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Recall

- 1. What is image enhancement
- 2. Enhancement vs. restoration
- 3. Brightness vs. contrast
- 4. Image Histogram
- 5. Intensity transformation functions

10/18/2023

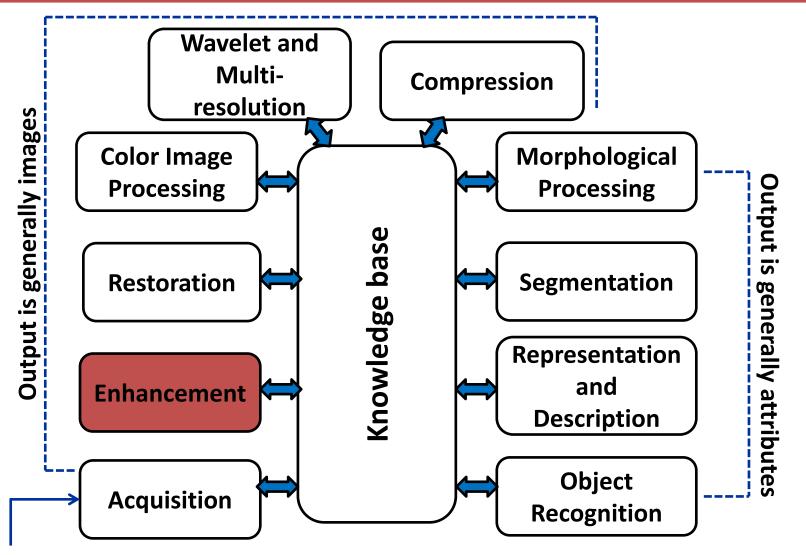
Image Enhancement II







Fundamental Steps of DIP



Problem Domain

3. Spatial Filtering (cont.)

Contents

- 1. Neighborhood Operations
- 2. What is Spatial Filtering? How?

Correlation and Convolution

3. Smoothing Filters

Linear and Nonlinear

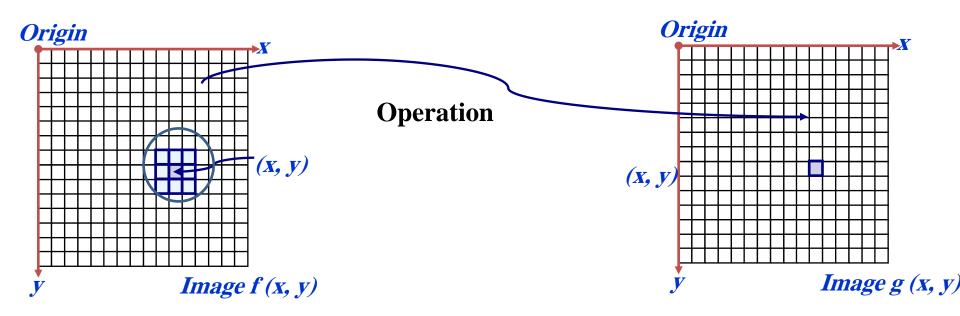
4. Sharpening Filters

First Derivatives

Second Derivatives

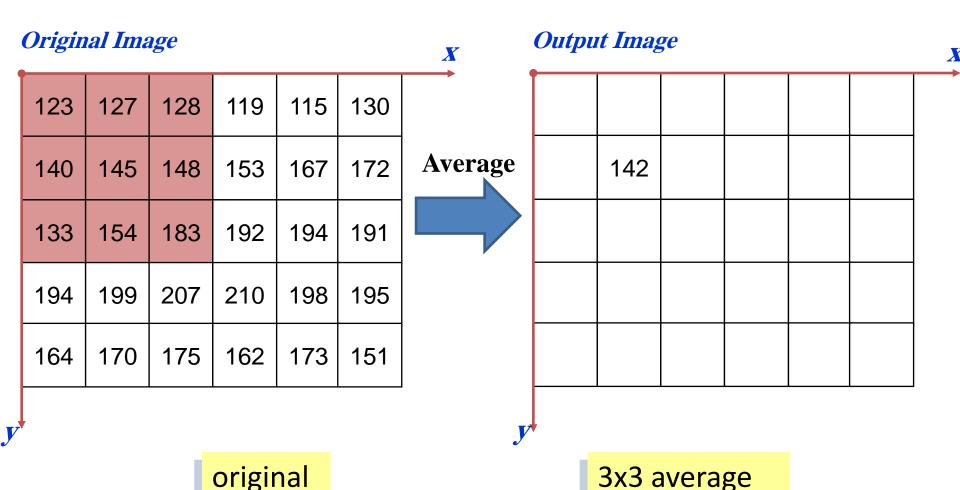
Neighborhood Operations

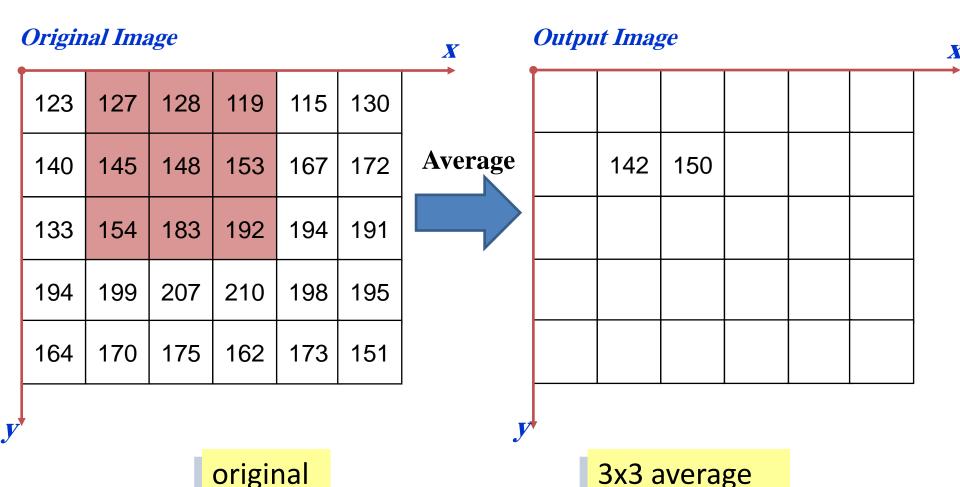
• For any specific location (x, y), the value of g at that location is the result of applying an operation to the pixels in the neighborhood with origin (x, y).

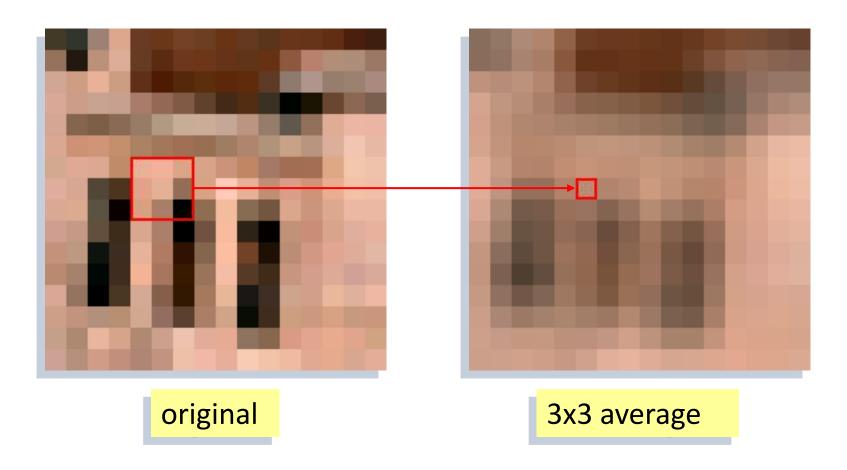


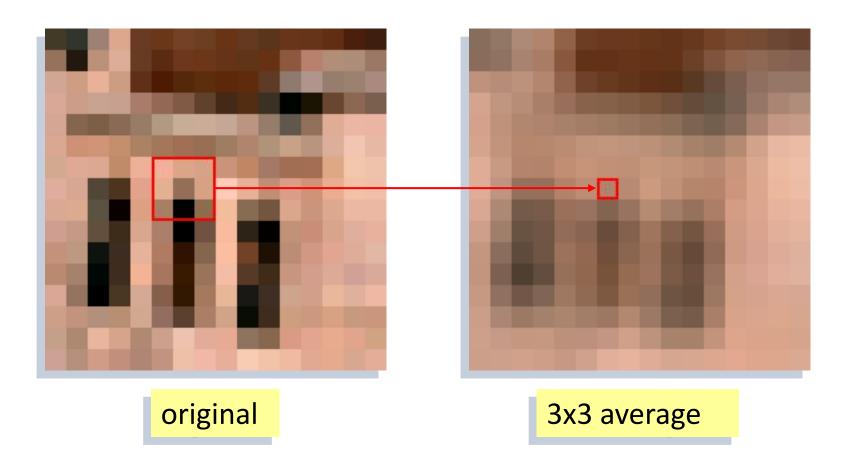
Some Simple Neighborhood Operations:

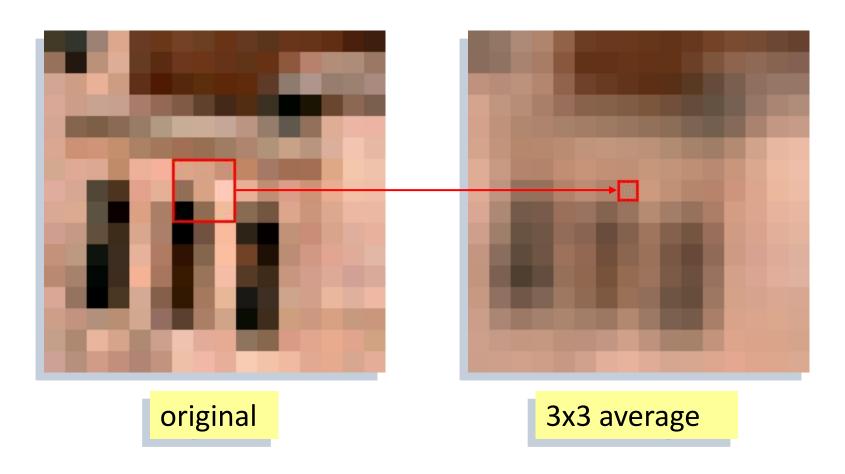
- Min: Set the pixel value to the minimum in the neighbourhood.
- Max: Set the pixel value to the maximum in the neighbourhood.
- Average: Set the pixel value to the sum of pixel divided by the size of the neighborhood.
- Median: Set the pixel value to the midpoint value in the ORDERED set. Sometimes the median works better than the average.

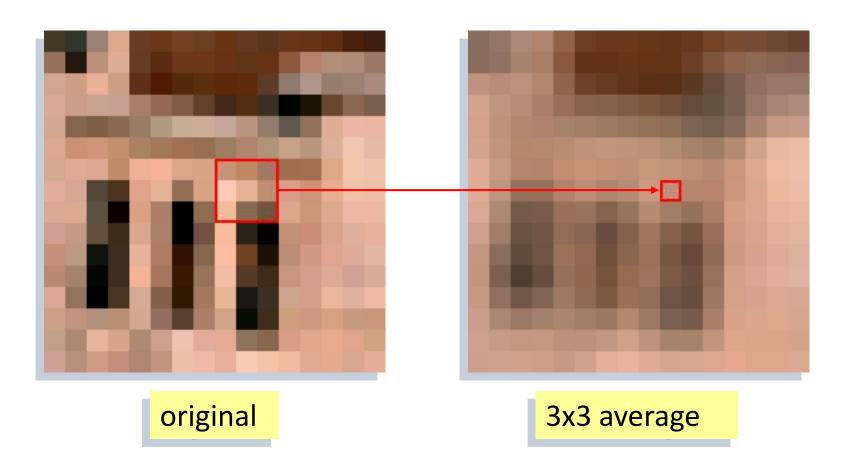






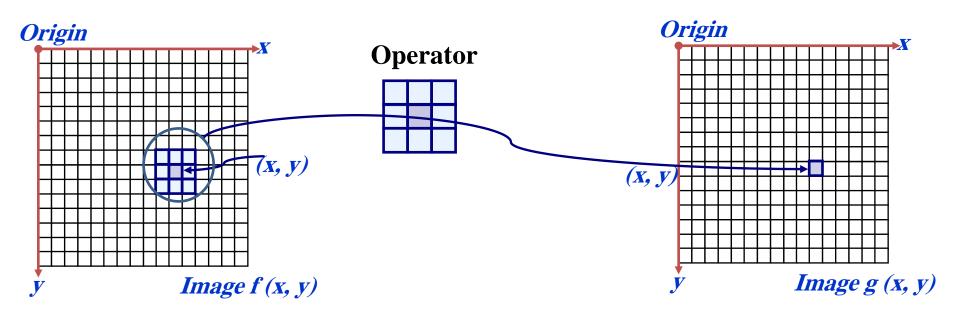






What is Spatial Filtering?

- Neighborhood size.
- Operator (filter/mask/weight matrix).

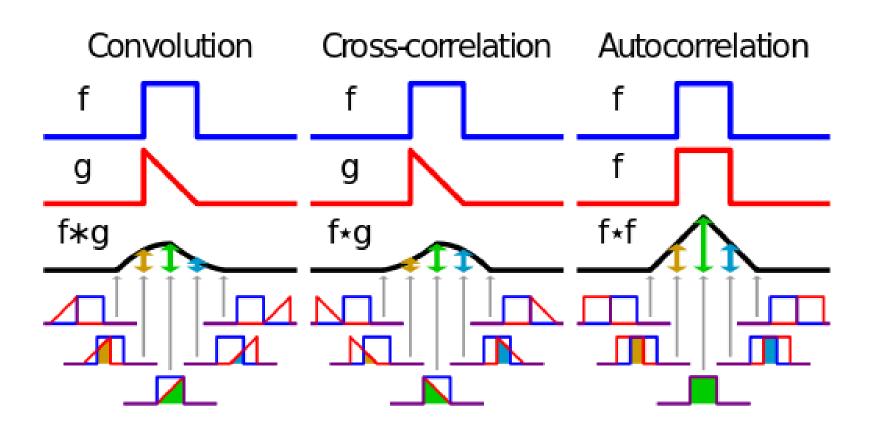


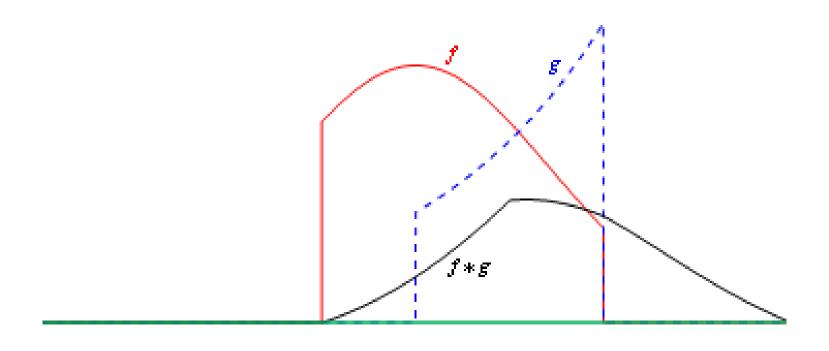
Basic Filtering Processes

 Convolution is used to linearly filter a signal, for example to smooth a spike train.

 Correlation is used to characterize the statistical dependencies between two signals.

Sum of products between two signals.





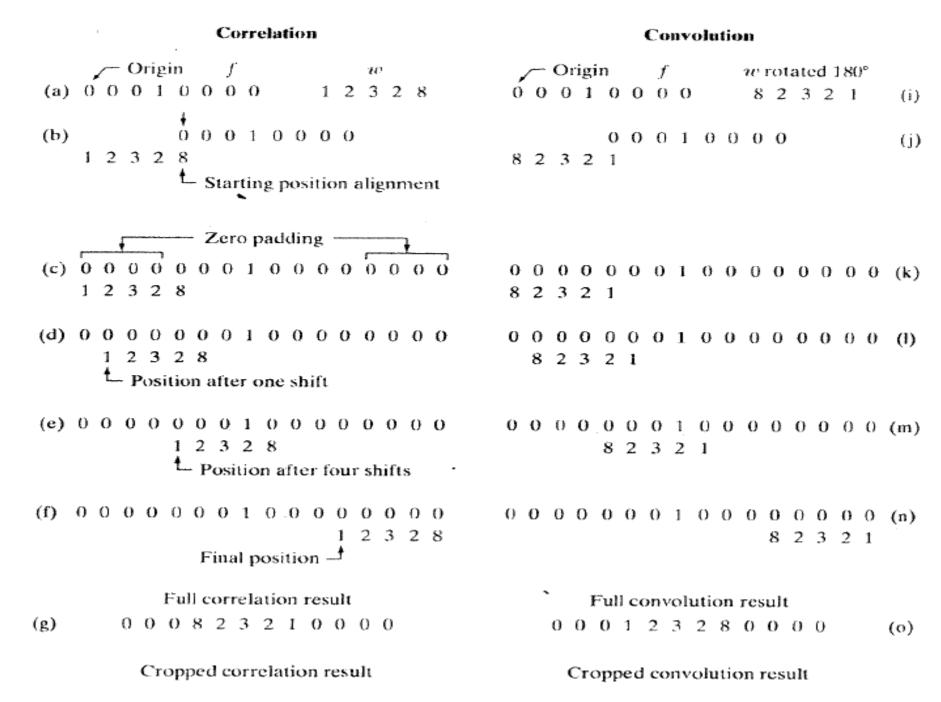
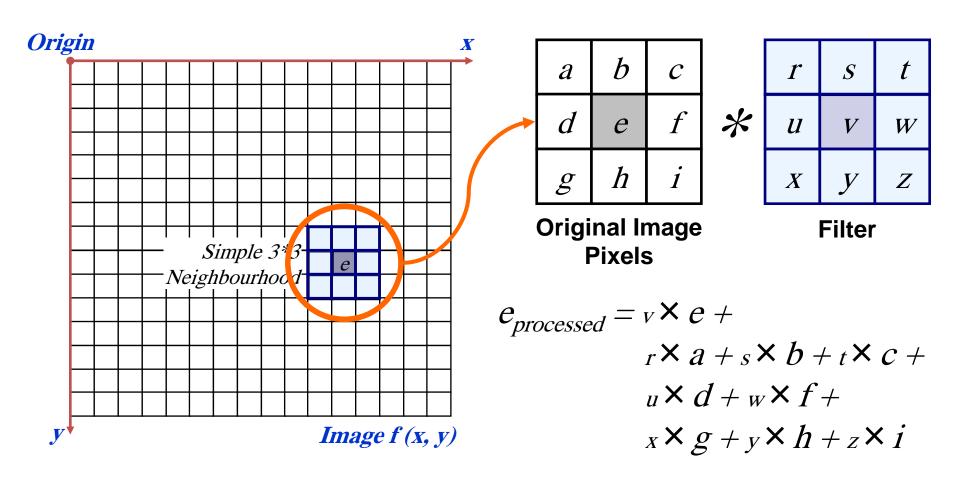


FIGURE 3.29 Illustration of 1-D correlation and convolution of a filter with a discrete unit impulse.

Correlation



Correlation

two remarks

f(x-1,y-1)	f(x-1,y)	f(x-1,y+1)
f(x,y-1)	f(x,y)	f(x,y+1)
f(x+1,y-1)	f(x+1,y)	f(x+1,y+1)

A 3×3 nighborhood

w(-1,-1)	w(-1,0)	w(-1,1)
w(0,-1)	w(0,0)	w(0,1)
w(1,-1)	w(1,0)	w(1,1)

An $m \times n = 3 \times 3$ filter

$$g(x,y) = \sum_{s=-at=-b}^{a} \sum_{s=-at=-b}^{b} w(s,t) f(x+s,y+t)$$

$$m = 2a+1, n = 2b+1$$

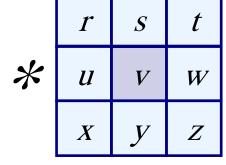
Convolution

two remarks

а	b	C
d	e	f
g	h	i

Original Image

Pixels



Filter

$$e_{processed} = v \times e +$$

$$z \times a + y \times b + x \times c +$$

$$w \times d + u \times f +$$

$$t \times g + s \times h + r \times i$$

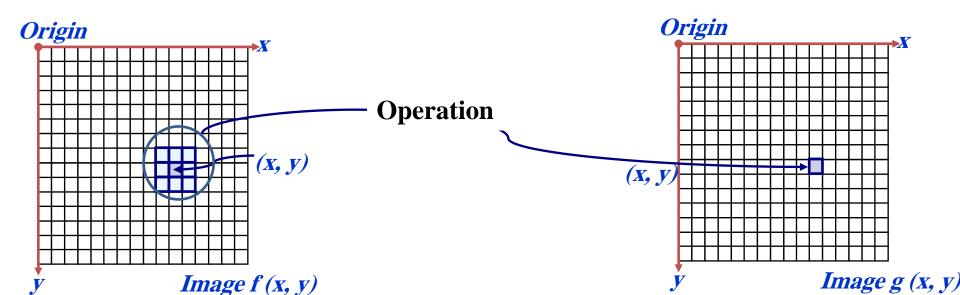
Mask is pre-rotated by 180° before operating

(flipping along one axis then the other).

Unless mask is symmetric

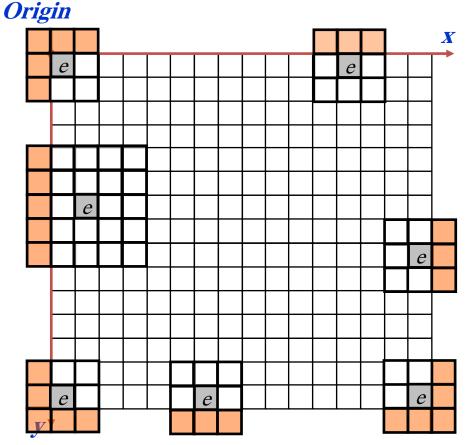
Moving Window Transform

For any specific location (x, y), the value of g at that location is the result of applying an operation to the pixels in the neighborhood with origin (x, y).



Dealing with Image Borders

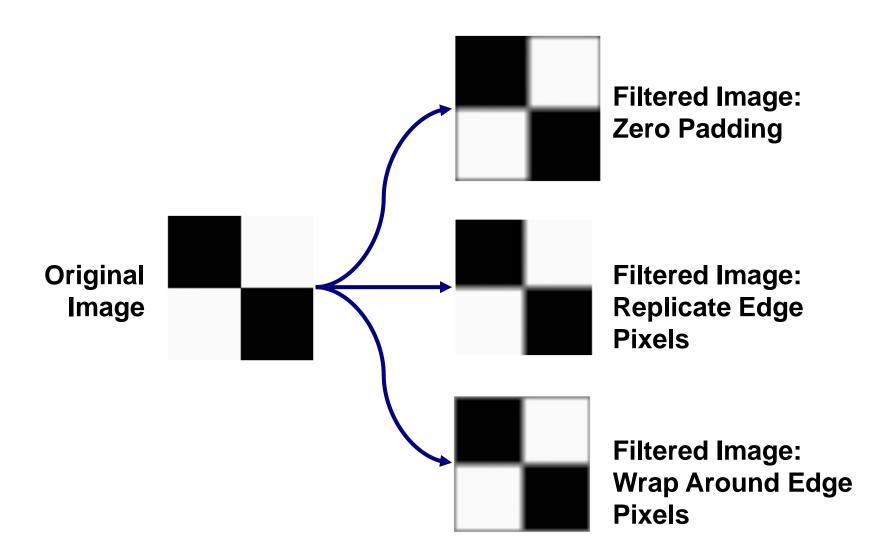
At the edges of an image we are missing pixels to form a neighbourhood.



Dealing with Image Borders

- Omit missing pixels.
 - Only works with some filters.
 - Can add extra code and slow down processing.
- Pad the image.
 - Typically with either all white or all black pixels.
- Replicate border pixels.
- Truncate the image.
- Allow pixels wrap around the image.
 - Can cause some strange image artifacts.

Dealing with Image Borders



Basic rule

- To generate an $m \times n$ linear spatial filter, we need to specify mn mask coefficients (weights).
- These are selected based on what the filter is intended to do.

1. Smoothing Filters

Smoothing Filters

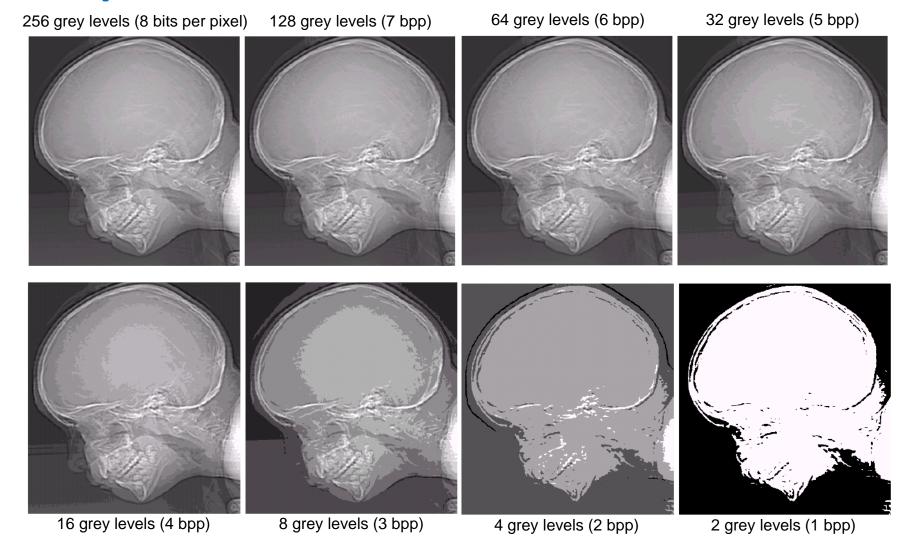
Main applications:

- Used for blurring and noise reduction.
- Removing small details prior to object extraction.
- Bridging small gaps in lines and curves.
- Linear and nonlinear filters.

Example: OCR preprocessing.

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.

Example: False contours



Averaging Filter

- One of the simplest linear spatial filtering operations.
- Response= average all of the pixels in a neighbourhood. $R = \frac{1}{9} \sum_{i=1}^{9} z_i$

1/9	1/9	1/9
1/9	1/9	1/9
1/9	1/9	1/9

Simple averaging filter

Called low-pass filter.

Averaging Filter

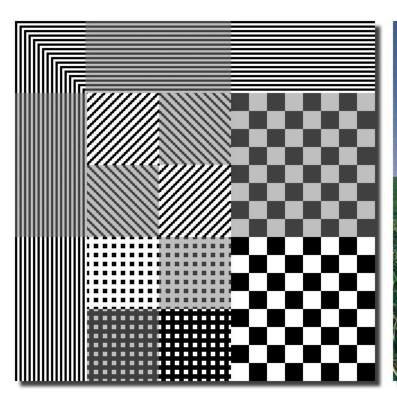
- Weighted average: allowing different pixels in the neighbourhood different weights in the averaging function.
- Pixels closer to the central pixel are more important.
- More effective in smoothing.

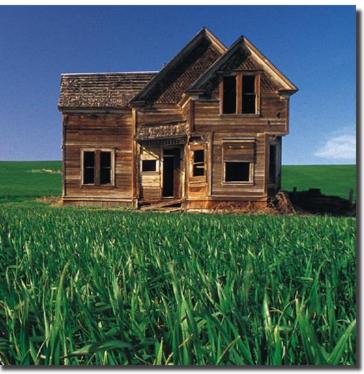
¹ / ₁₆	16 ² / ₁₆		16 ² / ₁₆ ¹ / ₁₆	
² / ₁₆	⁴ / ₁₆	² / ₁₆		
¹ / ₁₆	² / ₁₆	¹ / ₁₆		

Weighted averaging filter

Averaging Filter

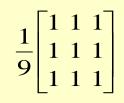
Original

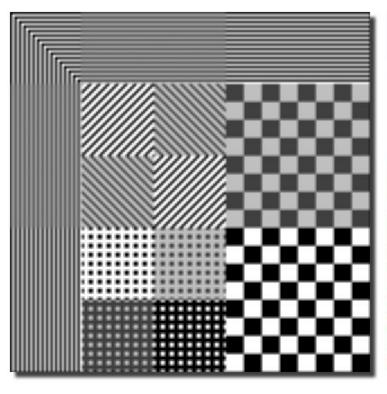




Averaging Filter

• 3×3



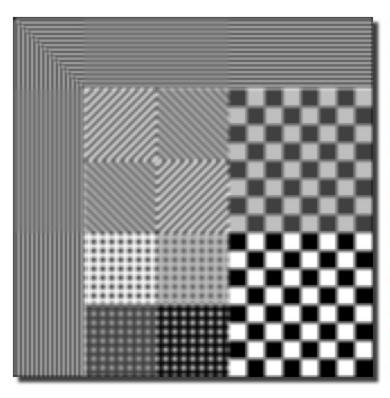




Averaging Filter

• 5×5

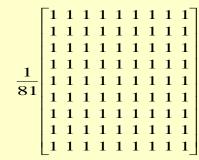
	Γ1	1	1	1	1
$\frac{1}{25}$	1	1	1	1	1
	1	1	1	1	1
	1	1	1	1	1
	1	1	1	1	1

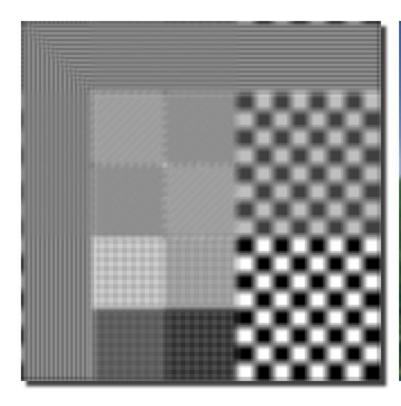




Averaging Filter

• 9×9

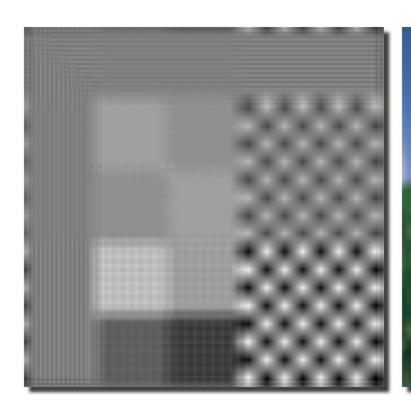


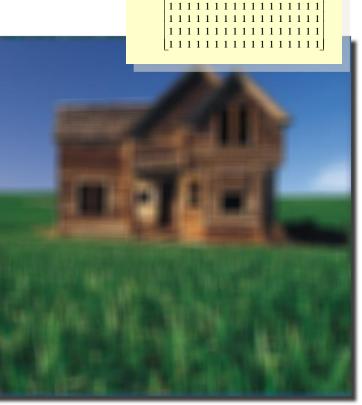




Averaging Filter

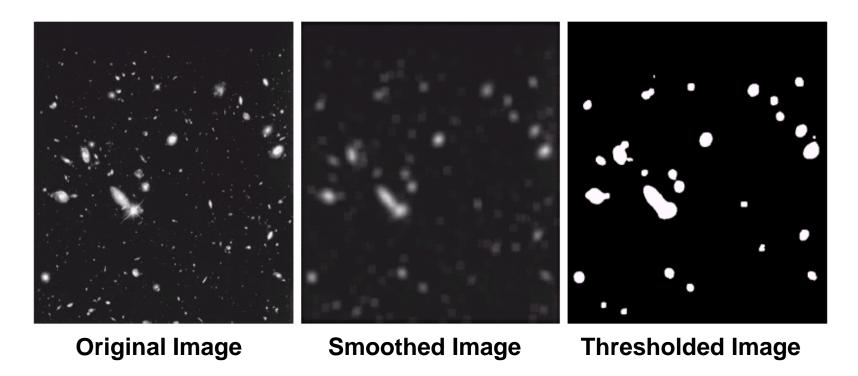
• 17×17





Averaging Filter

• **Highlighting gross detail:** the size of the mask determines the relative size of the objects blended.



Averaging Filter Usage

- Results an image with reduced sharp transitions in intensities.
- Useful in removing noise and reducing irrelevant detail (highlighting gross detail).
- Side effect: blurred edges.

Nonlinear Filters

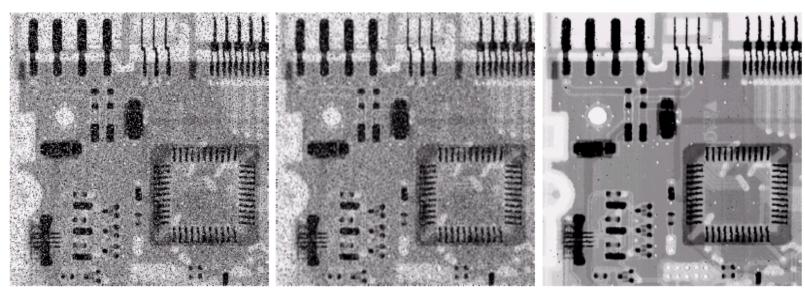
- Spatial filters whose response is based on ordering (ranking) the pixels in the image area encompassed by the filer, and replacing the center pixel with the value determined by the ranking result.
- Examples:
 - min filter, max filter, median filter.

Nonlinear Filters

- Median Filter: sort pixels in neighborhood, determine median, assign to center pixel.
- Forces points with distinct intensity levels to be like their neighbors.
- Eliminates isolated clusters of pixels that are light or dark with respect to their neighbors.

Median Filter

Excellent salt-and-pepper noise reduction.



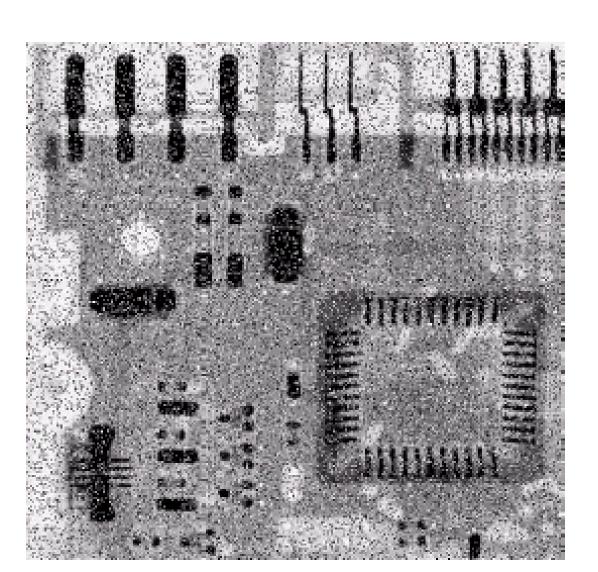
Original Image With Noise

Image After Averaging Filter

Image After Median Filter

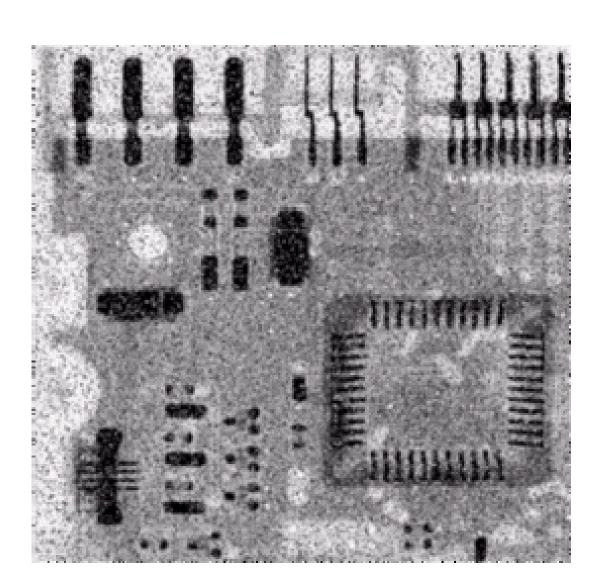
Example

Original



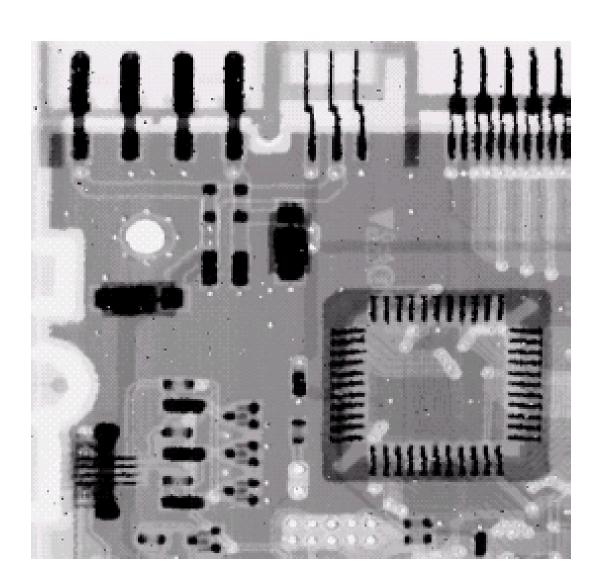
Example

Average



Example

Median



2. Sharpening Filters and Edge Detectors

Sharpening Filters

Main objectives:

- Highlight transitions in intensities

 highlight edges.
- Remove blurring

 enhance details.
- Sharpening filters are based on *spatial* differentiation, which measures the rate of change of a function.
- First and second derivatives are used for image enhancement.

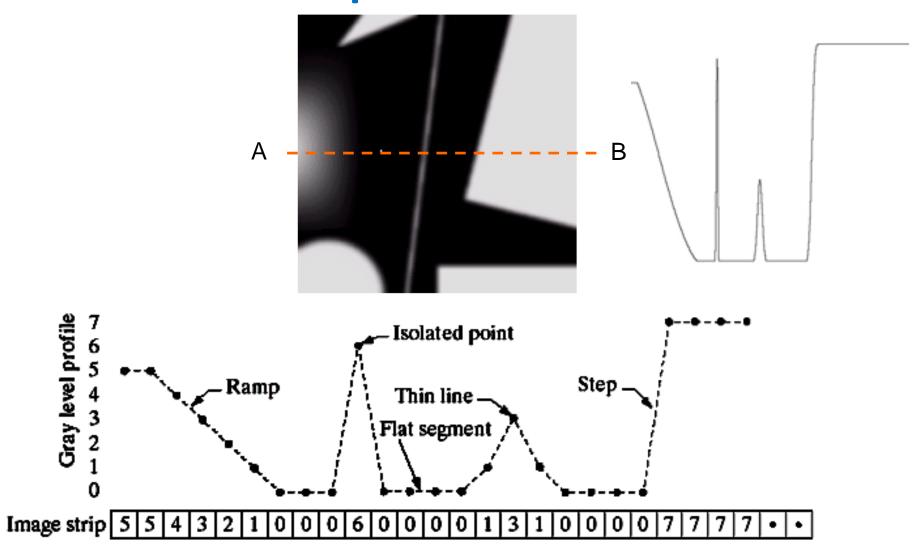
1st Derivative:

The formula for the 1st derivative of a function is as follows:

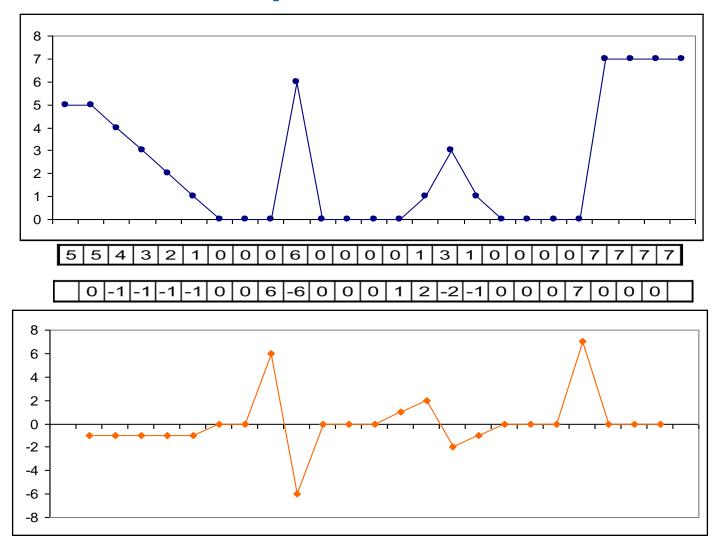
$$\frac{\partial f}{\partial x} = f(x+1) - f(x)$$

It's just the difference between subsequent values and measures the rate of change of the function.

1st Derivative Example in 1D:



1st Derivative Example in 1D:



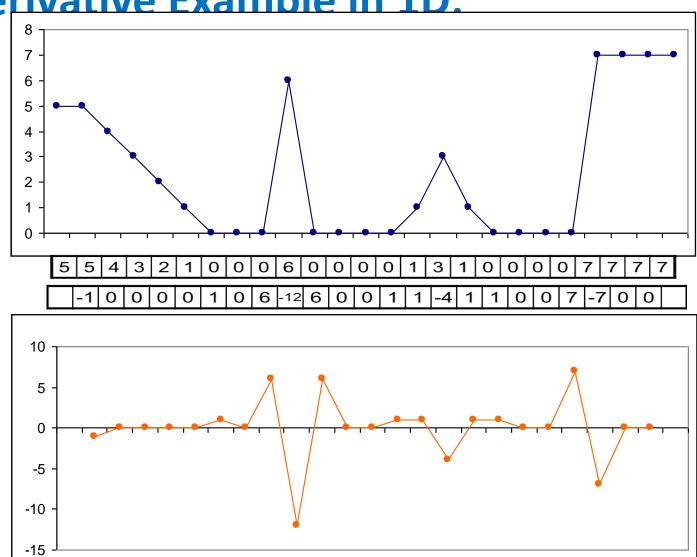
2nd Derivative:

The formula for the 2nd derivative of a function is as follows:

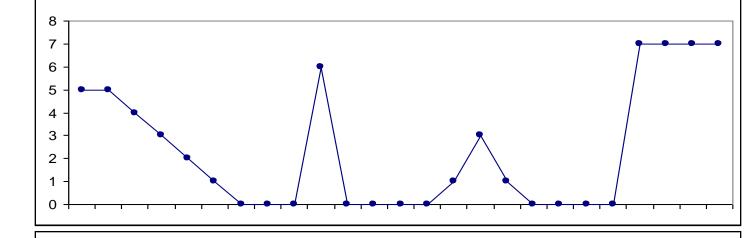
$$\frac{\partial^2 f}{\partial^2 x} = f(x+1) + f(x-1) - 2f(x)$$

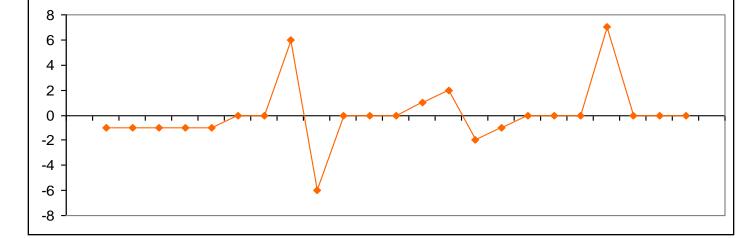
Simply takes into account the values both before and after the current value.

2nd Derivative Example in 1D:

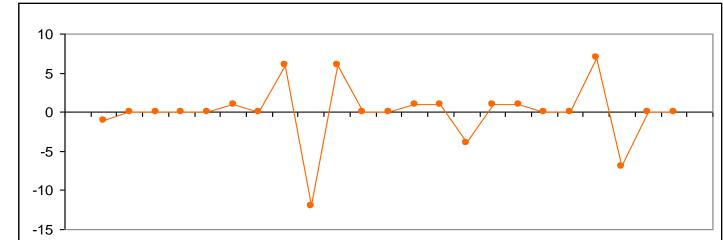








1st



2nd

Example in 1D:

- Note that the sign of the 2nd derivative changes at the onset and end of ramp and step → zero crossing → useful in locating edges.
- The 2nd derivative is more useful for image enhancement than the 1st derivative
 - -Stronger response to fine detail.
 - -Simpler implementation.

Second Derivative (Laplacian)

The Laplacian is defined as follows:

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

where in the *x* direction:

$$\frac{\partial^2 f}{\partial x^2} = f(x+1,y) + f(x-1,y) - 2f(x,y)$$
and in the y direction:

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

Second Derivative (Laplacian)

Hence the Laplacian is given by:

$$\nabla^{2} f = [f(x+1, y) + f(x-1, y) + f(x, y+1) + f(x, y+1) + f(x, y-1)]$$
$$-4f(x, y)$$

We can easily build a filter based on this.

Second Derivative (Laplacian)

Hence the Laplacian is given by:

$$\nabla^{2} f = [f(x+1, y) + f(x-1, y) + f(x, y+1) + f(x, y+1) + f(x, y-1)]$$

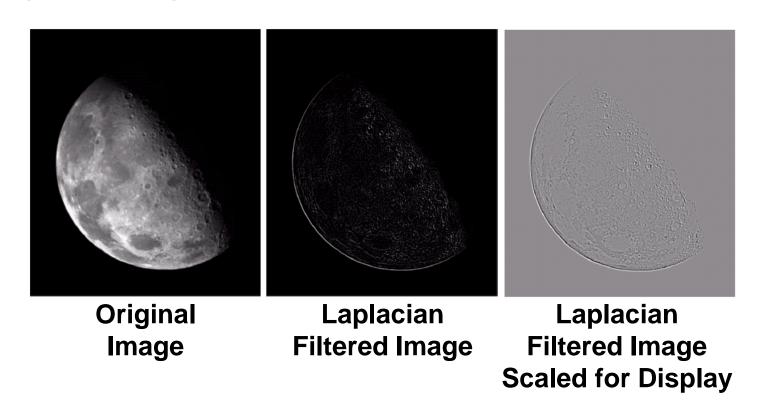
$$-4f(x, y)$$

We can easily build a filter based on this.

0	1	0
1	-4	1
0	1	0

Second Derivative (Laplacian)

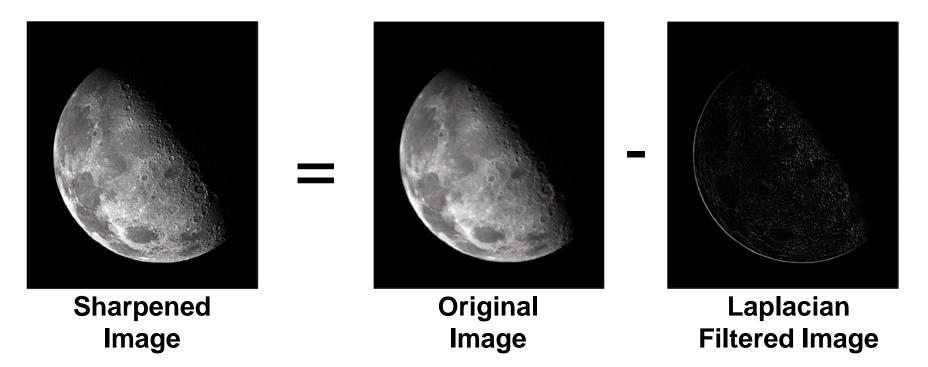
Applying the Laplacian gives a new image that highlights edges and other discontinuities.



Second Derivative (Laplacian)

Subtract a weighted Laplacian result from the original image to obtain the sharpened image.

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



Second Derivative (Laplacian)



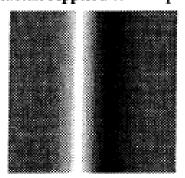


Second Derivative (Laplacian)

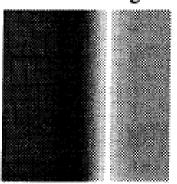
Ramp Edge Image



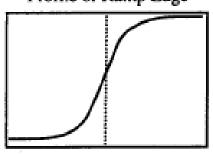
Laplacian Applied to Ramp Edge



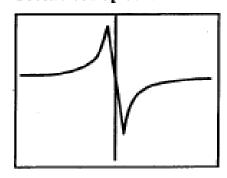
Result after Subtracting Laplacian from Original Image



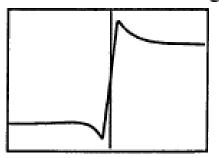
Profile of Ramp Edge



Profile of Laplacian Result

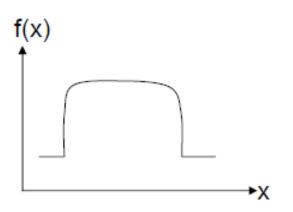


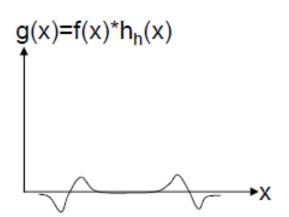
Profile of Enhanced Edge

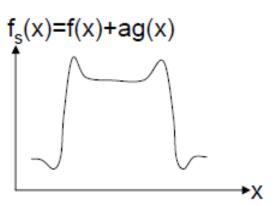


Second Derivative (Laplacian)

Subtracting or adding a weighted Laplacian depending on the sign of the mask coefficients.







Second Derivative (Laplacian)

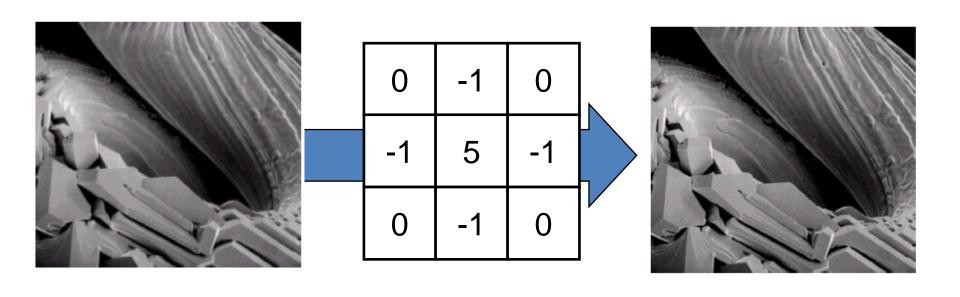
The entire enhancement can be combined into a single filtering operation,

$$g(x, y) = f(x, y) - \nabla^{2} f$$

$$= f(x, y) - [f(x+1, y) + f(x-1, y) + f(x, y+1) + f(x, y+1)$$

Second Derivative (Laplacian)

This gives us a new filter which does the whole job for us in one step.



Second Derivative (Laplacian)

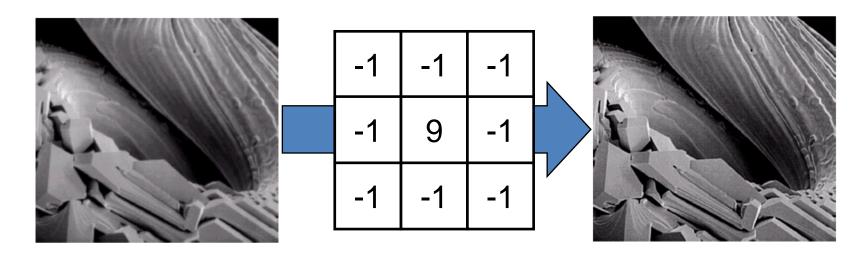
There are lots of slightly different versions:

0	1	0
1	-4	1
0	1	0

Simple Laplacian

1	1	1
1	-8	1
1	1	1

Variant of Laplacian



First Derivative (Gradient)

The Gradient of f(x, y) at coordinates (x, y) is defined as the column vector:

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

First Derivative (Gradient)

The magnitude of this vector is given by:

$$M(x, y) = mag(\nabla f)$$

$$= \left[G_x^2 + G_y^2\right]^{1/2}$$

$$= \left[\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2\right]^{1/2}$$

For practical reasons this can be simplified as:

$$M(x, y) \approx |G_x| + |G_y|$$

First Derivative (Gradient)

Approximating the partial derivative in the *x*-direction == third row – first row

Approximating the partial derivative in the y-direction == third column – first column

f(x-1,y-1)	f(x-1,y)	f(x-1,y+1)	Z ₁	z_2	z_3
f(x,y-1)	f(x,y)	f(x,y+1)	Z_4	Z ₅	Z ₆
f(x+1,y-1)	f(x+1,y)	f(x+1,y+1)	Z ₇	Z ₈	Z ₉

First Derivative (Gradient)

Approximating the partial derivative in the *x*-direction == third row – first row

Approximating the partial derivative in the y-direction == third column – first column

$$M(x, y) \approx |(z_7 + z_8 + z_9) - (z_1 + z_2 + z_3)|$$

 $+ |(z_3 + z_6 + z_9) - (z_1 + z_4 + z_7)|$

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

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

Perwitt masks

Z ₁	Z_2	Z_3
Z_4	Z ₅	Z ₆
Z ₇	Z ₈	z_9

First Derivative (Gradient)

Based on the previous equations we can derive the *Sobel Operators*

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

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

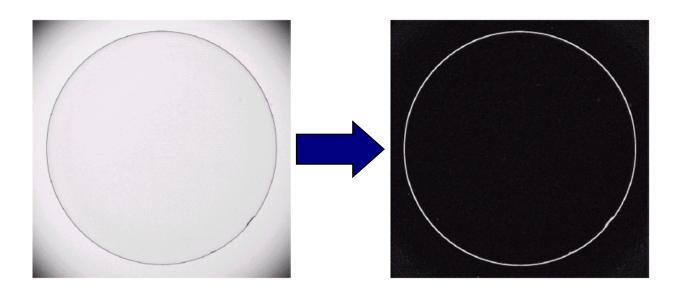
An image is filtered using both operators and the results are added together.

Note that they do not need to be

not need to be rotated before convolution.

First Derivative (Gradient)

Sobel filters are typically used for edge detection.



Original Image





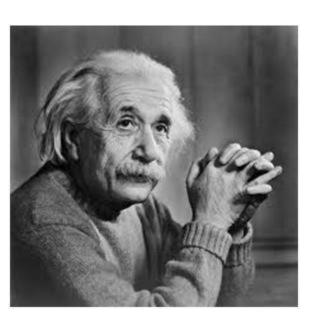








Combined Edge Image



Original Image



Vertical Gradient Component



Horizontal Gradient Component

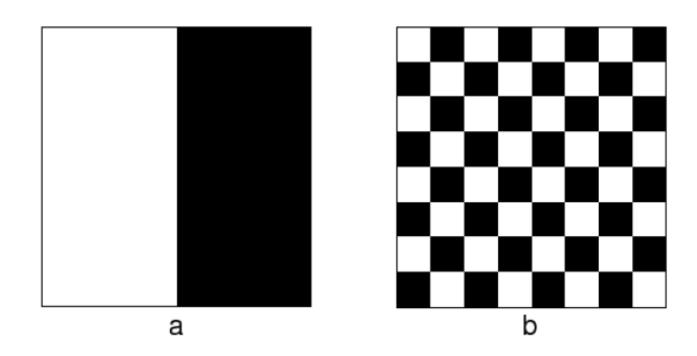
Comparing the 1st and 2nd derivatives we can conclude the following:

- 1st order derivatives generally produce thicker edges.
- 1st order derivatives have stronger response to grey level step.
- 2nd order derivatives produce a double response at step changes in grey level.
- 2nd order derivatives have a stronger response to fine detail e.g. thin lines.

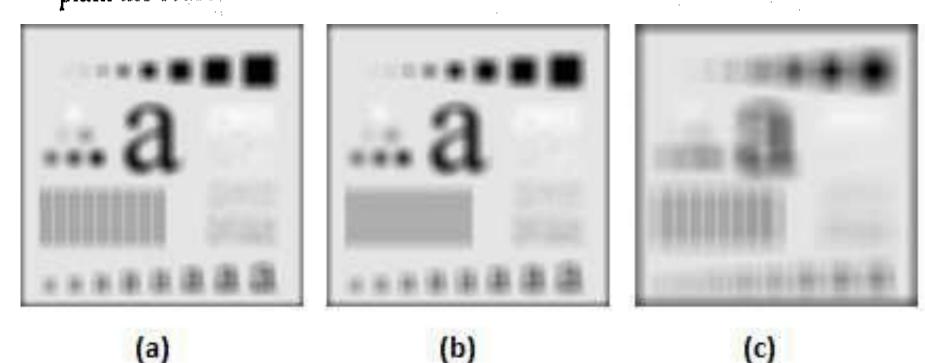
Selected Problems

3.14 The images shown on the next page are quite different, but their histograms are the same. Suppose that each image is blurred with a 3×3 averaging mask.

(a) Would the histograms of the blurred images still be equal? Explain.



3.21 The three images shown were blurred using square averaging masks of sizes n = 23, 25, and 45, respectively. The vertical bars on the left lower part of (a) and (c) are blurred, but a clear separation exists between them. However, the bars have merged in image (b), in spite of the fact that the mask that produced this image is significantly smaller than the mask that produced image (c). Explain the reason for this.



You saw in Fig. 3.38 that the Laplacian with a-8 in the center yields sharper results than the one with a-4 in the center. Explain the reason in detail.

0	1	0
1	4	7
0	1	0

1	1	1
1	-8	1
1	1	1

- 3.26 With reference to Problem 3.25,
 - (a) Would using a larger "Laplacian-like" mask, say, of size 5×5 with a -24 in the center, yield an even sharper result? Explain in detail.

Next Lecture

Frequency Domain

Assignment

- Textbook Chapter 3: 3, 4, 5, 6, 7
- Check associated problems

Chapter 3 14, 17, 18, 20, 21, 22, 23, 25, 26, 27, 30

10/18/2023

References

- Gonzalez and Woods, Digital Image Processing.
- Peters, Richard Alan, II, "Spatial Filtering 1 and 2", Lectures on Image Processing, Vanderbilt University, Nashville, TN, April 2008, Available on the web at the Internet Archive, http://www.archive.org/details/Lectures on Image Processing.

10/18/2023