

# CS-565 Computer Vision

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4. Approximating Derivatives

# Derivatives

- ▶ Derivative represents the rate of change.
- ▶ Image derivatives represent the rate of color changes in images.
- ▶ Interesting features in images (and in the real world) have high derivatives.
- ▶ Therefore, derivatives are used for detecting semantically important features such as edges, corners and lines.



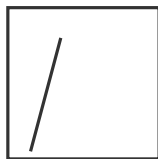
Vertical edge



Horizontal edge



Corner



Line

## Partial Derivatives and Gradient

- ▶ Let  $f(x, y)$  be a 2D function.
- ▶ *Partial derivative* in x-direction is denoted by  $f_x$ ,  $\partial_x f$ , or  $\frac{\partial f}{\partial x}$ .
- ▶ Higher order derivative can be computed in sequence

$$\frac{\partial^2 f}{\partial x \partial y} := \frac{\partial}{\partial x} \left( \frac{\partial f}{\partial y} \right)$$

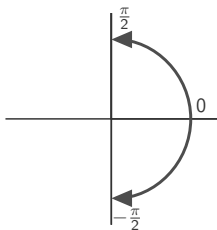
- ▶ Order of partial differentiation does not matter (under suitable smoothness assumptions)

$$f_{xy} = f_{yx}$$

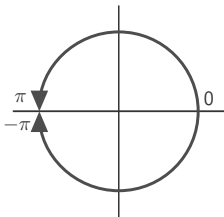
- ▶ The *gradient vector*  $\nabla f = (f_x, f_y)^T$  always points in the direction of highest rate of change.
- ▶ *Gradient magnitude*  $|\nabla f| = \sqrt{f_x^2 + f_y^2}$  is rotationally equivariant.
- ▶ *Gradient direction* can be computed as  $\theta = \arctan \left( \frac{f_y}{f_x} \right)$ .

## atan vs. atan2

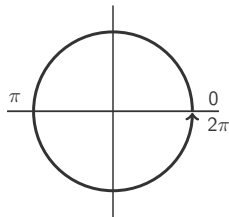
- ▶ The atan function returns angle in the range  $\theta \in (-\frac{\pi}{2}, \frac{\pi}{2})$  while atan2 returns angle in the range  $\theta \in (-\pi, \pi)$ .
  - ▶ Function atan does not differentiate between quadrants 1 and 3. Similarly for quadrants 2 and 4.
  - ▶ Function atan2 differentiates between all quadrants.
  - ▶ For example,  $\text{atan}(\frac{1}{1}) = \text{atan}(\frac{-1}{-1}) = \text{atan2}(1, 1) \neq \text{atan2}(-1, -1)$



$$\theta = \text{atan}\left(\frac{y}{x}\right)$$



$$\theta = \text{atan2}(y, x)$$



$$\theta = \begin{cases} \text{atan2}(y, x) & \text{if } y \geq 0 \\ 2\pi + \text{atan2}(y, x) & \text{if } y < 0 \end{cases}$$

## Numerical Approximation of Derivative

- ▶ Using 2nd order Taylor's expansion

$$f(x + h) = f(x) + hf'(x) + \frac{h^2}{2}f''(x) + O(h^3) \quad (1)$$

$$f(x - h) = f(x) - hf'(x) + \frac{h^2}{2}f''(x) + O(h^3) \quad (2)$$

- ▶ Subtracting (2) from (1) and solving for  $f'(x)$  yields

$$f'(x) = \frac{f(x + h) - f(x - h)}{2h} + O(h^2) \quad (3)$$

- ▶ Adding (2) and (1) and solving for  $f''(x)$  gives

$$f''(x) = \frac{f(x + h) - 2f(x) + f(x - h)}{h^2} + O(h) \quad (4)$$

- ▶ Equations (3) and (4) are 1st and 2nd derivative approximations using *central differences*.

# Numerical Approximation of Derivative

## Take-home Quiz 2:

1. (5 marks) Prove that using a 1st order Taylor's expansion for  $f(x + h)$  yields

$$f'(x) = \frac{f(x + h) - f(x)}{h} + O(h)$$

This is a derivative approximation using *forward difference*.

2. (5 marks) Prove that using a 1st order Taylor's expansion for  $f(x - h)$  yields

$$f'(x) = \frac{f(x) - f(x - h)}{h} + O(h)$$

This is a derivative approximation using *backward difference*.

Derivative approximations using central differences are more accurate since they employ 2nd order Taylor approximations. Higher than order 2 approximations will be even better but computationally more expensive.

## Derivative Filters

- ▶ In images, colours are stored at every pixel. Therefore,  $h$  is (almost) always taken to be 1.
- ▶ Commonly used approximate derivative filters via convolution are

Approximation	Mask	Difference					
$f'(x) = f(x + 1) - f(x)$	<table border="1"> <tr> <td>1</td> <td><b>-1</b></td> <td></td> </tr> </table>	1	<b>-1</b>		Forward		
1	<b>-1</b>						
$f'(x) = f(x) - f(x - 1)$	<table border="1"> <tr> <td><b>1</b></td> <td>-1</td> <td></td> </tr> </table>	<b>1</b>	-1		Backward		
<b>1</b>	-1						
$f'(x) = \frac{f(x+1) - f(x-1)}{2}$	<table border="1"> <tr> <td><math>\frac{1}{2}</math></td> <td>1</td> <td><b>0</b></td> <td>-1</td> <td></td> </tr> </table>	$\frac{1}{2}$	1	<b>0</b>	-1		Central
$\frac{1}{2}$	1	<b>0</b>	-1				
$f''(x) = f(x + 1) - 2f(x) + f(x - 1)$	<table border="1"> <tr> <td>1</td> <td><b>-2</b></td> <td>1</td> <td></td> </tr> </table>	1	<b>-2</b>	1		Central	
1	<b>-2</b>	1					

where each mask will be flipped during convolution and the origin (in bold blue) will be placed over location  $x$ .

## Derivative Filters

- ▶ Derivative filters are very important examples of linear shift invariant (LSI) filters.
- ▶ 1D filters can be applied on 2D images.

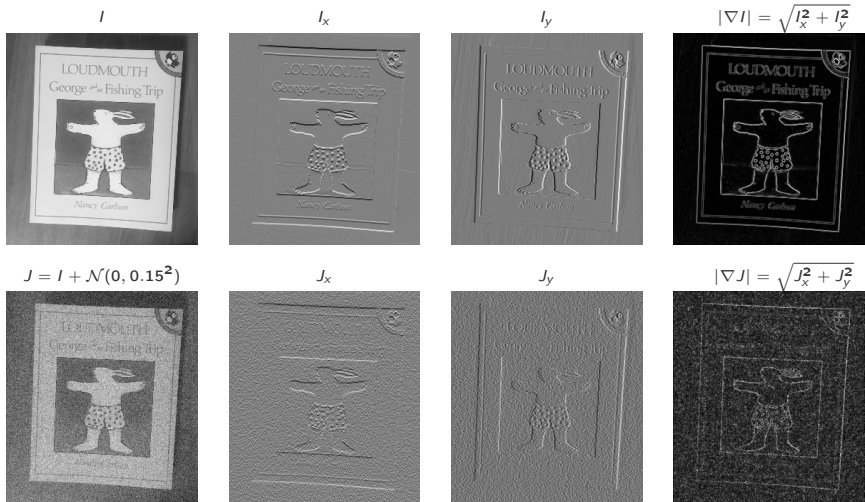
x-direction

$$\frac{1}{2} \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix}$$

y-direction

$$\frac{1}{2} \begin{bmatrix} 1 & 0 & -1 \end{bmatrix}$$





**Figure:** Derivative filters are sensitive to noise. Convolution with derivative filters yields high responses on edges as well as noise. Author: N. Khan (2018)

