INTRODUCTION TO DIGITAL IMAGE PROCESSING

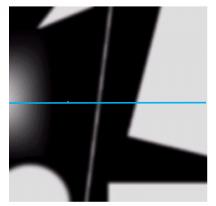


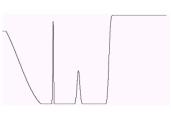
Lecture #7

Niels Volkmann Professor

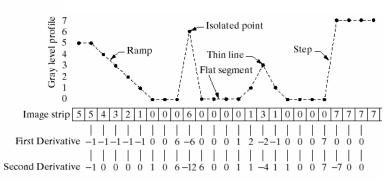
ECE Department
Department of Bioengineering
Quantitative Bioscience Program

Derivatives Illustration





Derivatives Illustration



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

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

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

Comparisons

- 1st-order derivatives:
 - produce thicker edges
 - strong response to graylevel steps
- · 2nd-order derivatives:
 - strong response to fine detail (thin lines, isolated points)
 - → very noise-sensitive
 - double response at step changes in graylevel

Laplacian Operator

- · Simplest isotropic derivative operator
- Response independent of direction of the discontinuities.
- Rotation-invariant: rotating the image and then applying the filter gives the same result as applying the filter to the image first and then rotating the result.
- Since derivatives of any order are linear operations, the Laplacian is a linear operator.

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

Laplacian Mask

Isotropic result for rotations in increments of 90°

0	1	0
1	-4	1
0	1	0

Isotropic result for rotations in increments of 45°

1	1	1
1	-8	1
1	1	1

Discrete Form of Laplacian

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

where

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

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

Another Rationalization

	1	1	1	
1/9*	1	1	1	Unweighted Average Smoothing Filter
	1	1	1	
	\equiv	_		•
	0	0	0	
	0	1	0	Retain Original
	0	0	0	
	_			
	-1	-1	-1	
/9*	-1	8	-1	Original – Average
	-1	-1	-1	
	not	ont	or	

In constant areas: 0 —— Summation of coefficients in masks equals 0. Near edges: high values

Effect of Laplacian Operator

- Since the Laplacian is a derivative operator
 - it highlights graylevel discontinuities in an image
 - it deemphasizes regions with slowly varying gray levels
- The Laplacian tends to produce images that have
 - grayish edge lines and other discontinuities all superimposed on a dark featureless background

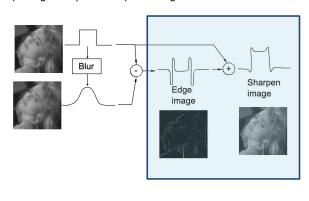
Example – MRI Image





Laplacian Sharpening

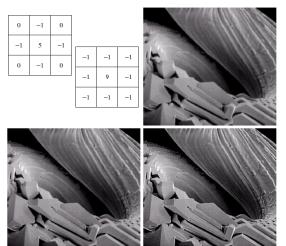
• Sharpening Recap: Unsharp Masking



Laplacian Sharpening

- Sharpening: Addition of Laplacian to image
- Can be combined into one operator

Laplacian Sharpening - Example



Common Gradient Operators

1	0	0	1
0	-1	-1	0

Robert Mask

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

Prewitt Mask

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

Sobel Mask

Gradient Operator - Summary

- The components of the gradient vector are linear operators, but the magnitude is not (square root).
- The partial derivatives are not rotation invariant (isotropic), but the magnitude is.
- The Laplacian operator yields a scalar: a single number indicating edge strength at point.
- The gradient is actually a vector from which we can compute edge magnitude and direction.

$$\begin{split} f_{mag}\left(i,j\right) &= \sqrt{f_{x}^{2} + f_{y}^{2}} & \text{ or } f_{mag}\left(i,j\right) = \left|f_{x}\right| + \left|f_{y}\right| \\ f_{angle}\left(i,j\right) &= \tan^{-1}\frac{f_{y}}{f_{x}} & \text{ where } \begin{bmatrix} f_{x}(i,j) = f(i+1,j) - f(i-1,j) \\ f_{y}(i,j) = f(i,j+1) - f(i,j-1) \end{bmatrix} \end{split}$$



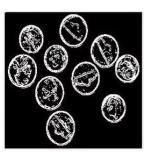




ROBERT

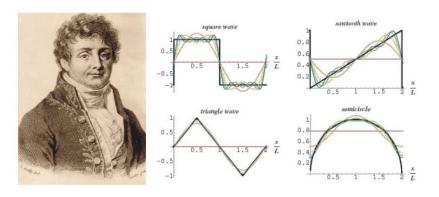




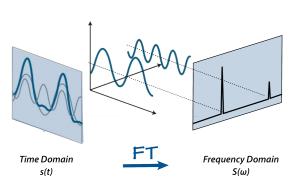


SOBEL

Jean-Baptiste Joseph Fourier

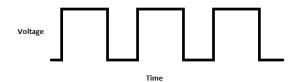


Fourier Transform



Fourier Transform

$$s(t) = \sin(\omega t) + \frac{1}{3}\sin(3\omega t) + \frac{1}{5}\sin(5\omega t) + \frac{1}{7}\sin(7\omega t) + \cdots$$



Fourier Transform

$$s(t) = \sin(\omega t) + \frac{1}{3}\sin(3\omega t) + \frac{1}{5}\sin(5\omega t) + \frac{1}{7}\sin(7\omega t) + \cdots$$

