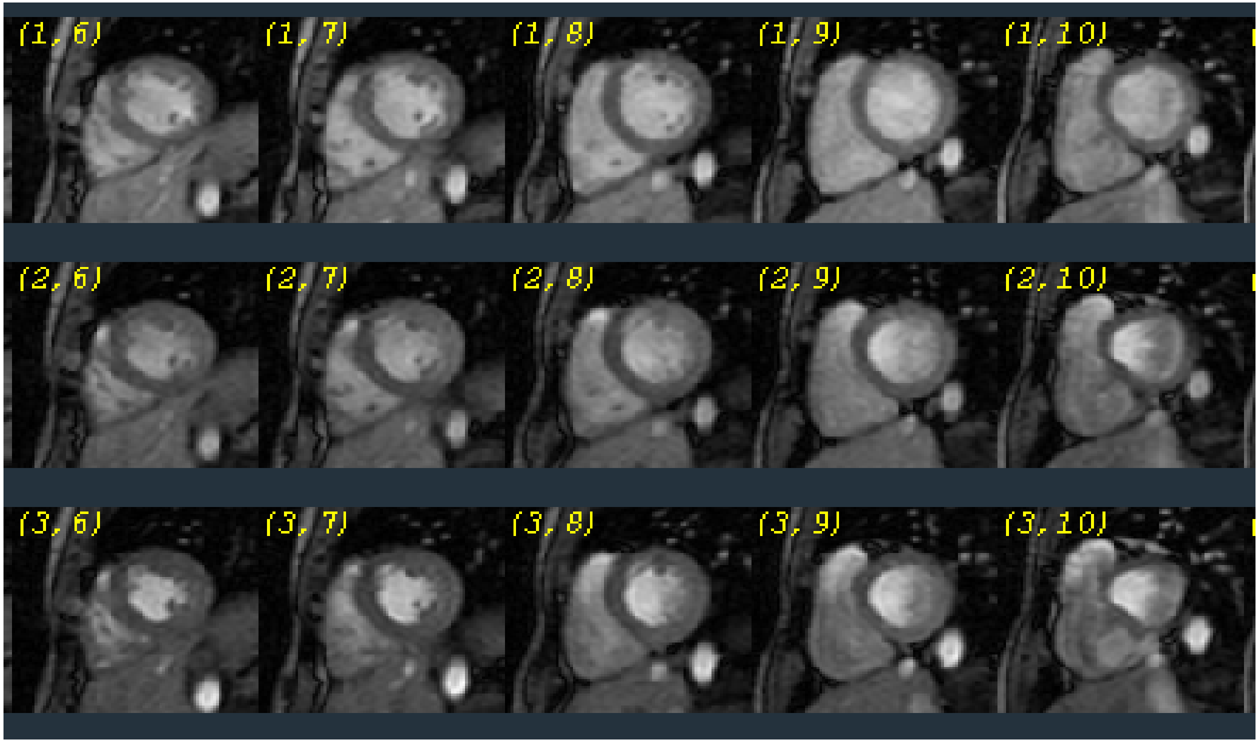
Segmentação de Imagens

- Motivação
  - Identificação de objetos
  - Quantização: contagens, área, perímetro, volume
  - Visualização 2D, 3D
  - Reconhecimento de padrões
  - Classificação

- Normal
- Patolog.
  - Congen.
  - Adquir.
  - ...

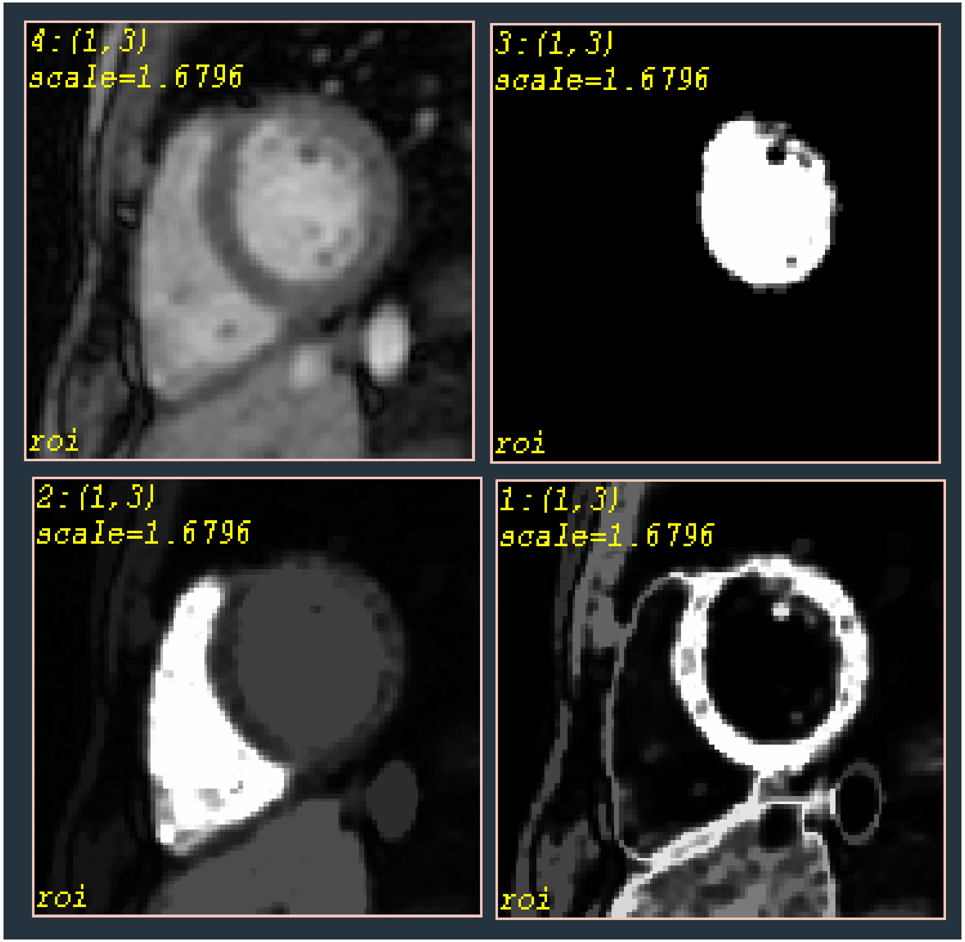
Motivação

- Processos convencionais (manual e semi-automático) : demorados e cansativos
  - gated MRI : 16 volumes, 12 cortes => 192 img
  - gated SPECT: idem



Resultados em RM

Transv.
RM

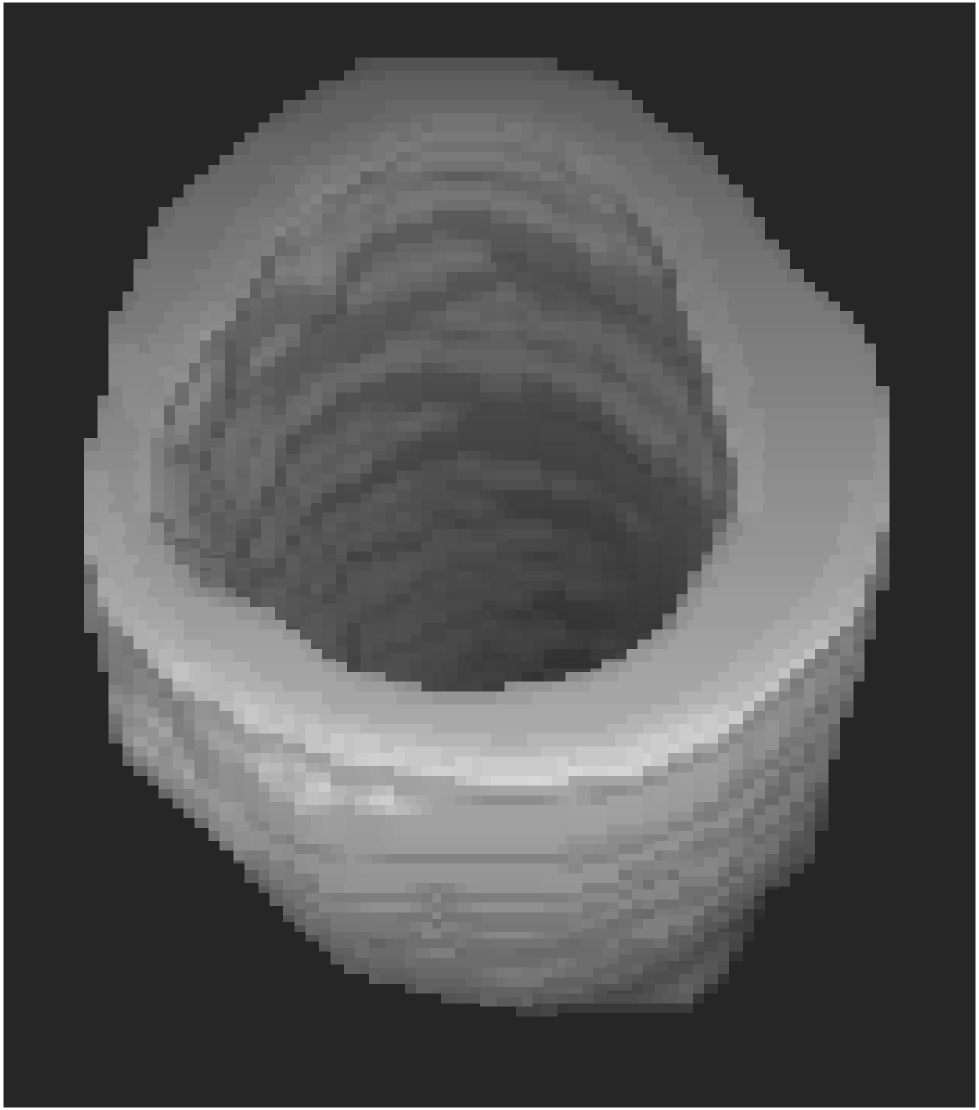


VE

VD

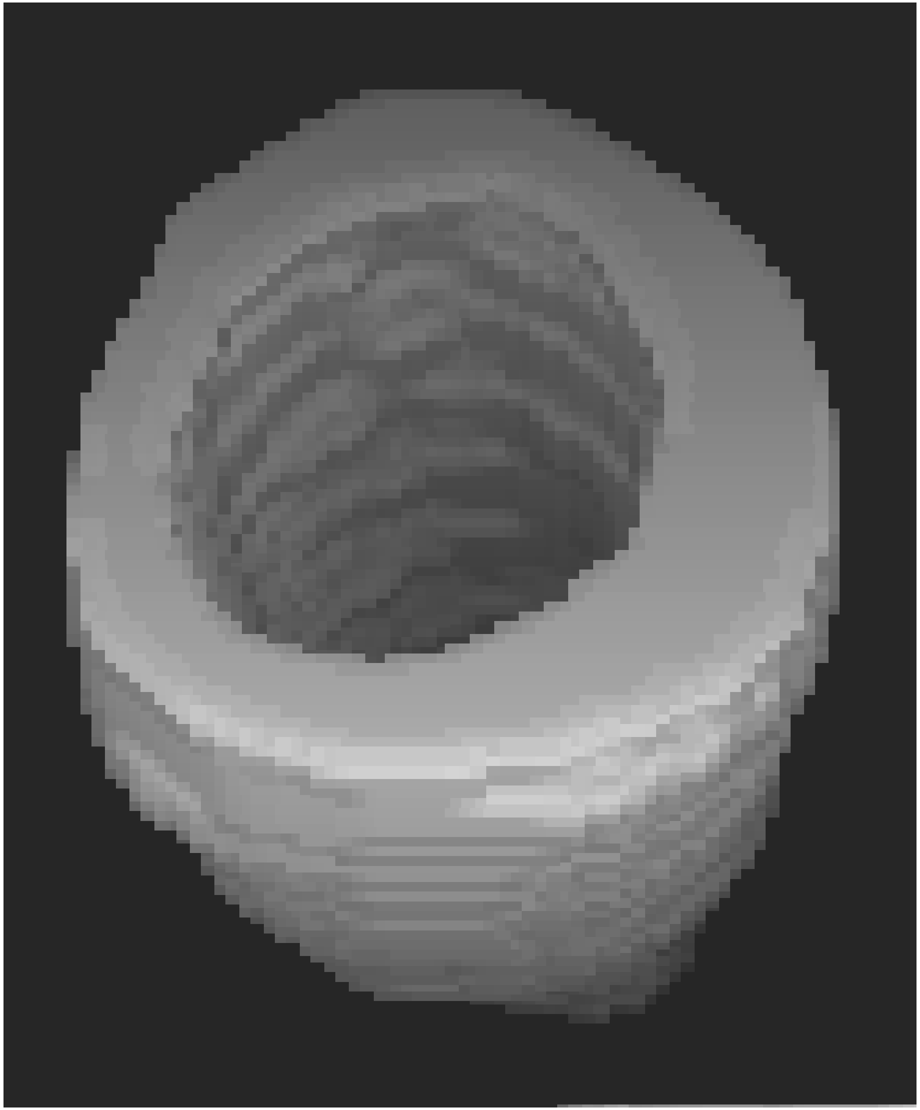
Mioc.

VE: pre-Ventriculotomia



Diástole

VE: pre-ventriculotomia



Sístole

Visão Global

- Operadores
- Representação dos resultados da segmentação
- Técnicas de segmentação
  - thresholding
  - snakes
  - region-growing
  - split-merge
  - fuzzy connectedness
  - redes neurais
  - métodos estatísticos
- Interpretação

Segmentação de Imagens

- Por descontinuidade
  - operadores (detetores)
    - ponto
    - linha
    - borda (gradiente,laplaciano e LoG)
  - contornos
    - manual
    - semi-automático
    - automático (conexão de bordas,Transf. de Hough)
- Por similariedade
  - thresholding
  - region-growing
  - split and merge

Gradiente

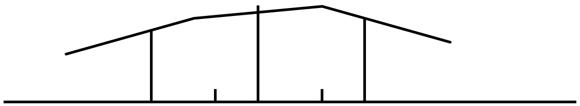
$$\nabla f(x,y) = \frac{\partial f(x,y)}{\partial x} u_x + \frac{\partial f(x,y)}{\partial y} u_y$$

$$\left.\frac{\partial f(x,y)}{\partial x}\right|_{x=i} = f\left(i+\frac{1}{2}\right) - f\left(i-\frac{1}{2}\right)$$

$$f\left(i+\frac{1}{2}\right) = \frac{f(i)+f(i+1)}{2}$$

$$f\left(i-\frac{1}{2}\right) = \frac{f(i-1)+f(i)}{2}$$

$$\left.\frac{\partial f(x,y)}{\partial x}\right|_{x=i} = \frac{f(i+1)-f(i-1)}{2}$$



i-1	i	i+1
-1	0	1

$$\left.\frac{\partial f(x,y)}{\partial x}\right|$$

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

Sobel

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

$$\left.\frac{\partial f(x,y)}{\partial y}\right|$$

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

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

Algoritmo p/ Laplaciano em x?

$$\left.\frac{\partial f(x,y)}{\partial x}\right|_{x=i} = f(i+\frac{1}{2}) - f(i-\frac{1}{2})$$

$$f(i+\frac{1}{2}) = \frac{f(i)+f(i+1)}{2}$$

$$f(i-\frac{1}{2}) = \frac{f(i-1)+f(i)}{2}$$

$$\left.\frac{\partial f(x,y)}{\partial x}\right|_{x=i} = \frac{f(i+1)-f(i-1)}{2}$$

$$\nabla^2 f(x,y) = \frac{\partial^2 f(x,y)}{\partial x^2} + \frac{\partial^2 f(x,y)}{\partial y^2}$$

Sobel, Laplace,...

Sobel $\quad (f(x,y)) = \sqrt{\left(\frac{\partial f(x,y)}{\partial x}\right)^2 + \left(\frac{\partial f(x,y)}{\partial y}\right)^2}$

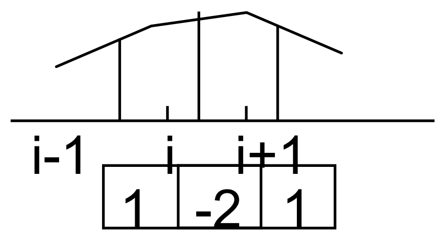
Laplace $\quad \nabla^2 f(x,y) = \frac{\partial^2 f(x,y)}{\partial x^2} + \frac{\partial^2 f(x,y)}{\partial y^2}$

$$\left.\frac{\partial^2 f(x,y)}{\partial x^2}\right|_i = \frac{\partial\left(\frac{\partial f}{\partial x}\right)}{\partial x} = \left(\frac{\partial f}{\partial x}\right)_{i+\frac{1}{2}} - \left(\frac{\partial f}{\partial x}\right)_{i-\frac{1}{2}}$$

$$= (f(i+1) - f(i)) - (f(i) - f(i-1))$$

$$= f(i-1) - 2f(i) + f(i+1)$$

0	1	0
1	-4	1
0	1	0

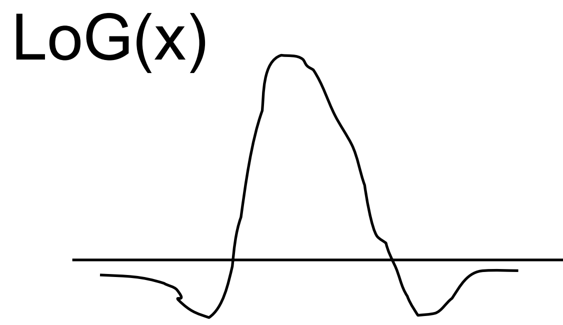


$$H(z) = (z^{-1} - 2 + z)$$

$$H(w) = -2(1 - \cos(wT))$$

Laplaciano da Gaussiana (LoG)

- Edge detector
  - Gauss=>Smooth
  - Laplace=>Zero crossing



$$Gauss(x,y) = \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right)$$

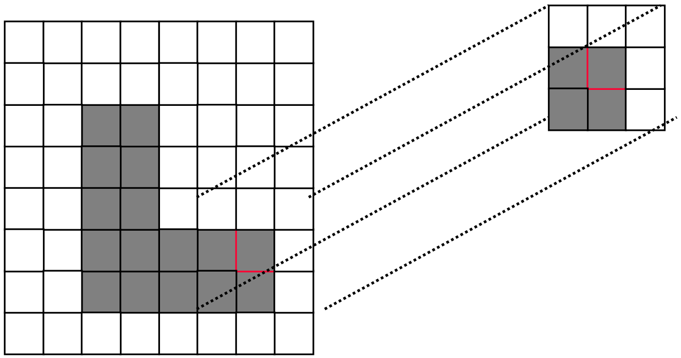
$$g(x,y) = \nabla^2 Gauss(x,y) * f(x,y)$$

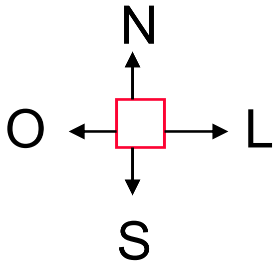
Segmentação por região

- Região: Region-growing
  - conectividade, afinidade, tamanho, forma, possibilidade
    - semente
    - para cada vizinho, agregar o mesmo se similar. Se agregado, considerar os vizinhos deste.
- Região: Split and Merge
  - quadtree, octree
    - testar homogeneidade de cada quadrante
      - se não homogêneo, subdividir e continuar até último quadrante
    - merge de quadrantes vizinhos com homogeneidades similares.

Região: Region-growing

- conectividade, afinidade, tamanho, forma, possibilidade
  - semente
  - para cada vizinho não visitado, agregar o mesmo se similar. Se agregado, considerar os vizinhos deste (usar fila)





- extensão p/ tons de cinza e 3D

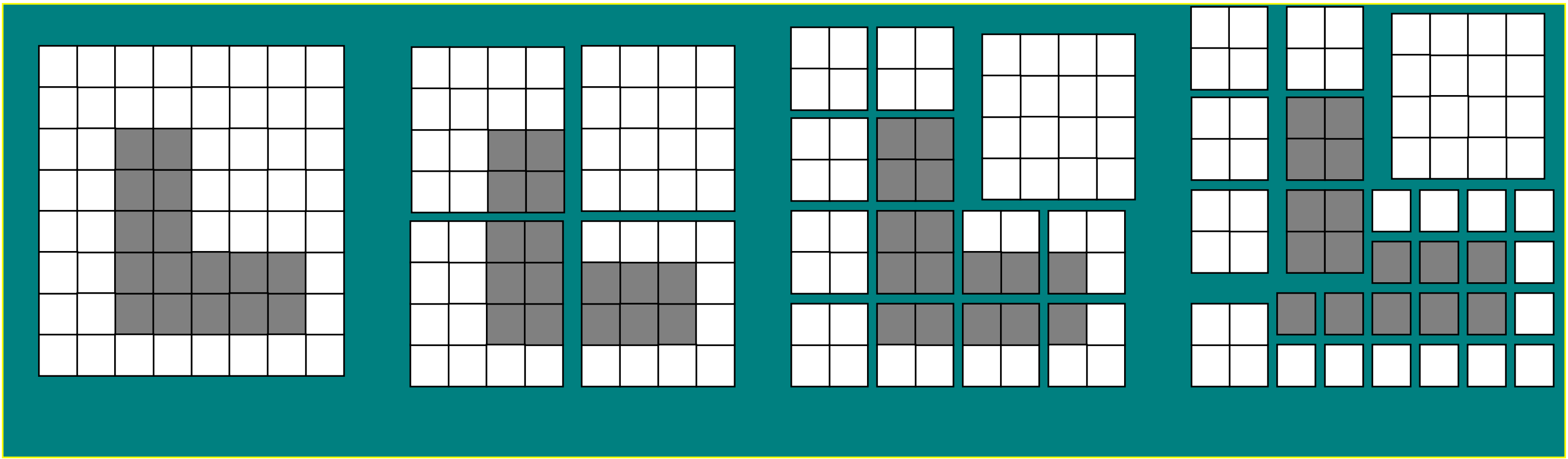
Região: Split and Merge

- quadtree, octree
  - testar homogeneidade de cada quadrante
    - se não homogêneo, subdividir e continuar até último quadrante
  - merge de quadrantes vizinhos com homogeneidades similares.

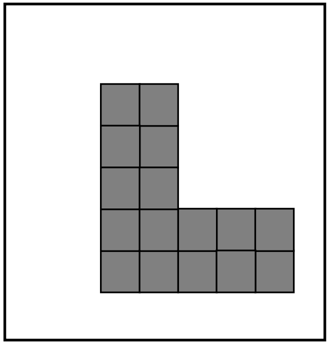
Split and Merge

- Split
  - Quadtrees: 2^n

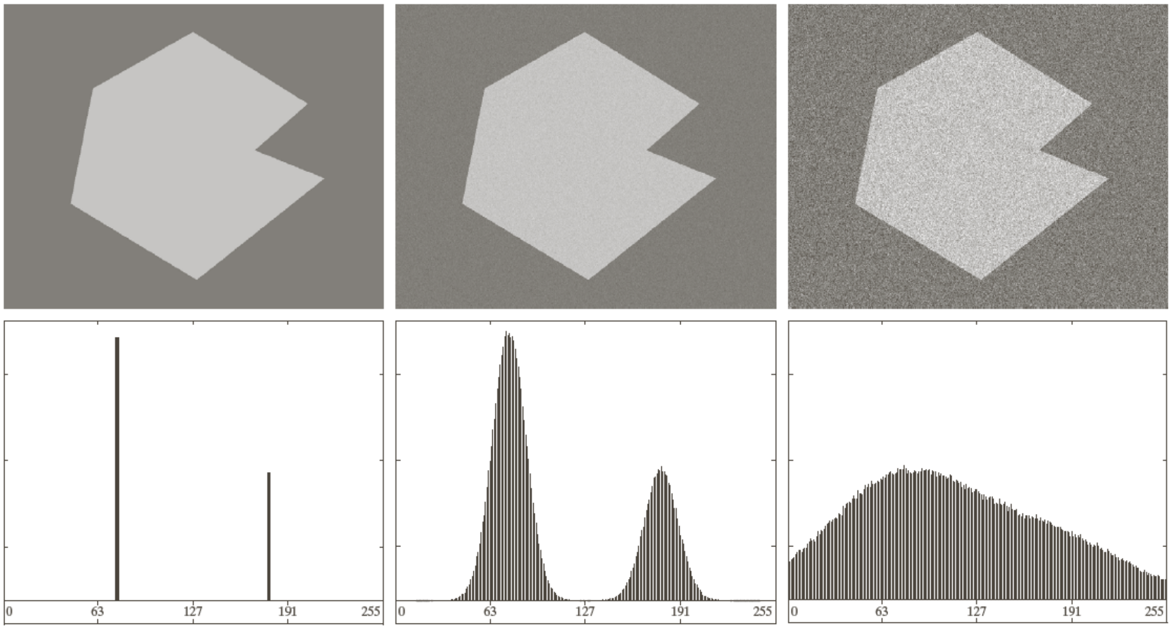
Palavra-chave: <u>similaridade</u>



- Merge (p. ex. labeling)
- Estender p/ tons de cinza
- Estender p/ 3D



Thresholding: Efeito do ruído no histograma



| a | b | c |
| d | e | f |

FIGURE 10.36 (a) Noiseless 8-bit image. (b) Image with additive Gaussian noise of mean 0 and standard deviation of 10 intensity levels. (c) Image with additive Gaussian noise of mean 0 and standard deviation of 50 intensity levels. (d)–(f) Corresponding histograms.

Técnicas: Thresholding

- T=T[f(x,y), x, y, p(x,y)]
  - de imagem f(x,y)
  - p(x,y): propriedade local
- Global
- Ótimo:
- local : baseado na região das bordas
- baseado em características: grad. e laplaciano
- multi-banda

$$min_T Erro(T)$$

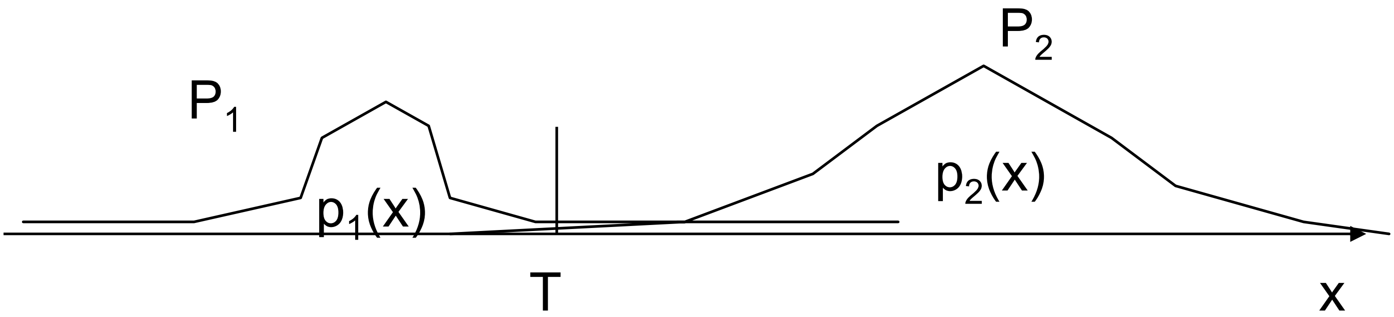
$$Erro(T) = P_2 . \int_{-\infty}^{T} p_2(x)dx + P_1 . \int_{T}^{\infty} p_1(x)dx$$

$$\frac{\partial Erro(T)}{\partial T} = 0 => P_1 . p_1(T) = P_2 . p_2(T)$$

$$p_1(x), p_2(x): \text{se Gaussian}$$

$$\mathrm{T} = \frac{\mu_1 + \mu_2}{2} + \frac{\sigma^2}{\mu_1 - \mu_2} \ln\left(\frac{P_2}{P_1}\right)$$

Optimal thresholding



$$p(x) = P_1 . p_1(x) + P_2 . p_2(x)$$

$$p_i(x) = \frac{1}{\sqrt{2\pi}\sigma_i} \exp(-\frac{(x-\mu_i)^2}{2\sigma_i^2})$$

$$P_1 + P_2 = 1$$

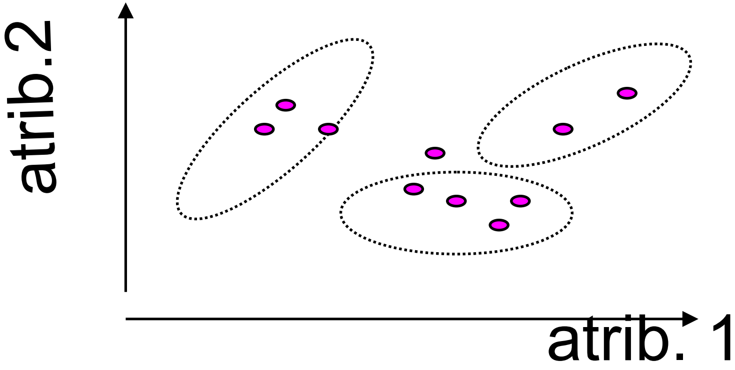
$$Erro = P_2 . \int_{-\infty}^{T} p_2(x).dx + P_1 . \int_{T}^{\infty} p_1(x).dx$$

$$\min_T Erro \Rightarrow \frac{\partial Erro}{\partial T} = 0$$

$$\Rightarrow P_1 . p_1(T) = P_2 . p_2(T)$$

$$T = \frac{\mu_1 + \mu_2}{2} + \frac{\sigma^2}{\mu_1 - \mu_2} \ln(\frac{P_2}{P_1})$$

Isodata (k-means)



0) K classes com centro em c_i

1) Inicializar $c_j^{(0)}$

2) Para cada x_i => atribuir x_i p / classe j
com menor distancia

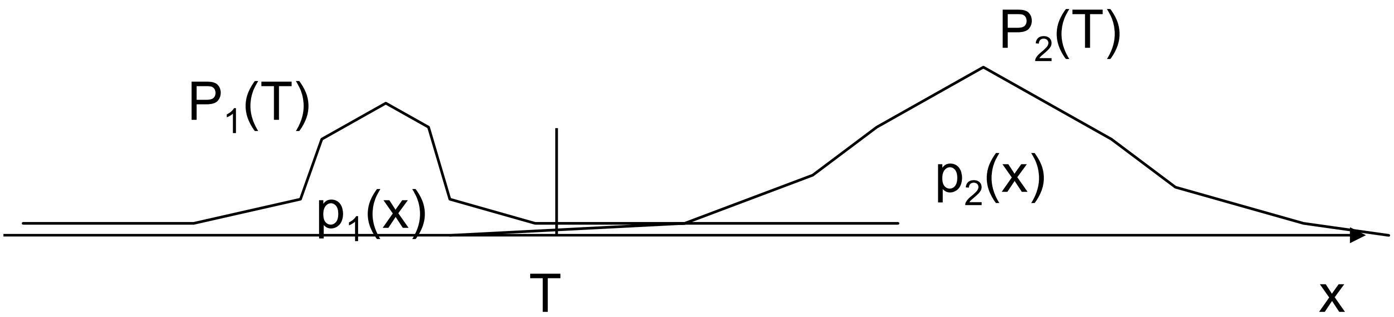
3) Recalcular c_j

4) Repetir 2) e 3) ate nao haver mais alter.

Técnicas: Thresholding por Otsu

- Global
- Baseado no histograma
- Ótimo para casos discretos (intensidade): maximiza a separabilidade entre classes
- Definição de separabilidade ?

Otsu



$$S(C_1, C_2) = \frac{\sigma_B^2(C_1, C_2)}{\sigma_0^2}$$

$$\sigma_0^2 = \sum_{i=0}^{L} (i - m_0)^2 . P(i)$$

$$m_0 = \sum_{i=0}^{L} i . P(i)$$

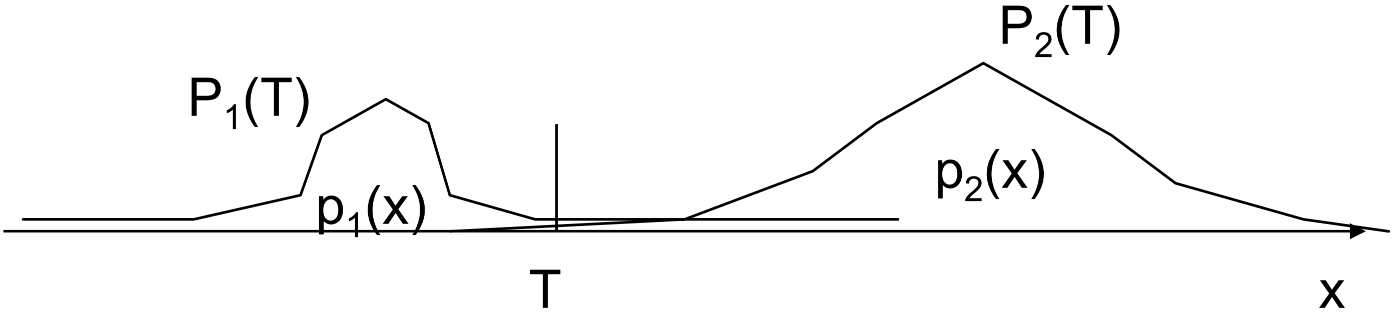
$$\sigma_B^2(C_1, C_2) = P_1.(m_1 - m_0)^2 + P_2.(m_2 - m_0)^2$$

$$m_1 = m_1(T) = \sum_{i=0}^{T} i.P(i \mid C_1)$$

$$m_2 = m_2(T) = \sum_{i=T+1}^{L} i.P(i \mid C_2)$$

$$\Rightarrow \max_T \sigma_B^2(C_1, C_2)$$

Optimal thresholding: Otsu



$$m_1 = \sum_{i=0}^{T} i.P(i \mid C_1) = \sum_{i=0}^{T} i.\frac{P(C_1 \mid i).P(i)}{P(C_1)} = \frac{1}{P_1}\sum_{i=0}^{T} i..P(i) = \frac{m(T)}{P_1}$$

$$m(T) = \sum_{i=0}^{T} i..P(i)$$

$$m_2 = \sum_{i=T+1}^{L} i.P(i \mid C_2) = \frac{m_0 - m(T)}{P_2}$$

$$\Rightarrow \sigma_B^2(C_1, C_2; T) = \frac{(m_0 P_1(T) - m(T))^2}{P_1(T).(1-.P_1(T))}$$

Efeito da filtragem

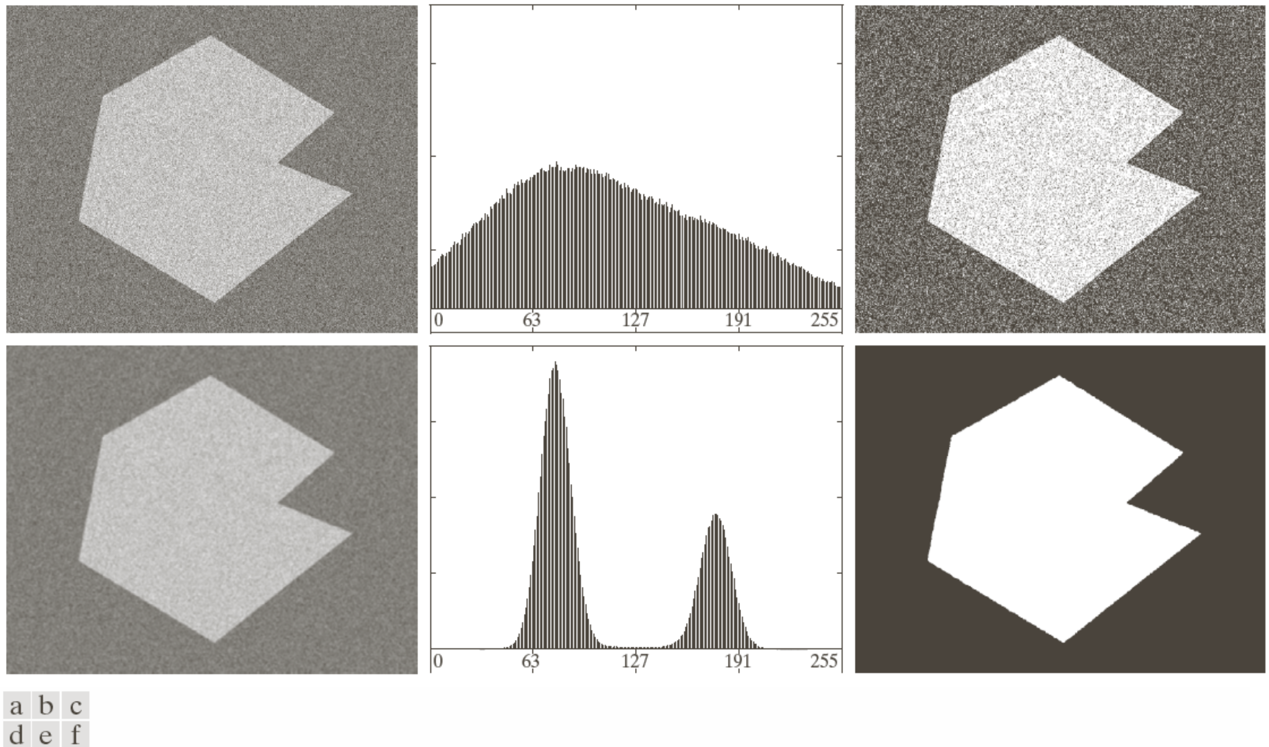


FIGURE 10.40 (a) Noisy image from Fig. 10.36 and (b) its histogram. (c) Result obtained using Otsu's method. (d) Noisy image smoothed using a 5 × 5 averaging mask and (e) its histogram. (f) Result of thresholding using Otsu's method.

Efeito da falta de bimodalidade

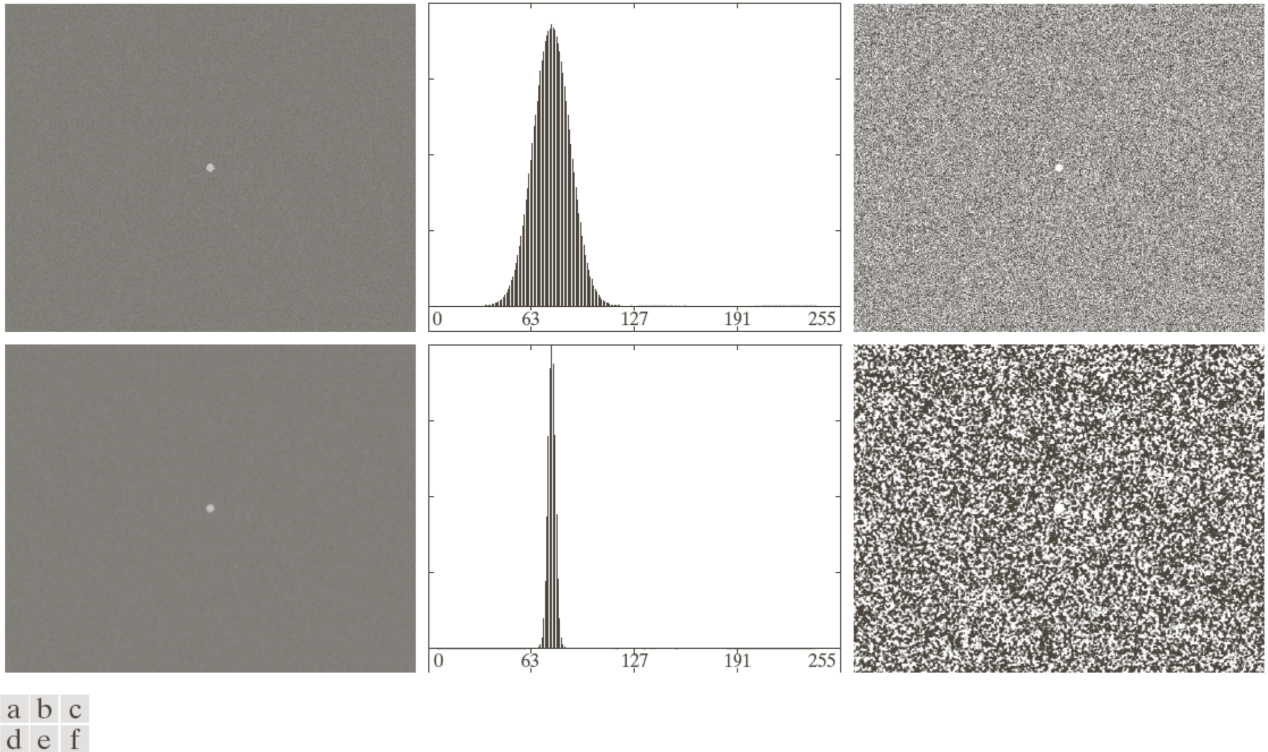


FIGURE 10.41 (a) Noisy image and (b) its histogram. (c) Result obtained using Otsu's method. (d) Noisy image smoothed using a 5 × 5 averaging mask and (e) its histogram. (f) Result of thresholding using Otsu's method. Thresholding failed in both cases.

Histograma focado na região da borda (bimodal)

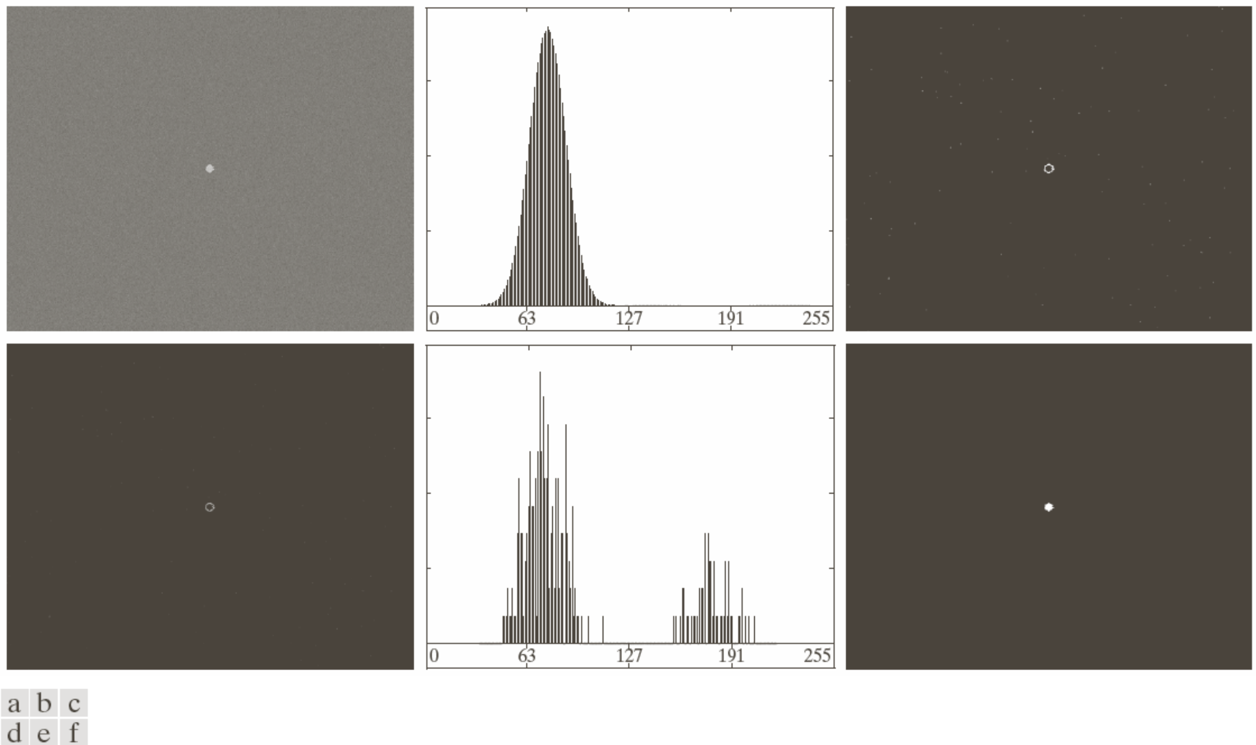
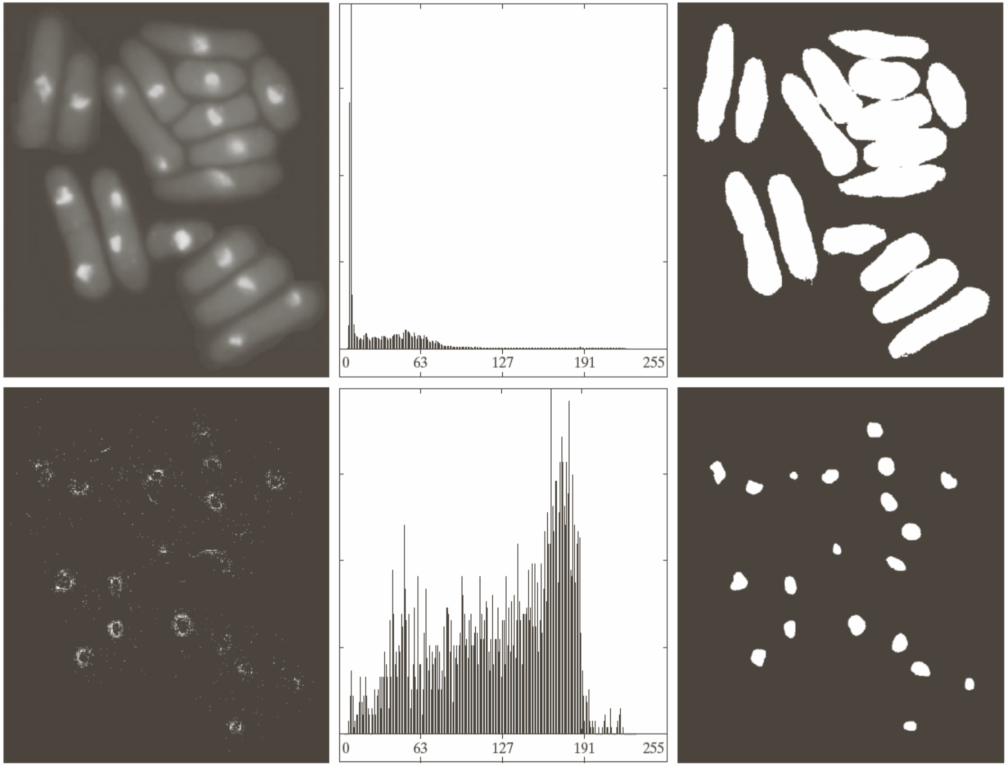


FIGURE 10.42 (a) Noisy image from Fig. 10.41(a) and (b) its histogram. (c) Gradient magnitude image thresholded at the 99.7 percentile. (d) Image formed as the product of (a) and (c). (e) Histogram of the nonzero pixels in the image in (d). (f) Result of segmenting image (a) with the Otsu threshold based on the histogram in (e). The threshold was 134, which is approximately midway between the peaks in this histogram.

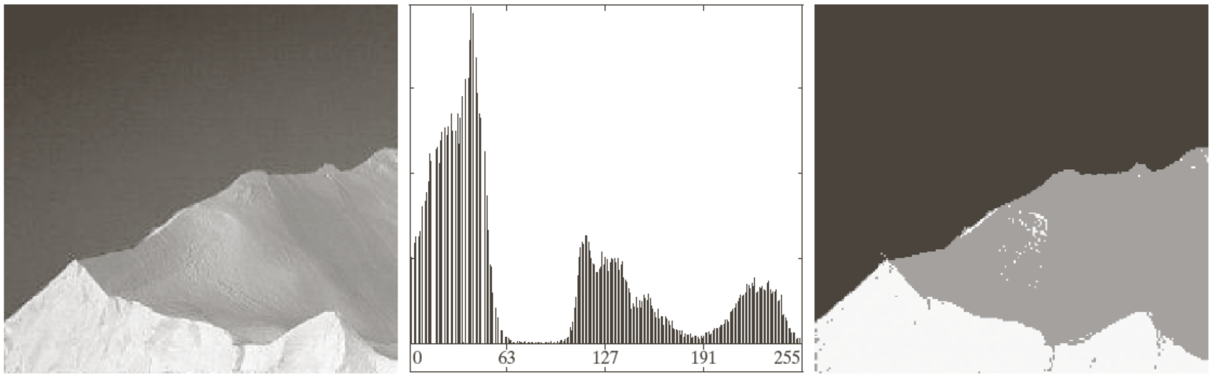
Histograma focado na região da borda (bimodal)



a b c
d e f

FIGURE 10.43 (a) Image of yeast cells. (b) Histogram of (a). (c) Segmentation of (a) with Otsu's method using the histogram in (b). (d) Thresholded absolute Laplacian. (e) Histogram of the nonzero pixels in the product of (a) and (d). (f) Original image thresholded using Otsu's method based on the histogram in (e). (Original image courtesy of Professor Susan L. Forsburg, University of Southern California.)

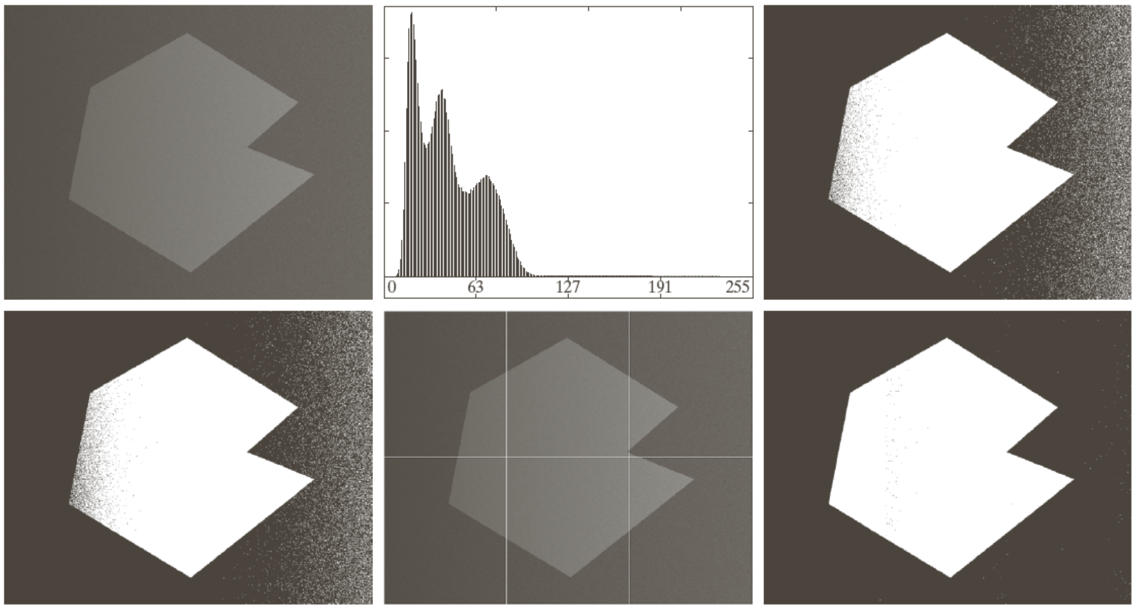
Mais do que 2 classes: generalização da separabilidade



a b c

FIGURE 10.45 (a) Image of iceberg. (b) Histogram. (c) Image segmented into three regions using dual Otsu thresholds. (Original image courtesy of NOAA.)

Otsu em subimagens



a	b	c
d	e	f

FIGURE 10.46 (a) Noisy, shaded image and (b) its histogram. (c) Segmentation of (a) using the iterative global algorithm from Section 10.3.2. (d) Result obtained using Otsu's method. (e) Image subdivided into six subimages. (f) Result of applying Otsu's method to each subimage individually.

Otsu em subimagens

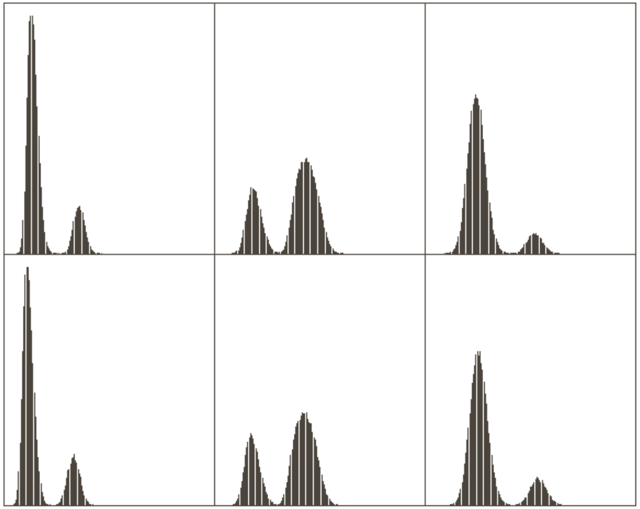


FIGURE 10.47 Histograms of the six subimages in Fig. 10.46(e).