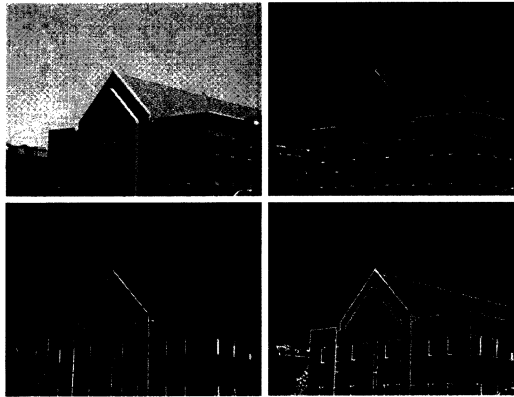


modified Prewitt & Sobel masks for detecting diagonal edges.



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a b
c d
FIGURE 10.10
(a) Original
image. (b) $|G_x|$,
component of the
gradient in the
x-direction.
(c) $|G_y|$,
component in the
y-direction.
(d) Gradient
image, $|G_x| + |G_y|$.



1200x1600 pixel
original image

$|G_y|$

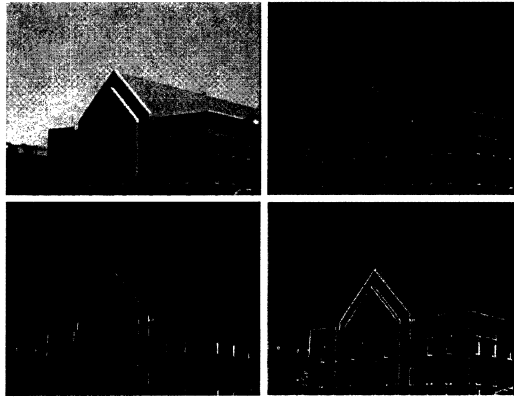
$|G_x|$

gradient approximation
 $|G_x| + |G_y|$



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1200x1600
5x5 avg. filter →



a b
c d

FIGURE 10.11
Same sequence as in Fig. 10.10, but with the original image smoothed with a 5×5 averaging filter.

$|G_y|$

$|G_x| + |G_y|$

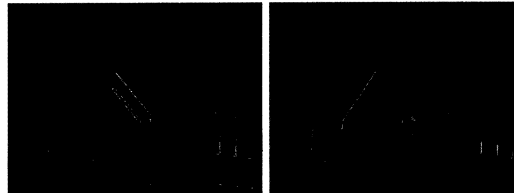
$|G_x|$

*

* Averaging causes all the edges to be weaker.
Removed edges of bricks.



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a b

FIGURE 10.12
Diagonal edge
detection.
(a) Result of using
the mask in
Fig. 10.9(c).
(b) Result of using
the mask in
Fig. 10.9(d). The
input in both cases
was Fig. 10.11(a).

-45° sobel

+45° sobel

Both can detect horizontal & vertical edges but
with a weaker response than a horizontal
or vertical operator.



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FIGURE 10.13
Laplacian masks
used to
implement
Eqs. (10.1-14) and
(10.1-15),
respectively.

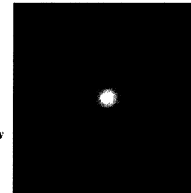
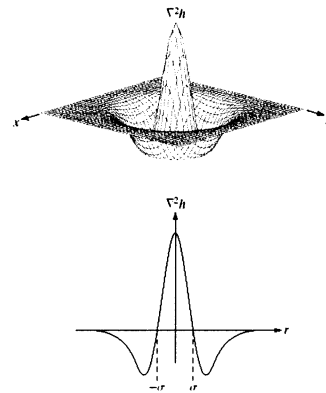
0	-1	0	-1	-1	-1
-1	4	-1	-1	8	-1
0	-1	0	-1	-1	-1

The Laplacian is a second-order derivative which is usually approximated by the above masks.



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LoG
Sometimes
called the
Mexican hat
function



a b
c d

FIGURE 10.14
Laplacian of a
Gaussian (LoG).
(a) 3-D plot.
(b) Image (black
is negative, gray is
the zero plane,
and white is
positive).
(c) Cross section
showing zero
crossings.
(d) 5×5 mask
approximation to
the shape of (a).

0	0	-1	0	0
0	-1	-2	-1	0
-1	-2	16	-2	-1
0	-1	-2	-1	0
0	0	-1	0	0

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The Laplacian is never used directly because of its strong noise sensitivity.

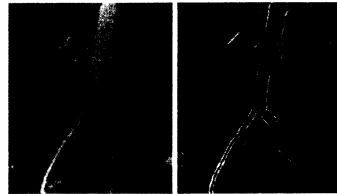
We usually use it with a Gaussian smoothing (low-pass) filter to minimize noise. $h(r) = -e^{-\frac{r^2}{2\sigma^2}}$

Combining these operators leads to the Laplacian of a Gaussian (LoG)

$$\nabla^2 h(r) = - \left[\frac{r^2 - \sigma^2}{\sigma^4} \right] e^{-\frac{r^2}{2\sigma^2}}$$



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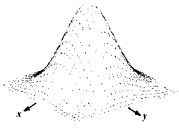


a b
c d
e f g

FIGURE 10.15 (a) Original image. (b) Sobel gradient (shown for comparison). (c) Spatial Gaussian smoothing function. (d) Laplacian mask. (e) LoG. (f) Thresholded LoG. (g) Zero crossings. (Original image courtesy of Dr. David R. Pickens, Department of Radiology and Radiological Sciences, Vanderbilt University Medical Center.)

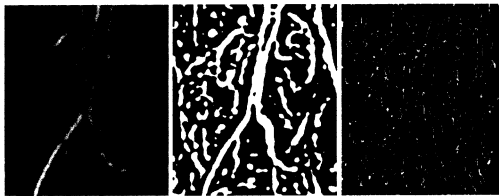
— Sobel image

27x27 pixel
Gaussian
smoothing mask



-1	-1	-1
-1	8	-1
-1	-1	-1

— gradient mask $\nabla^2 f$



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gray scale LoG
result

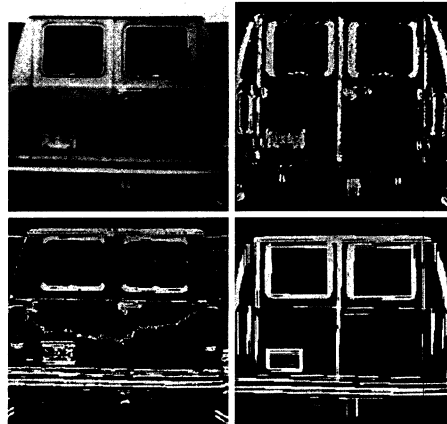
thresholded
LoG image
gradient
output is
+ and -

Zero-crossings
obtained from thresholded
image.



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a b
c d
FIGURE 10.16
(a) Input image.
(b) G_x component
of the gradient.
(c) G_y component
of the gradient.
(d) Result of edge
linking. (Courtesy
of Perceptics
Corporation.)



$|G_x|$

$|G_y|$

simply
 $\alpha = 15^\circ$
 $|\nabla f| > 25$

↑
detect license plate using 2:1 rectangle ratio

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edge linking — uses similarity of edge pixels
to produce meaningful edges

in a neighborhood (usually 3×3 or 5×5)

Edge pixels are similar if

$$|\nabla f(x, y) - \nabla f(x_0, y_0)| \leq E$$

$$|\alpha(x, y) - \alpha(x_0, y_0)| < A$$

Remember the edge direction is perpendicular
to ∇f .



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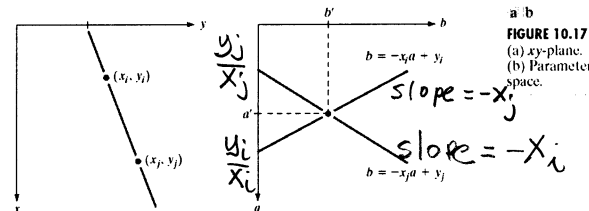


FIGURE 10.17
(a) xy-plane.
(b) Parameter space.

equation of line
 $y_i = ax_i + b$

rewrite line as $b = -x_i a + y_i$

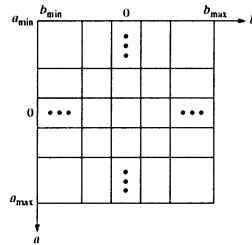
these come from image edge point

This is a line in a-b parameter space.
Intersections of lines from
all image edge points locates lines,



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FIGURE 10.18
Subdivision of the
parameter plane
for use in the
Hough transform.



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To compute the hough transform divide the parameter space into accumulator cells which span the expected ranges of a and b . Set all values to zero.

Enter each edge point incrementing all appropriate accumulator cells. Round-off a and b as appropriate.



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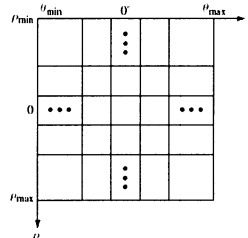
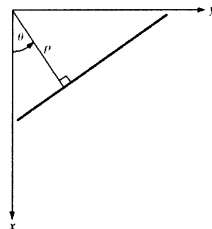


FIGURE 10.19
(a) Normal representation of a line.
(b) Subdivision of the ρ - θ -plane into cells.

accumulator array for ρ - θ
note zero at center of each axis.

A major problem with using lines of the form $y = ax + b$ is that the slope $\rightarrow \infty$ which exceeds the accumulator array.

Solution is to use the polar form of the line

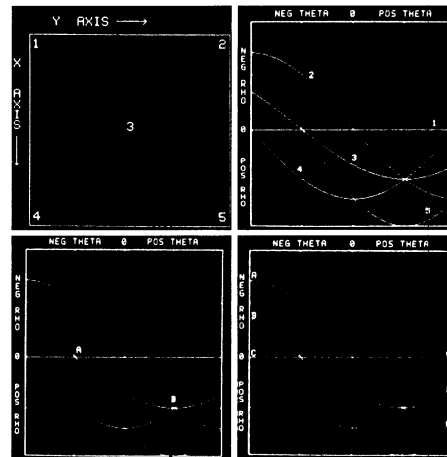
$$\rho = x \cos \theta + y \sin \theta$$



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a b
c d
FIGURE 10.20
Illustration of the
Hough transform.
(Courtesy of Mr.
D. R. Cate, Texas
Instruments, Inc.)

original
image →



each edge point gives
 $x_i \cos \theta + y_i \sin \theta = \rho$
which a sinusoidal curve
in $\rho\theta$ space
Note: point 1 is $\rho = 0$

Note how ρ and θ
change signs across
 $\rho\theta$ space

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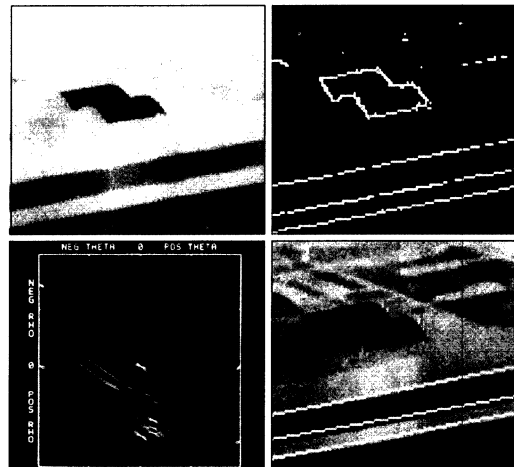
points 1, 3, 5
intersect at A
in $\rho\theta$ space

points 2, 3, 4
intersect at B
in $\rho\theta$ space

Note: you can do Hough transforms based upon
more complex and generalized functions



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a b
c d
FIGURE 10.21
(a) Infrared image.
(b) Thresholded gradient image.
(c) Hough transform.
(d) Linked pixels.
(Courtesy of Mr. D. R. Cate, Texas Instruments, Inc.)

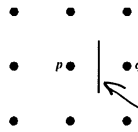
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- (a) IR image of a runway and two hangers
- (b) thresholded gradient image
- (c) Hough transform of (b) using $p = x \cos \theta + y \sin \theta$
- (d) Linked pixels from strongest points in (c)
No gaps in linked image.



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FIGURE 10.22
Edge element
between pixels p
and q .



each edge element
has a cost

$$c(p, q) = H - [f(p) - f(q)]$$

highest
gray scale value
in image

gray scale
image values

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$$\text{let } f(p) = 7$$

$$f(q) = 0$$

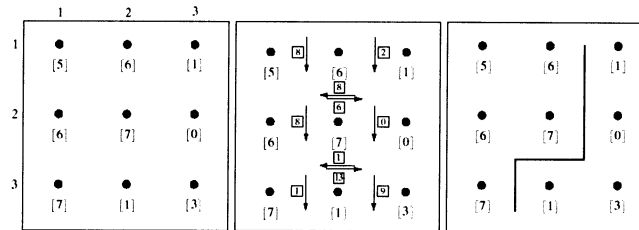
$$H = 7$$

$$\text{Then } c(p, q) = 7 - [7 - 0] = 0$$

cost is low traveling along
edge from top to bottom



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a b c

FIGURE 10.23 (a) A 3×3 image region, (b) Edge segments and their costs, (c) Edge corresponding to the lowest-cost path in the graph shown in Fig. 10.24.

edge segments
and all
computed
costs

pick lowest starting
cost and traverse
lowest cost path to
bottom



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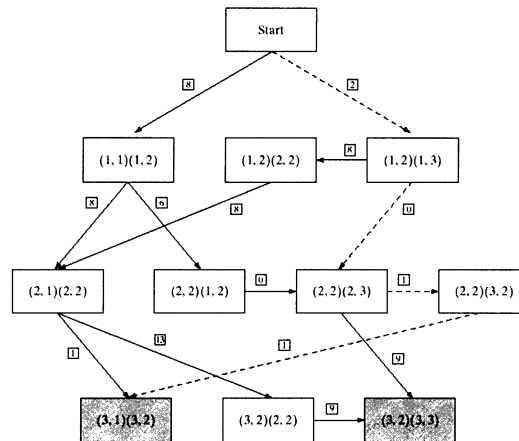


FIGURE 10.24
Graph for the
image in
Fig. 10.23(a). The
lowest-cost path is
shown dashed.

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graph of problem in previous figure
nodes correspond to edge pixels in figures
arcs are potential linked edges

lowest cost path shown in dashes



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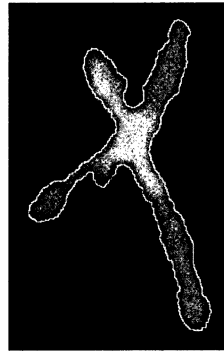


FIGURE 10.25
Image of noisy
chromosome
silhouette and
edge boundary
(in white)
determined by
graph search.

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improved algorithm will estimate the cost to the
end as well

$$r(n) = \underbrace{g(n)}_{\text{lowest cost path found to } n} + \underbrace{h(n)}_{\text{estimated cost to goal node}}$$

estimate of minimum cost path