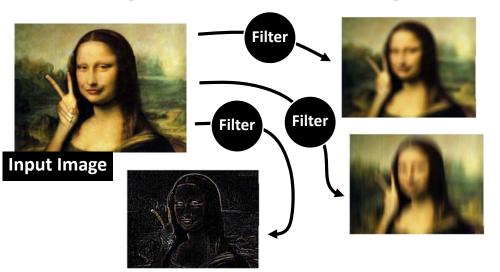
Image Enhancement

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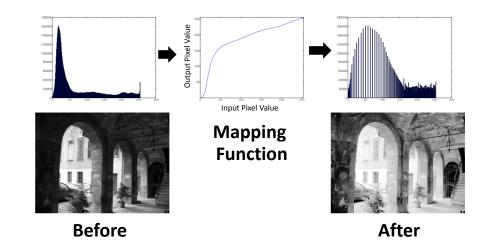
#2

3

Image Filtering



Histogram Equalization

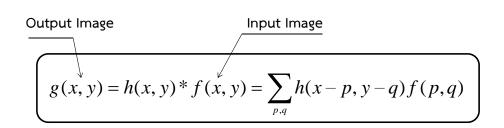


http://www.janeriksolem.net/2009/06/histogram-equalization-with-python-and.htm

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#2

Linear Filter

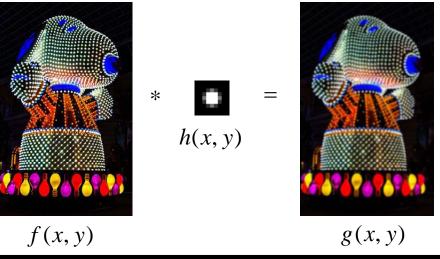


 $\Rightarrow h(x, y)$: Filter kernel, Filter mask, Convolution kernel, Convolution mask, Impulse response, Point spread function.

 \Rightarrow * : Convolution operator

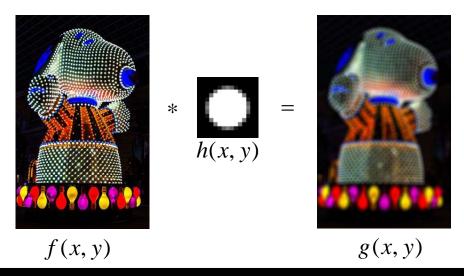
..._

Linear Filter



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Linear Filter

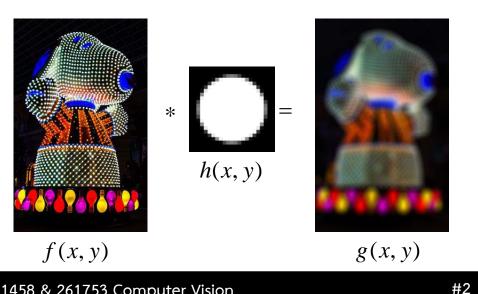


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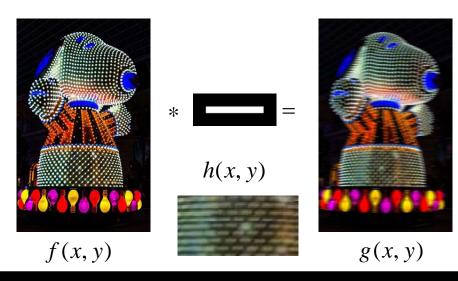
#2

7

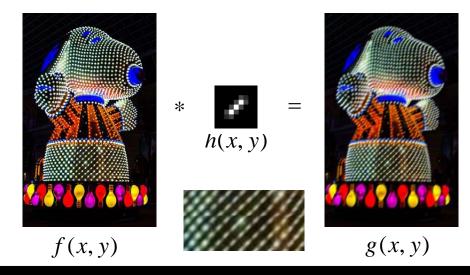
Linear Filter



Linear Filter



Linear Filter



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#2

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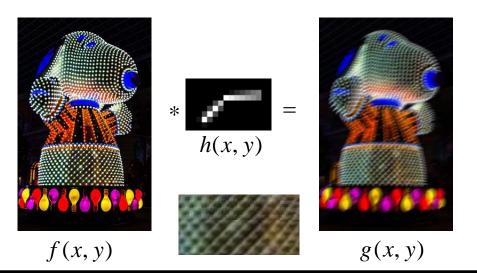
f(x, y)

#2

11

g(x, y)

Linear Filter



h(x, y)

2D Convolution

f_{00}	f_{01}	f_{02}	f_{03}	f_{04}
f_{10}	f_{11}	f_{12}	f_{13}	$f_{\scriptscriptstyle 14}$
f_{20}	f_{21}	f_{22}	$f_{\scriptscriptstyle 23}$	f_{24}
f_{30}	$f_{\scriptscriptstyle 31}$	$f_{\scriptscriptstyle 32}$	$f_{\scriptscriptstyle 33}$	f_{34}
f_{40}	$f_{\scriptscriptstyle 41}$	$f_{\scriptscriptstyle 42}$	f_{43}	$f_{\scriptscriptstyle 44}$

Input Image f(x, y)

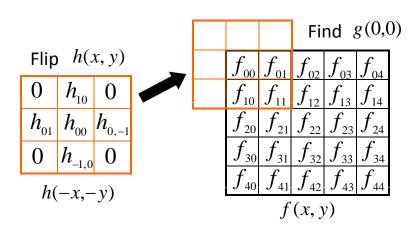
0	$h_{-1,0}$	0
$h_{0,-1}$	h_{00}	$h_{\scriptscriptstyle 01}$
0	h_{10}	0

Kernel h(x, y)

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#2

2D Convolution



$$g(0,0) = \sum_{p,q} h(-p,-q) f(p,q) = h_{00} f_{00} + h_{0,-1} f_{01} + h_{-1,0} f_{10}$$

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#2

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	Find $g(0,1)$
Flip $h(x, y)$	$f_{00} f_{01} f_{02} f_{03} f_{04}$
$0 \mid h_{10} \mid 0$	$f_{10} f_{11} f_{12} f_{13} f_{14}$
$h_{\scriptscriptstyle 01} \mid h_{\scriptscriptstyle 00} \mid h_{\scriptscriptstyle 0,-1}$	$\left f_{20}\right f_{21}\left f_{22}\right f_{23}\left f_{24}\right $
$0 h_{-1,0} 0$	$\left f_{30}\right f_{31}\left f_{32}\right f_{33}\left f_{34}\right $
h(-x,-y)	$\left f_{40} \right f_{41} \left f_{42} \right f_{43} \left f_{44} \right $
(,, ,,	f(x, y)

$$g(0,1) = \sum_{p,q} h(-p,1-q) f(p,q) = h_{01} f_{00} + h_{00} f_{01} + h_{0,-1} f_{02} + h_{-1,0} f_{11}$$

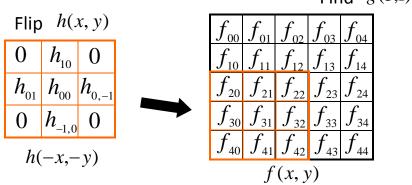
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#2

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2D Convolution

Find g(3,1)

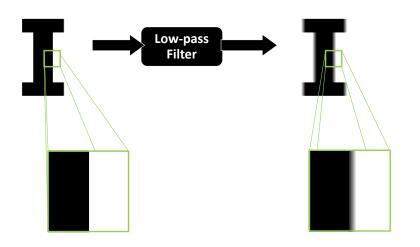


$$g(3,1) = \sum_{p,q} h(3-p,1-q) f(p,q) = h_{10} f_{21} + h_{01} f_{30} + h_{00} f_{31} + h_{0.-1} f_{32} + h_{-1,0} f_{41}$$

2D Convolution

#2

Smoothing

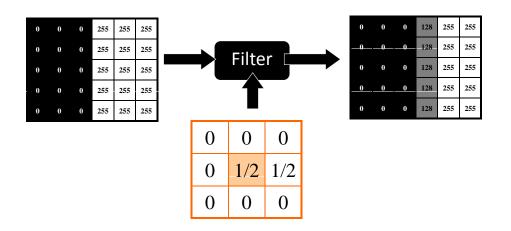


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#2

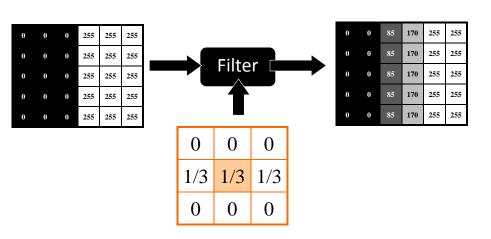
19

Smoothing



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Smoothing



Moving Average Filter

1/2 1/2

1/3 1/3 1/3

1/3 0 1/3 1/3

1 × 2 Kernel

1×3 Kernel

3×1 Kernel

1/21	1/21	1/21	1/21	1/21	1/21	1/21
1/21	1/21	1/21	1/21	1/21	1/21	1/21
1/21	1/21	1/21	1/21	1/21	1/21	1/21

3×7 Kernel

1	1/25	1/25	1/25	1/25	1/25
1	1/25	1/25	1/25	1/25	1/25
1	1/25	1/25	1/25	1/25	1/25
1	1/25	1/25	1/25	1/25	1/25
1	1/25	1/25	1/25	1/25	1/25
	_				

[Mean Filter]

0	0	1/37	1/37	1/37	0	0
0	1/37	1/37	1/37	1/37	1/37	0
1/37	1/37	1/37	1/37	1/37	1/37	1/37
1/37	1/37	1/37	1/37	1/37	1/37	1/37
1/37	1/37	1/37	1/37	1/37	1/37	1/37
0	1/37	1/37	1/37	1/37	1/37	0
0	0	1/37	1/37	1/37	0	0

Circular Kernel

5×5 Kernel

Moving Average Filter

[Mean Filter]







5×5 Kernel

15×15 Kernel

25×25 Kernel

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#2

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Derivatives

The 1st Order Derivative

$$\frac{\partial f}{\partial x} = f(x+1, y) - f(x, y)$$

Convolution Kernel for $\frac{\partial f}{\partial x}$

0	1	0
0	-1	0
0	0	0

∂f	-f(r, v + 1) - f(r, v)
${\partial y}$	= f(x, y+1) - f(x, y)

Convolution Kernel for $\frac{\partial f}{\partial y}$

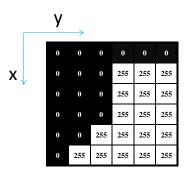
0	0	0
1	-1	0
0	0	0

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#2

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Derivatives







0	0	0	255	255	255
0	0	0	0	0	0
0	0	0	0	0	0
0	0	255	0	0	0
0	255	0	0	0	0
0	0	0	0	0	0

0	0	0	0	0	0
0	0	255	0	0	0
0	0	255	0	0	0
0	0	255	0	0	0
0	255	0	0	0	0
255	0	0	0	0	0

Derivatives



 $\partial f / \partial x$



 $\partial f / \partial y$



#2

The 2nd Order Derivative

$$\frac{\partial^2 f}{\partial x^2} = f(x+1, y) - 2f(x, y) + f(x-1, y)$$
$$\frac{\partial^2 f}{\partial y^2} = f(x, y+1) - 2f(x, y) + f(x, y-1)$$

Convolution Kernel for $\frac{\partial^2 f}{\partial x^2}$

0	1	0
0	-2	0
0	1	0

Convolution Kernel for $\frac{\partial^2 f}{\partial v^2}$

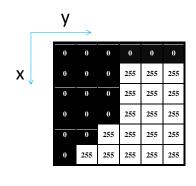
0	0	0
1	-2	1
0	0	0

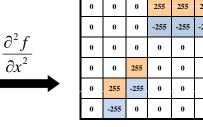
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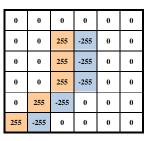
#2

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Derivatives







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#2

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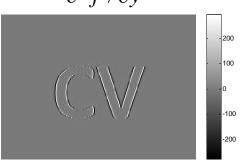
Derivatives

CV

 $\partial^2 f / \partial x^2$



$$\partial^2 f / \partial y^2$$



Gradient

Image Gradient = Vector that points in the direction of the greatest rate of increase

$$\nabla \mathbf{f} = \begin{bmatrix} f_x \\ f_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial x} \end{bmatrix} \quad \blacksquare$$

Magnitude

$$M(x, y) = \sqrt{f_x^2 + f_y^2} \approx |f_x| + |f_y|$$

Direction

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

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#2

The 1-st order derivative

0	1	0
0	-1	0
0	0	0

 h_{r}

$$h_{y}$$
 $\begin{array}{c|cccc}
0 & 0 & 0 \\
\hline
1 & -1 & 0 \\
0 & 0 & 0
\end{array}$

Prewitt

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

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

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

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

$$f_x = h_x * f$$
 $f_y = h_y * f$

Gradient

The 1st Order Derivatives

$$\nabla \mathbf{f}(1,5) = \begin{bmatrix} \frac{\partial f}{\partial x}(1,5) \\ \frac{\partial f}{\partial x}(1,5) \end{bmatrix} = \begin{bmatrix} 255 \\ 0 \end{bmatrix}$$

$$M(1,5) = \sqrt{255^2 + 0^2} = 255$$

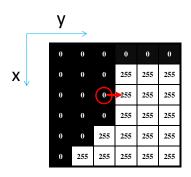
$$\alpha(1,5) = \tan^{-1}\left(\frac{0}{255}\right) = 0^{\circ}$$

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#2

32

Gradient



The 1st Order Derivatives

$$\nabla \mathbf{f}(3,3) = \begin{bmatrix} \frac{\partial f}{\partial x}(3,3) \\ \frac{\partial f}{\partial x}(3,3) \end{bmatrix} = \begin{bmatrix} 0 \\ 255 \end{bmatrix}$$

$$M(3,3) = \sqrt{0^2 + 255^2} = 255$$

$$\alpha(3,3) = \tan^{-1}\left(\frac{255}{0}\right) = 90^{\circ}$$

Gradient

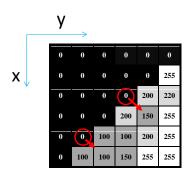
The 1st Order Derivatives

$$\nabla \mathbf{f}(5,2) = \begin{bmatrix} \frac{\partial f}{\partial x}(5,2) \\ \frac{\partial f}{\partial x}(5,2) \end{bmatrix} = \begin{bmatrix} 255 \\ 255 \end{bmatrix}$$

$$M(5,2) = \sqrt{255^2 + 255^2} = 361$$

$$\alpha(5,2) = \tan^{-1}\left(\frac{255}{255}\right) = 45^{\circ}$$

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$$\nabla \mathbf{f}(4,4) = \begin{bmatrix} 200 \\ 200 \end{bmatrix}$$

$$M(4,4) = 282$$

$$\alpha(4,4) = 45^{\circ}$$

$$\nabla \mathbf{f}(5,2) = \begin{bmatrix} 100 \\ 100 \end{bmatrix}$$

$$M(5,2) = 141$$

$$\alpha(3,4) = 45^{\circ}$$

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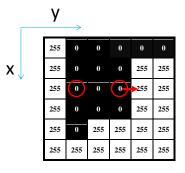
#2

35

33

Gradient

The 1st Order Derivatives



$$\nabla \mathbf{f}(3,4) = \begin{bmatrix} 0 \\ 255 \end{bmatrix}$$

$$M(3,4) = 255$$

$$\alpha(3,4) = 90^{\circ}$$

$$\nabla \mathbf{f}(3,2) = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

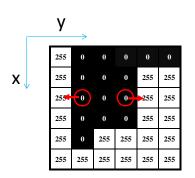
$$M(3,2) = 0$$

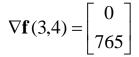
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#2

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Gradient





$$M(3,4) = 765$$

$$\alpha(3,4) = 90^{\circ}$$

$$\nabla \mathbf{f}(3,2) = \begin{bmatrix} 0 \\ -765 \end{bmatrix}$$

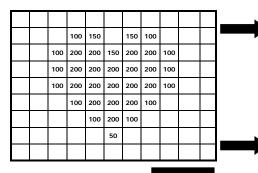
$$M(3,2) = 765$$

$$\alpha(3,2) = -90^{\circ}$$



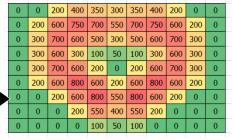
1	0	-1	
1	0	-1	
1	0	-1	

Gradient

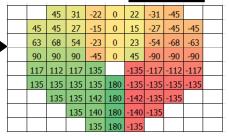


Prewitt

Magnitude



Direction



 $M(x, y) \approx |f_x| + |f_y|$

Edge Detection

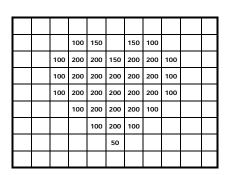


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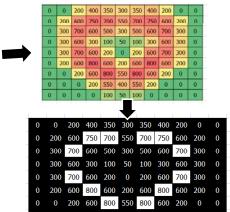
#2

Magnitude

Basic Edge Detection



EdgeThreshold: $M(x, y) \ge 700$



100 50 100 0 0 0

Basic Edge Detection

Image Smoothing

Average filter, Gaussian filter, Median filter, Morphological operators

Image Gradient

Ordinary 1st order derivatives, Prewitt, Sobel Thresholding

Gradient vector Gradient vector α Gradient

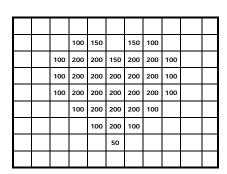
Gradient magnitude is corresponding to edge strength

Gradient direction is perpendicular to edge direction

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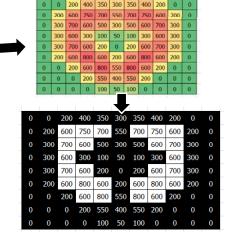
#2

Basic Edge Detection



EdgeThreshold: $M(x, y) \ge 600$

Magnitude



Canny Edge Detection

Image Smoothing with $n \times n$ Gaussian Filter

 $f_s(x,y)$

Gradient Magnitude and Angle

 $M(x,y),\alpha(x,y)$

Nonmaxima Suppression

 $g_N(x,y)$

Hysteresis Thresholding and Connectivity Analysis

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#2

Canny Edge Detection

Gradient Magnitude and Direction

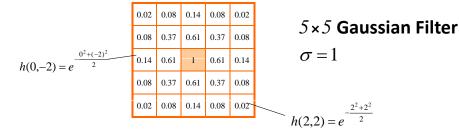
$$\nabla \mathbf{f}_{S} = \begin{bmatrix} f_{x} \\ f_{y} \end{bmatrix} = \begin{bmatrix} \frac{\partial f_{S}}{\partial x} \\ \frac{\partial f_{S}}{\partial x} \end{bmatrix} \qquad M(x, y) = \sqrt{f_{x}^{2} + f_{y}^{2}}$$

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

Canny Edge Detection

Image Smoothing with $n \times n$ Gaussian Filter

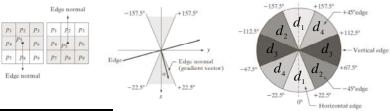
 $f_S(x, y) = h(x, y) * f(x, y)$ where $h(x, y) = e^{-\frac{x^2 + y^2}{2\sigma^2}}$



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#2

Canny Edge Detection



Nonmaxima Suppression

 d_1, d_2, d_3, d_4 = Four basic edge direction in 3×3 region

For every pixel (x, y); Find the direction d_k that is closest to $\alpha(x, y)$

 $g_N(x, y) = \begin{cases} 0; & M(x, y) \text{ is less than at least one neighbor along } d_k \\ M(x, y); & \text{otherwise} \end{cases}$

TT Z

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Canny Edge Detection

Hysteresis Thresholding and Connectivity Analysis

Strong Edges
$$\Rightarrow g_{NH}(x, y) = \begin{cases} 1; & g_N(x, y) \ge T_H \\ 0; & \text{otherwise} \end{cases}$$

Weak Edges
$$\Rightarrow g_{NL}(x, y) = \begin{cases} 1; & T_L < g_N(x, y) < T_H \\ 0; & \text{otherwise} \end{cases}$$

Edge Pixels includes

- (1) Every pixel belongs to the strong edge ($g_{NH} = 1$)
- (2) Pixels belong to the weak edge ($g_{NL} = 1$) that are neighbors of the strong edge (consider as blobs)

 $f_{v}(x,y)$ (Prewitt)

-17

-11

 $f_{s}(x,y)$

0	14	7	14	0	0
0	19	6	19	0	0
0	20	7	16	12	0
4	12	12	14		12
6	20	21		25	20
6	17	17	16	21	19

16 21 21 21 M(x, y)

	45	0	-45		
	65	0	-65		
	-72	80	-86	-45	
45	90	63	37		45
63	62	58		-65	-62
-63	-61	-35	-8	48	65
-45	-38	-17	0	27	45

 $\alpha(x,y)$

 $f_{x}(x, y)$ (Prewitt)

0	14	7	14	0	0		
0	19	0	19	0	0		
0	20	0	16	0	0		
0	12	0	0		0		
0	20	21		25	0		
0	0	17	0	21	0		
0	0	21	21	21	0		
	g(x,y)						

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12 13 13

11

5

 $g_N(x,y)$

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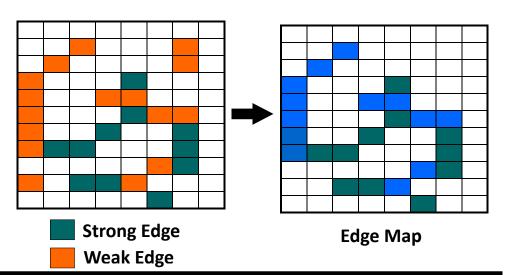
#2

#2

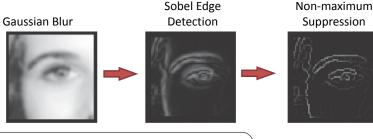
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#2

Canny Edge Detection



Canny Edge Detection





Upper Threshold



Lower Threshold



Hysteresis Thresholding

Median Filter

- Non-linear Filter
- Removing Impulsive Noise (Salt & Pepper Noise)

 $g(x, y) = \underset{(p,q) \in R(x,y)}{\text{MEDIAN}} \{ f(p,q) \}$

R(x, y) is set of neighborhood region around (x, y)

 $g(2,3) = \underset{(p,q) \in R(x,y)}{\text{MEDIAN}} \{ f_{12}, f_{13}, f_{14}, f_{22}, f_{23}, f_{24}, f_{32}, f_{33}, f_{34} \}$

			f	f(x, y)
f_{00}	f_{01}	f_{02}	f_{03}	f_{04}
f_{10}	f_{11}	$f_{_{12}}$	f_{13}	$f_{_{14}}$
f_{20}	$f_{\scriptscriptstyle 21}$	$f_{\scriptscriptstyle 22}$	f_{2}	$f_{\scriptscriptstyle 24}$
$f_{\scriptscriptstyle 30}$	$f_{\scriptscriptstyle 31}$	$f_{\scriptscriptstyle 32}$	f_{33}	f_{34}
$f_{\scriptscriptstyle 40}$	$f_{\scriptscriptstyle 41}$	f_{42}	$f_{\scriptscriptstyle 43}$	$f_{\scriptscriptstyle 44}$

 3×3 neighborhood region

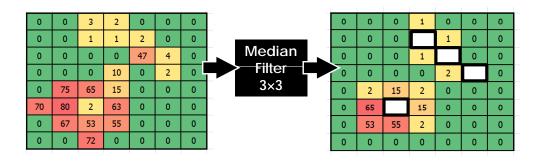
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#2

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#2

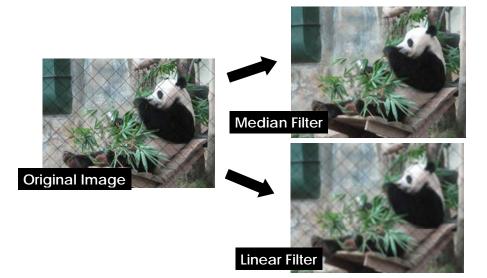
Median Filter



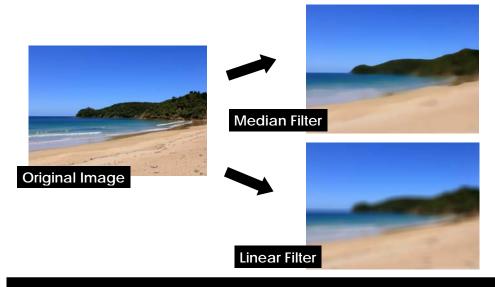
261458 & 261753 Computer Vision

#2

Median Filter



Median Filter



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261458 & 261753 Computer Vision

#2

Morphological Operators

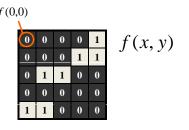
Binary Image morphology = Set Operation

- Binary image $f(x, y) \in \{0,1\}$
- Set of all white pixel (foreground)

$$B = \{ w = (x, y) | f(x, y) = 1 \}$$

• The complement of *B*

$$B^{c} = \{ w = (x, y) | f(x, y) = 0 \}$$



$$B = \{(0,4), (1,3), (1,4), (2,1), (2,2), (4,0), (4,1)\}$$

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15×15

#2

261458 & 261753 Computer Vision

#2

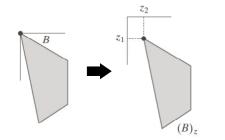
Morphological Operators

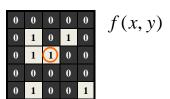
Translation

5×5

$$(B)_z = \{c | c = b + z \text{ for } b \in B\}$$

$$z=(z_1,z_2)$$

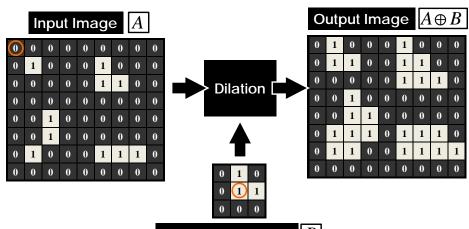




25×25

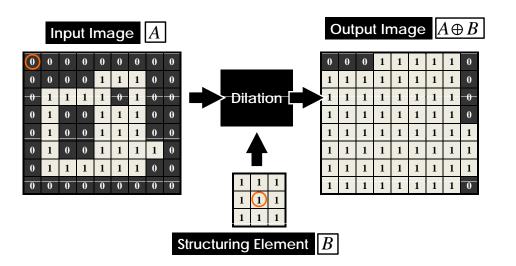
$$(B)_{\scriptscriptstyle (-1,2)} = \{(0,3), (0,5), (1,3), (1,4), (3,3), (3,6)\}$$

Dilation



Structuring Element B

Dilation

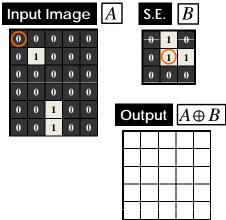


261458 & 261753 Computer Vision

#2

59

Dilation



 $A \oplus B = \bigcup (A)_{b}$

 $A = \{(1,1), (4,3), (5,3)\}$ $B = \{(0,0), (-1,0), (0,1)\}$

 $A_{(0,0)} = \{(1,1), (4,3), (5,3)\}$

 $A_{(-1,0)} = \{(0,1), (3,3), (4,3)\}$

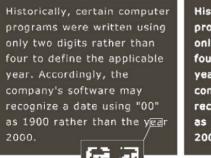
 $A_{(0,1)} = \{(1,2), (4,4), (5,4)\}$

 $A \oplus B = A_{(0,0)} \cup A_{(-1,0)} \cup A_{(0,1)}$

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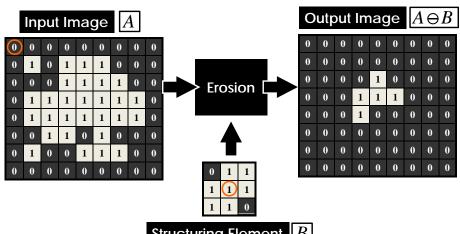
#2

Dilation



Historically, certain computer programs were written using only two digits rather than four to define the applicable year. Accordingly, the company's software may recognize a date using "00" as 1900 rather than the year 2000.

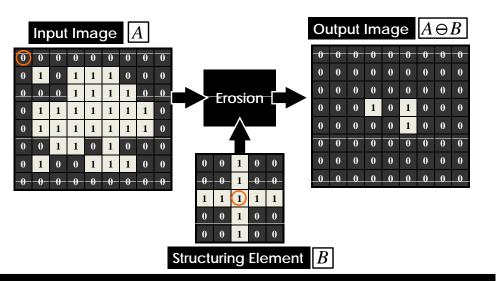
Erosion



Structuring Element B

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Erosion

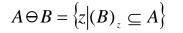


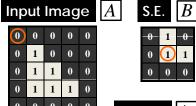
261458 & 261753 Computer Vision

#2

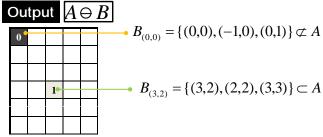
63

Erosion





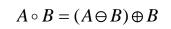
 $A = \{(1,1), (2,1), (2,2), (3,1), (3,2), (3,3)\}$ $B = \{(0,0), (-1,0), (0,1)\}$

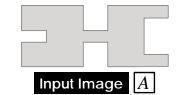


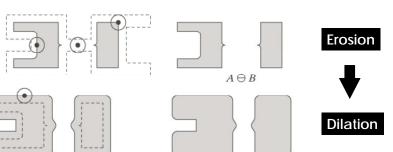
261458 & 261753 Computer Vision

#2

Opening



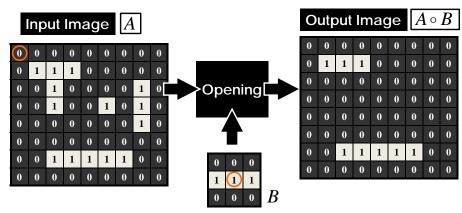




 $A \circ B = (A \ominus B) \oplus B$

#2

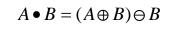
Opening

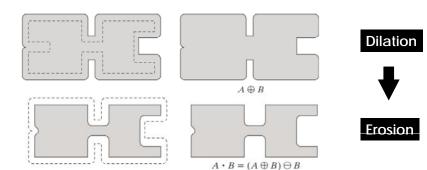


Structuring Element B

Closing







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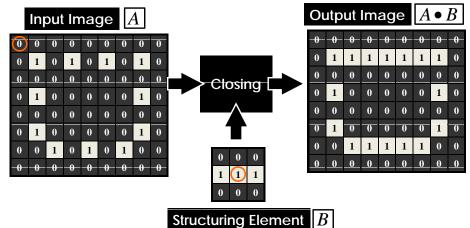
#2

67

#2

65





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#2

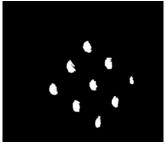
68



Morphological Operators



Opening



Closing