

Limiarização Adaptativa com Imagem Integral

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Sumário

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Objetivo

Implementar Técnica de Limiarização Adaptativa com Imagem Integral e comparar com outras técnicas de limiarização

- Linguagem de programação: Python

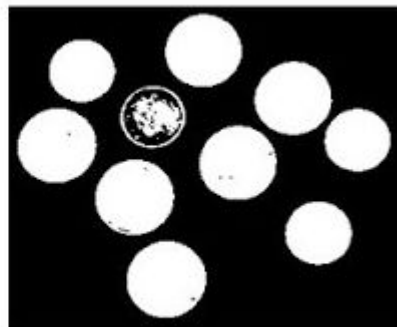
Fundamentação Teórica

Limiarização

- Classificar pixels em duas categorias: claros ou escuros com base em um limiar
- Problema com iluminação
- Método de Otsu



Input Image



threshold output

Limiarização adaptativa

- Forma de limiarização onde cada pixel possui um limiar diferente com base em características locais, como a média dos pixels vizinhos

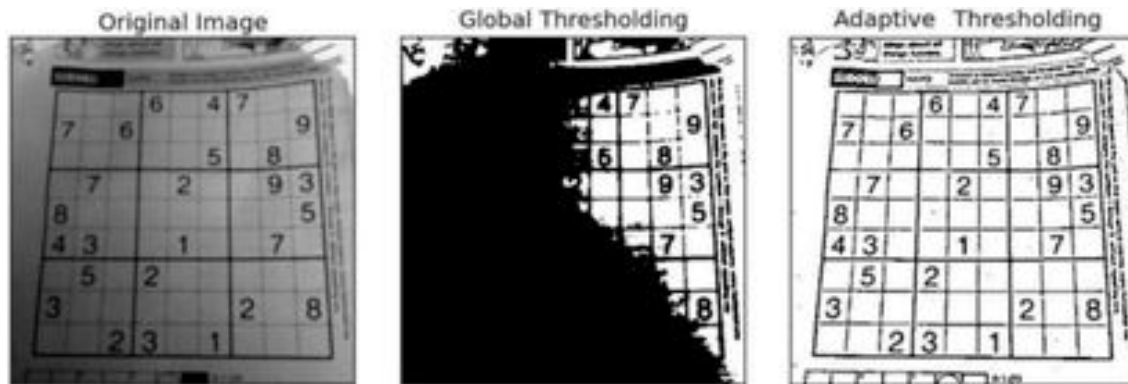


Imagem Integral (Tabela de Área Somada)

- Forma eficiente de calcular a área de uma parte de uma imagem
- Custo linear



| | | | | |
|-----|-----|-----|-----|----|
| 98 | 84 | 4 | 5 | 10 |
| 123 | 123 | 16 | 11 | 11 |
| 123 | 123 | 63 | 18 | 20 |
| 123 | 120 | 119 | 82 | 40 |
| 123 | 115 | 107 | 102 | 71 |

| | | | | |
|-----|------|------|------|------|
| 98 | 182 | 186 | 191 | 201 |
| 221 | 428 | 448 | 464 | 485 |
| 344 | 671 | 757 | 813 | 854 |
| 467 | 917 | 1119 | 1257 | 1338 |
| 590 | 1155 | 1464 | 1704 | 1856 |

(left) An original grayscale image and (right) an integral image

Fonte: https://miro.medium.com/v2/resize:fit:640/format:webp/1*Bj5dt4XsTfwp8w81hal8yQ.png

Cálculo Imagem Integral

$$I(x,y) = \underline{f(x,y)} + \underline{I(x-1,y)} + \underline{I(x,y-1)} - \underline{I(x-1,y-1)}.$$

I é o valor da integral nos pontos (x,y)

f é a intensidade nos pontos (x,y)



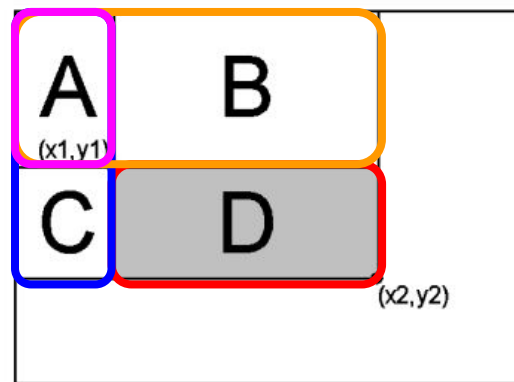
(left) An original grayscale image and (right) an integral image

Cálculo Área de um retângulo

$$\sum_{x=x_1}^{x_2} \sum_{y=y_1}^{y_2} f(x,y) = I(x_2,y_2) - I(x_2,y_1 - 1) - I(x_1 - 1,y_2) + I(x_1 - 1,y_1 - 1).$$

D
B
C
A

| | | | | |
|-----|------|------|------|------|
| 98 | 182 | 186 | 191 | 201 |
| 221 | 428 | 448 | 464 | 485 |
| 344 | 674 | 757 | 813 | 854 |
| 467 | 917 | 1119 | 1257 | 1338 |
| 590 | 1155 | 1464 | 1704 | 1856 |



$$(A+B+C+D) - (A+B) - (A+C) + A.$$

Limiarização Adaptativa com Imagem Integral

- Maior robustez quanto a mudanças fortes de luminosidade
- Algoritmo de performance real-time
 - limiarização normalmente faz parte de um processo maior
- Pontos positivos:
 - fácil de implementar; produz mesma saída independente da ordem de processamento dos pixels; competitivo real time; ordem de complexidade linear
- Pontos negativos:
 - usa uma iteração a mais na imagem para gerar a saída
 - Menos flexível para definir a forma da região de vizinhança, se limita a regiões retangulares.

Aplicações práticas

- Limiarização normalmente faz parte de um processo maior
- Detecção de bordas
- Real-time video streams
- Realidade aumentada
 - Detecção de marcadores



Algoritmo

1. Calcula integral da imagem
2. Efetua limiarização:
 - a. Parâmetros: Tamanho do bloco S ; valor do limiar em porcentagem T
 - b. Para cada pixel, realiza a média dos valores dentro do bloco, e efetua a comparação para limiarização: se o valor do pixel for T por cento menor que a média, é preto, senão é branco

Calcula integral da imagem



```
1  intImg = np.zeros((w, h))
2      for i in range(w):
3          sum = 0
4          for j in range(h):
5              sum += in_img[i, j]
6              if i == 0:
7                  intImg[i, j] = sum
8              else:
9                  intImg[i, j] = intImg[i-1, j] + sum
```

Efetua limiarização

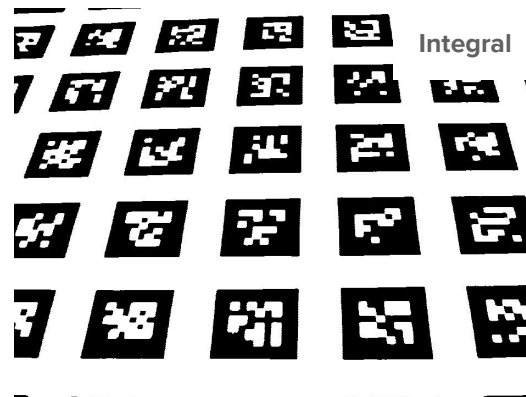
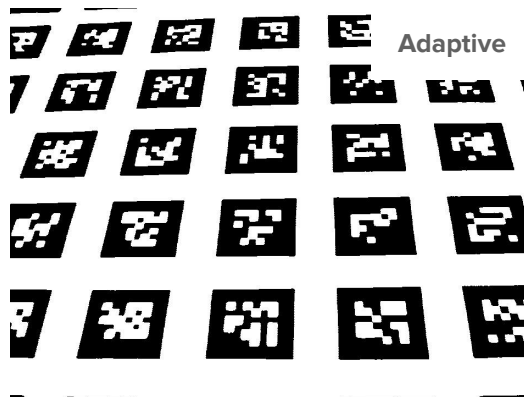
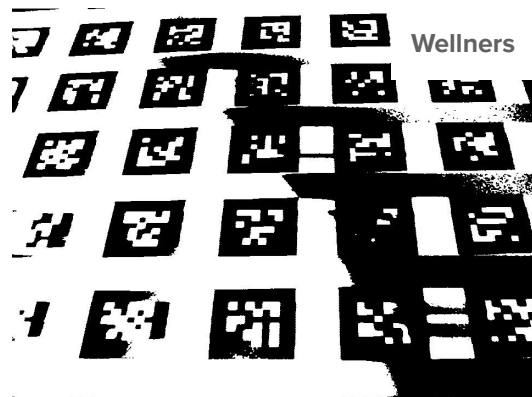
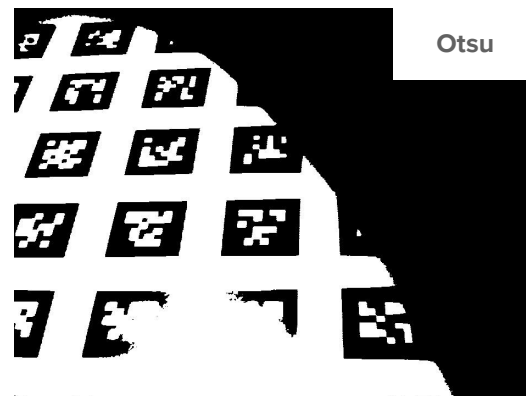
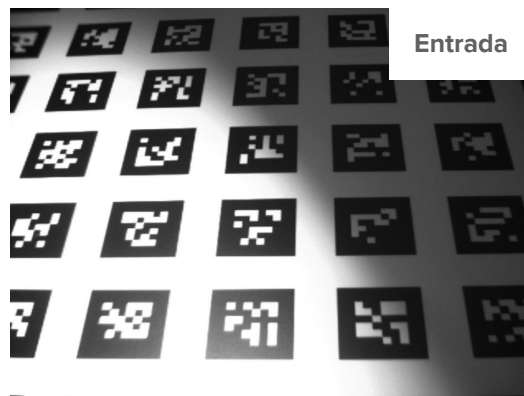
```
1 out_img = np.zeros((w, h))
2 # Itera sobre cada pixel da imagem.
3 for i in range(w - 1):
4     for j in range(h - 1):
5         # Define as coordenadas do bloco.
6         x1 = max(0, i - block_size // 2)
7         x2 = min(w - 1, i + block_size // 2)
8         y1 = max(0, j - block_size // 2)
9         y2 = min(h - 1, j + block_size // 2)
10        # Calcula a soma dos pixels no bloco.
11        block_sum = intImg[x2, y2] - intImg[x1, y2] - intImg[x2, y1] + intImg[x1, y1]
12        # Calcula a quantidade de pixels no bloco.
13        block_count = (x2 - x1) * (y2 - y1)
14        # Compara o pixel com a média do bloco.
15        if in_img[i, j] * block_count <= (block_sum * (100 - threshold) / 100):
16            out_img[i, j] = 0
17        else:
18            out_img[i, j] = 255
```

Exemplo 1

$w = 713$, $h = 954$

$\text{block_size} = 89$

$\text{threshold} = 15$



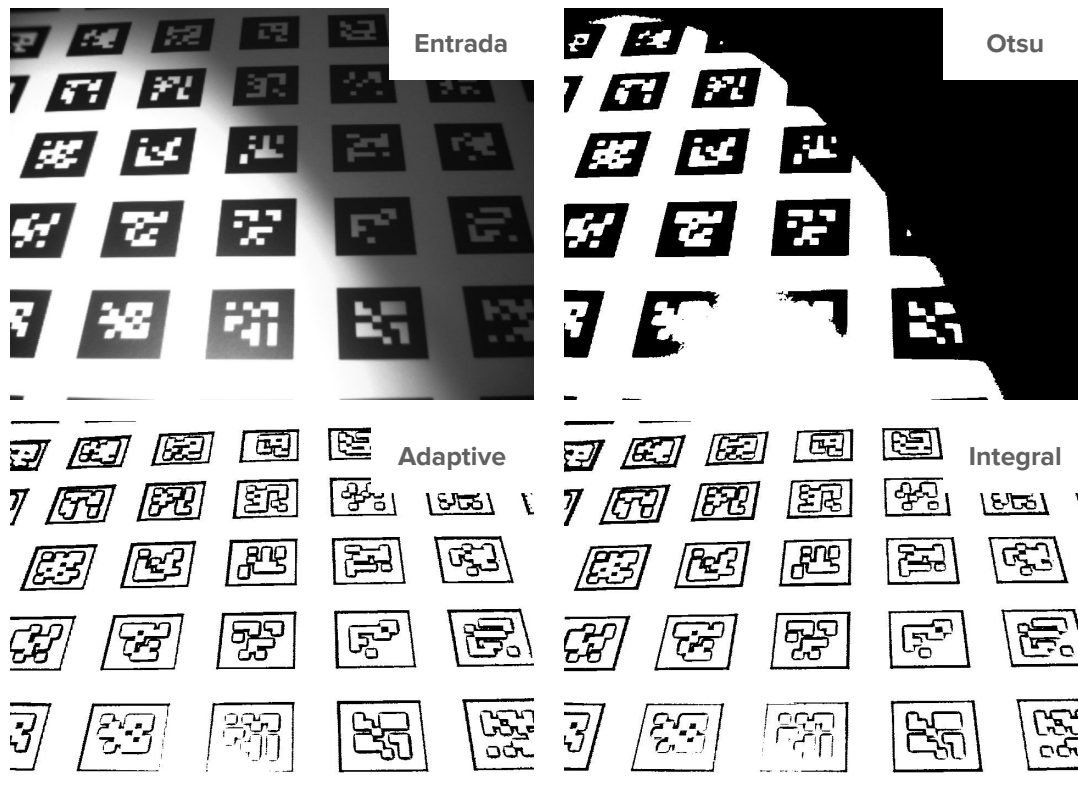
| Algoritmo | Tempo | Num. Iterações |
|-----------|-----------|----------------|
| Otsu | 1.5153 s | 1360659 |
| Wellners | 0.6405 s | 680202 |
| Medium | 11.2971 s | 4981626810 |
| Integral | 3.0514 s | 1358738 |

Exemplo 2

w = 713, h = 954

block_size = 10

threshold = 15



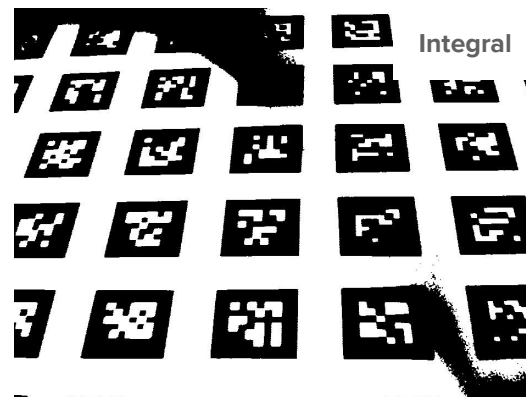
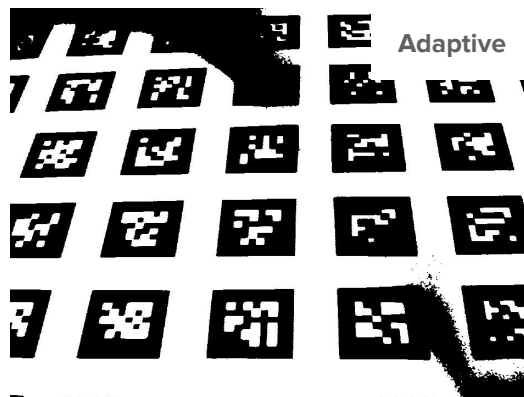
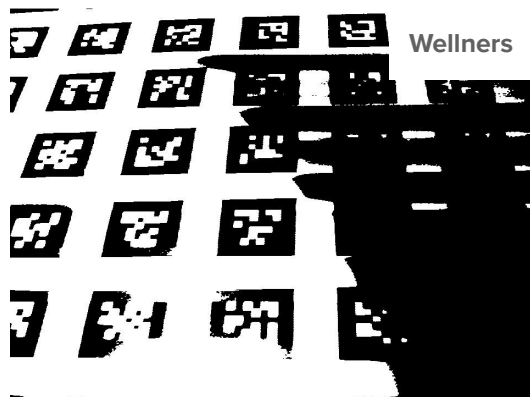
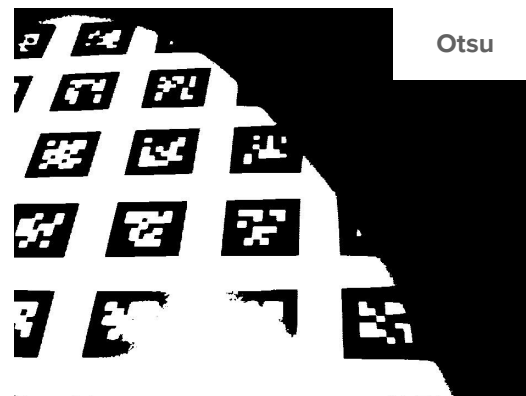
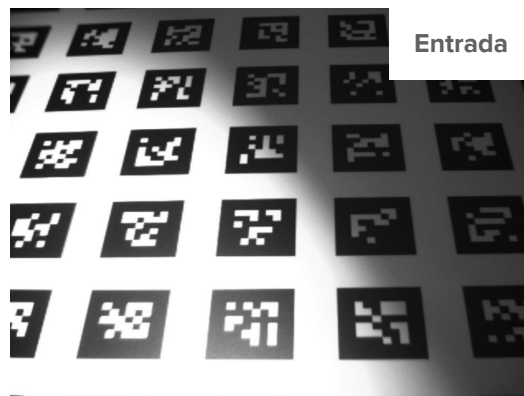
| Algoritmo | Tempo | Num. Iterações |
|-----------|---------|----------------|
| Otsu | 1.6077 | 1360659 |
| Wellners | 0.6271 | 680202 |
| Medium | 11.0732 | 4981626810 |
| Integral | 3.0770 | 1358738 |

Exemplo 3

w = 713, h = 954

block_size = 500

threshold = 15



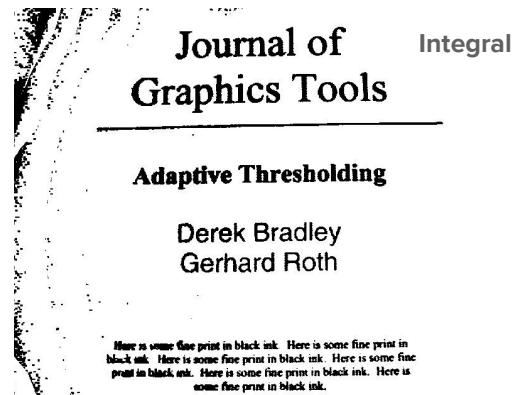
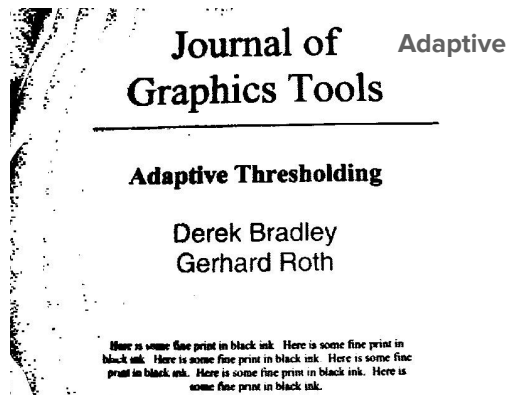
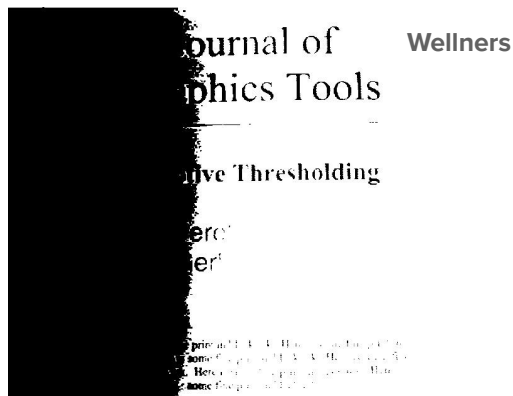
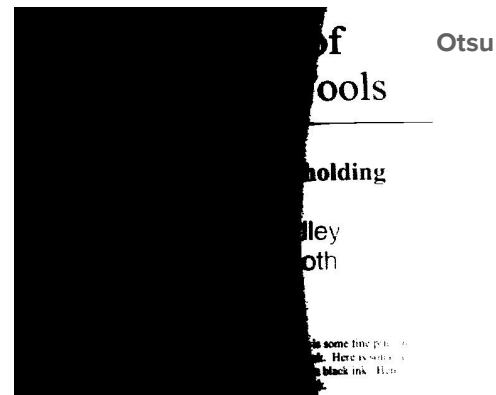
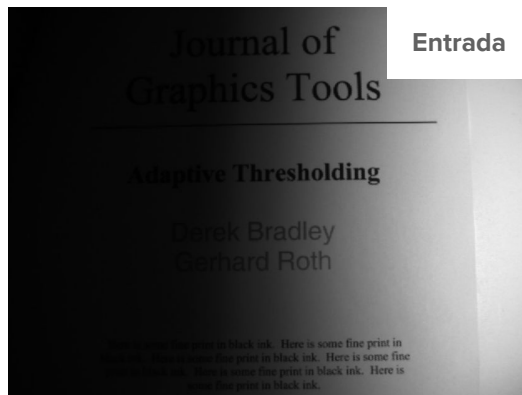
| Algoritmo | Tempo | Num. Iterações |
|-----------|----------|----------------|
| Otsu | 1.5840 | 1360659 |
| Wellners | 0.6949 | 680202 |
| Medium | 110.6432 | 121686617702 |
| Integral | 3.3581 | 1358738 |

Exemplo 4

$w = 624, h = 841$

$\text{block_size} = 78$

$\text{threshold} = 15$



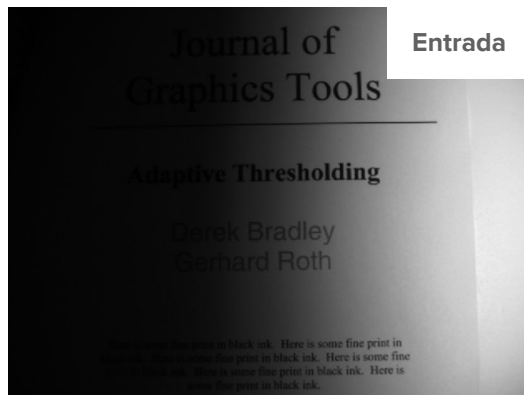
| Algoritmo | Tempo | Num. Iterações |
|-----------|--------|----------------|
| Otsu | 1.1603 | 1049823 |
| Wellners | 0.4600 | 524784 |
| Medium | 8.0946 | 3017483040 |
| Integral | 2.4127 | 1048104 |

Exemplo 5

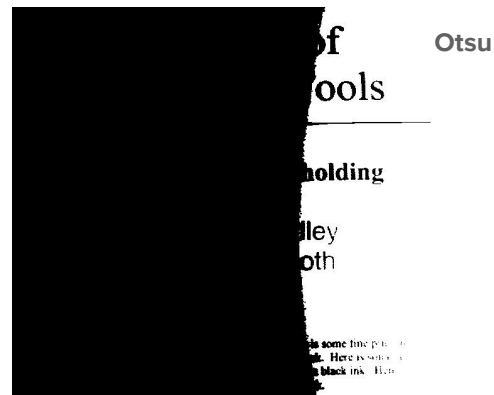
$w = 624, h = 841$

$\text{block_size} = 78$

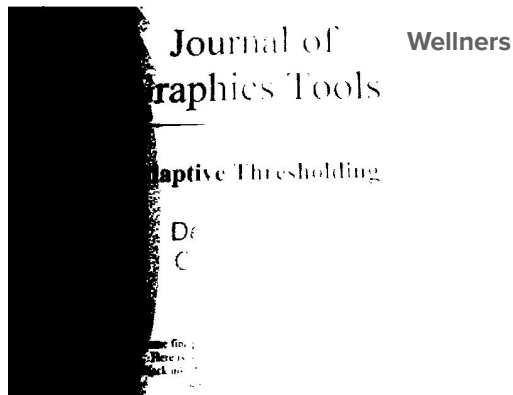
$\text{threshold} = 50$



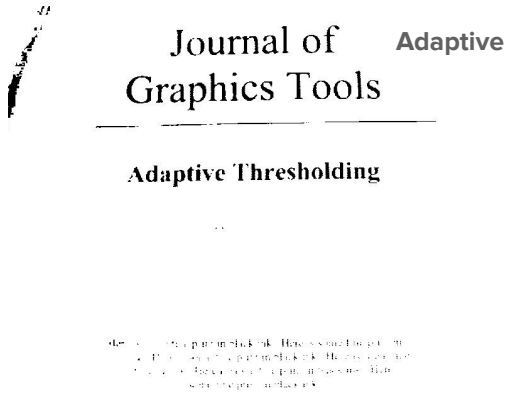
Entrada



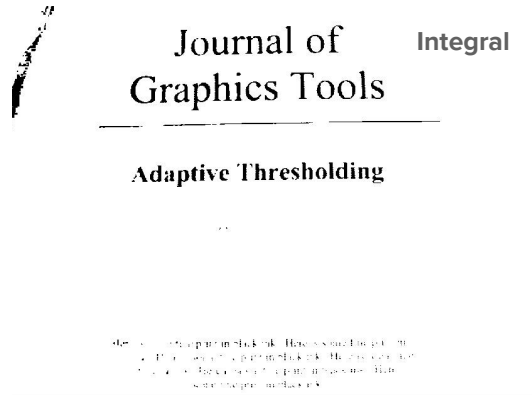
Otsu



Wellners



Adaptive



Integral

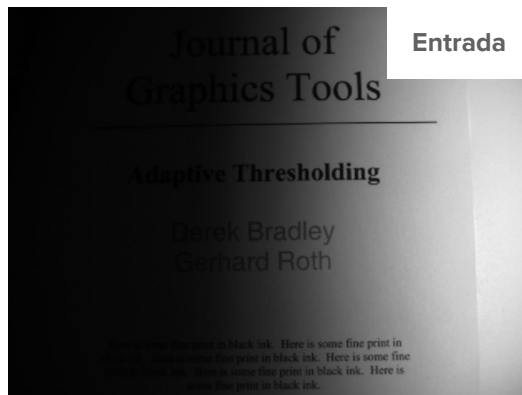
| Algoritmo | Tempo | Num. Iterações |
|-----------|--------|----------------|
| Otsu | 1.2193 | 1049823 |
| Wellners | 0.5313 | 524784 |
| Medium | 9.6168 | 3017483040 |
| Integral | 2.6812 | 1048104 |

Exemplo 6

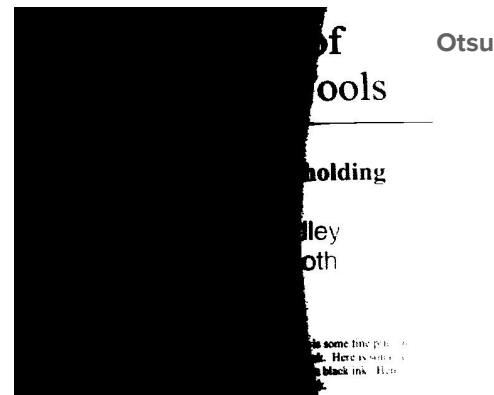
w = 624, h = 841

block_size = 78

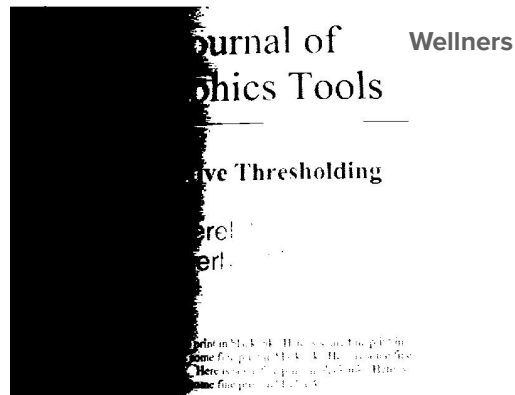
threshold = 5



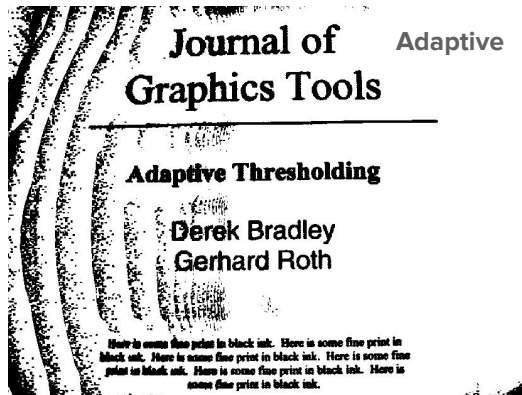
Entrada



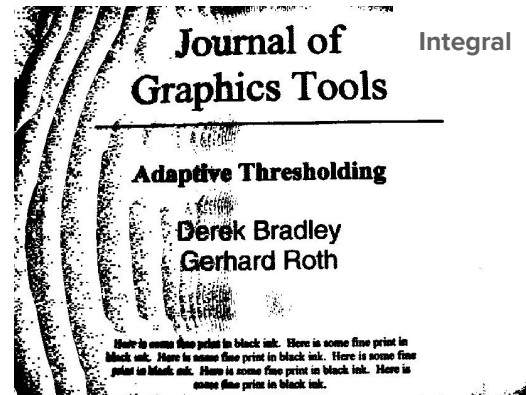
Otsu



Wellners



Adaptive



Integral

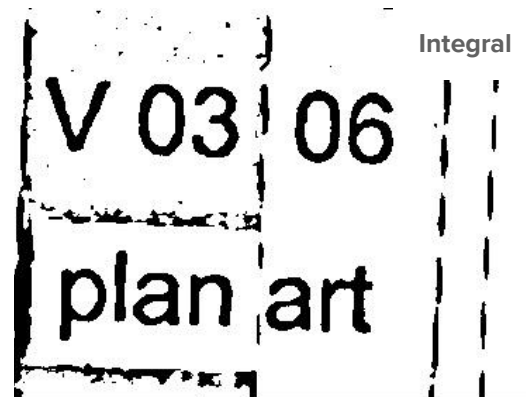
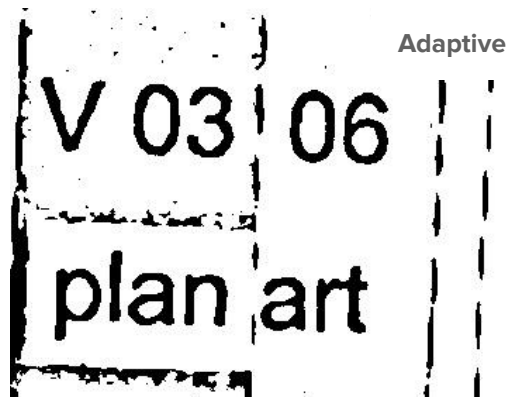
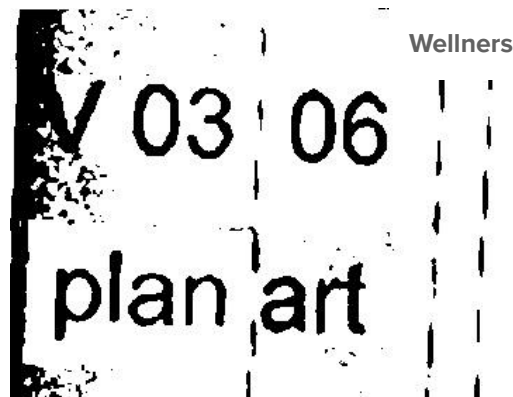
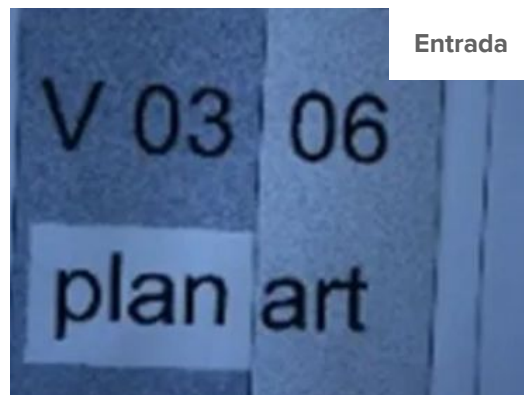
| Algoritmo | Tempo | Num. Iterações |
|-----------|--------|----------------|
| Otsu | 1.2652 | 1049823 |
| Wellners | 0.4999 | 524784 |
| Medium | 7.6402 | 3017483040 |
| Integral | 2.4057 | 1048104 |

Exemplo 7

$w = 278, h = 420$

$\text{block_size} = 34$

$\text{threshold} = 15$



| Algoritmo | Tempo | Num. Iterações |
|-----------|--------|----------------|
| Otsu | 0.3239 | 233775 |
| Wellners | 0.1099 | 116760 |
| Medium | 1.1802 | 127922964 |
| Integral | 0.6074 | 232823 |

Exemplo 8

w = 773, h = 1378
block_size = 96
threshold = 15

Is Image Filtering in the Spatial Domain

Wellners

A technique for modifying or enhancing an image. For example, you can filter an image to emphasize or remove other features. Image processing operations implemented with filtering include smoothing, sharpening, and edge detection.

A **neighborhood operation**, in which the value of any given pixel in the output image is determined by the values of the pixels in the neighborhood of the corresponding input pixel. A pixel's neighborhood is defined by its locations relative to that pixel. (See Neighborhood or Block Processing: An Introduction to Neighborhood Operations.) **Linear filtering** is filtering in which the value of an output pixel is the weighted sum of the values of the pixels in the input pixel's neighborhood.

Filtering of an image is accomplished through an operation called **convolution**. Convolution is a neighborhood operation in which each output pixel is the weighted sum of neighboring input pixels. The matrix of weights is called the **kernel**, also known as the **filter**. A convolution kernel is a correlation kernel that has been rotated 180 degrees.

Suppose the image is

| | | | |
|----|----|----|----|
| 24 | 1 | 8 | 15 |
| 5 | 7 | 14 | 16 |
| 6 | 13 | 20 | 22 |
| 12 | 19 | 21 | 3 |

Is Image Filtering in the Spatial Domain

Entrada

A technique for modifying or enhancing an image. For example, you can filter an image to emphasize or remove other features. Image processing operations implemented with filtering include smoothing, sharpening, and edge detection.

A **neighborhood operation**, in which the value of any given pixel in the output image is determined by the values of the pixels in the neighborhood of the corresponding input pixel. A pixel's neighborhood is defined by its locations relative to that pixel. (See Neighborhood or Block Processing: An Introduction to Neighborhood Operations.) **Linear filtering** is filtering in which the value of an output pixel is the weighted sum of the values of the pixels in the input pixel's neighborhood.

Filtering of an image is accomplished through an operation called **convolution**. Convolution is a neighborhood operation in which each output pixel is the weighted sum of neighboring input pixels. The matrix of weights is called the **kernel**, also known as the **filter**. A convolution kernel is a correlation kernel that has been rotated 180 degrees.

Suppose the image is

| | | | |
|----|----|----|----|
| 24 | 1 | 8 | 15 |
| 5 | 7 | 14 | 16 |
| 6 | 13 | 20 | 22 |
| 12 | 19 | 21 | 3 |

Is Image Filtering in the Spatial Domain

Otsu

A technique for modifying or enhancing an image. For example, you can filter an image to emphasize or remove other features. Image processing operations implemented with filtering include smoothing, sharpening, and edge detection.

A **neighborhood operation**, in which the value of any given pixel in the output image is determined by the values of the pixels in the neighborhood of the corresponding input pixel. A pixel's neighborhood is defined by its locations relative to that pixel. (See Neighborhood or Block Processing: An Introduction to Neighborhood Operations.) **Linear filtering** is filtering in which the value of an output pixel is the weighted sum of the values of the pixels in the input pixel's neighborhood.

Filtering of an image is accomplished through an operation called **convolution**. Convolution is a neighborhood operation in which each output pixel is the weighted sum of neighboring input pixels. The matrix of weights is called the **kernel**, also known as the **filter**. A convolution kernel is a correlation kernel that has been rotated 180 degrees.

Suppose the image is

| | | | |
|----|----|----|----|
| 24 | 1 | 8 | 15 |
| 5 | 7 | 14 | 16 |
| 6 | 13 | 20 | 22 |
| 12 | 19 | 21 | 3 |

Is Image Filtering in the Spatial Domain

Adaptive

A technique for modifying or enhancing an image. For example, you can filter an image to emphasize or remove other features. Image processing operations implemented with filtering include smoothing, sharpening, and edge detection.

A **neighborhood operation**, in which the value of any given pixel in the output image is determined by the values of the pixels in the neighborhood of the corresponding input pixel. A pixel's neighborhood is defined by its locations relative to that pixel. (See Neighborhood or Block Processing: An Introduction to Neighborhood Operations.) **Linear filtering** is filtering in which the value of an output pixel is the weighted sum of the values of the pixels in the input pixel's neighborhood.

Filtering of an image is accomplished through an operation called **convolution**. Convolution is a neighborhood operation in which each output pixel is the weighted sum of neighboring input pixels. The matrix of weights is called the **kernel**, also known as the **filter**. A convolution kernel is a correlation kernel that has been rotated 180 degrees.

Suppose the image is

| | | | |
|----|----|----|----|
| 24 | 1 | 8 | 15 |
| 5 | 7 | 14 | 16 |
| 6 | 13 | 20 | 22 |
| 12 | 19 | 21 | 3 |

Is Image Filtering in the Spatial Domain

Integral

A technique for modifying or enhancing an image. For example, you can filter an image to emphasize or remove other features. Image processing operations implemented with filtering include smoothing, sharpening, and edge detection.

A **neighborhood operation**, in which the value of any given pixel in the output image is determined by the values of the pixels in the neighborhood of the corresponding input pixel. A pixel's neighborhood is defined by its locations relative to that pixel. (See Neighborhood or Block Processing: An Introduction to Neighborhood Operations.) **Linear filtering** is filtering in which the value of an output pixel is the weighted sum of the values of the pixels in the input pixel's neighborhood.

Filtering of an image is accomplished through an operation called **convolution**. Convolution is a neighborhood operation in which each output pixel is the weighted sum of neighboring input pixels. The matrix of weights is called the **kernel**, also known as the **filter**. A convolution kernel is a correlation kernel that has been rotated 180 degrees.

Suppose the image is

| | | | |
|----|----|----|----|
| 24 | 1 | 8 | 15 |
| 5 | 7 | 14 | 16 |
| 6 | 13 | 20 | 22 |
| 12 | 19 | 21 | 3 |

| Algoritmo | Tempo | Num. Iterações |
|-----------|---------|----------------|
| Otsu | 2.2678 | 2130643 |
| Wellners | 0.9188 | 1065194 |
| Medium | 17.2660 | 9337746410 |
| Integral | 4.5984 | 2128238 |

Exemplo 9

Imagem com alta intensidade

$w = 599$, $h = 919$

$\text{block_size} = 74$

$\text{threshold} = 15$



Wellners



Adaptive



Integral



| Algoritmo | Tempo | Num. Iterações |
|-----------|--------|----------------|
| Otsu | 1.2851 | 1101217 |
| Wellners | 0.4971 | 550481 |
| Medium | 9.8246 | 2859022481 |
| Integral | 2.4825 | 1099445 |

Exemplo 10

Imagem com baixa
intensidade

$w = 599$, $h = 919$

$\text{block_size} = 74$

$\text{threshold} = 15$



Entrada



Otsu



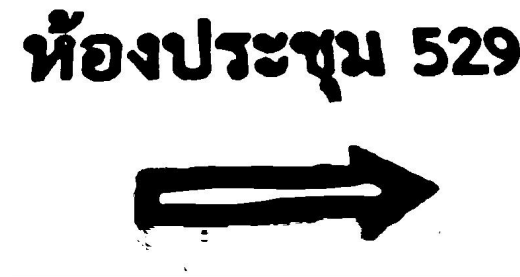
Wellners



Adaptive



Integral



Resultados

| Algoritmo | Vantagens | Desvantagens | Quando Usar |
|-----------|--|--|---|
| Otsu | Fácil implementação Baixo custo | Problemas ao lidar com iluminação | Histogramas com distribuição bimodal de intensidade Fundo uniforme |
| Wellners | Fácil implementação Adapta-se melhor com variação da iluminação | Depende da ordem de leitura dos pixels Baixa representação dos vizinhos | Pequenas variações de iluminação |
| Medium | Grande representação dos vizinhos Robusto quanto a variação de iluminação Grande parametrização | Custo computacional | Imagens com grande variação de iluminação |
| Integral | Eficiência computacional | Menos flexível Necessita de uma iteração a mais | Necessidade de alta performance: performance real-time |

Limitações

- Baixa taxa de recall quando objeto de interesse está em áreas de alta intensidade
- Caso objeto de interesse seja maior do que $S \times S$, ele pode ser classificado como fundo. Para resolver, basta aumentar o tamanho de S , porém pode perder detalhes da imagem
- Ajustes dos parâmetros Block size e Threshold interferem, porém percebeu-se que utilizar `block_size = 1/8` da largura da imagem e `threshold = 15` apresentou bons resultados
- Menos eficiente para imagens grandes:
 - Cálculo linear da imagem integral
 - Acesso a memória

Ponto de melhoria

- Computar métricas de qualidade da segmentação (taxa recall)
- Otimização do algoritmo
 - Podemos realizar a limiarização simultaneamente ao cálculo da imagem integral, pois a limiarização de um pixel, não exige que toda a matriz da imagem integral esteja completa

Referências

Bradley, D., & Roth, G. (2004). Adaptive thresholding using the integral image. *Journal of Graphics Tools*, 9(1), 11-17.

Pintaric, T. (2023, 14 de junho). Concept of Modified Adaptive Thresholding Using Integral Image to Decompose Text Under Illumination. Kittipop-P.
<https://kittipop-p.medium.com/concept-of-modified-adaptive-thresholding-using-integral-image-to-decompose-text-under-illumination-f8ced99e271>