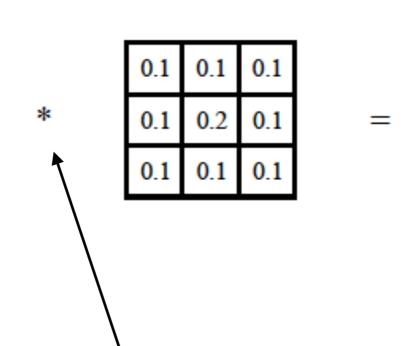


Neighborhood Operations (cont'd)

CS 355: Interactive Graphics and Image Processing

Spatial Filtering

45	60	98	127	132	133	137	133
46	65	98	123	126	128	131	133
47	65	96	115	119	123	135	137
47	63	91	107	113	122	138	134
50	59	80	97	110	123	133	134
49	53	68	83	97	113	128	133
50	50	58	70	84	102	116	126
50	50	52	58	69	86	101	120



69	95	116	125	129	132
68	92	110	120	126	132
66	86	104	114	124	132
62	78	94	108	120	129
57	69	83	98	112	124
53	60	71	85	100	114

notation for convolution operator

$$I' = I * w$$

Negative Weights

 Detecting <u>edges</u> or <u>sharpening</u> images involve finding and/or accentuating differences

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

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

 All involve a mix of <u>positive</u> and <u>negative</u> weights

1	-2	1
1	-2	1
1	-2	1

0	-1	0
-1	5	-1
0	-1	0

- Originated in analog darkrooms
- Key idea: subtract out the blur
- Procedure:
 - Blur more (yes, really!)
 - Subtract from original
 - Multiply by some fraction
 - Add back to the original

Mathematically:

$$I' = I + \alpha(I - \overline{I})$$

Input image

I

Blurred input image

 \overline{I}

Weighting (controls sharpening)

 α

Output image

I'

Let
$$\alpha = \frac{5}{A}$$
, then

$$I' = I + \alpha(I - \overline{I}) = \frac{1}{A} \left(AI + 5(I - \overline{I}) \right)$$

$$\frac{1}{A} \begin{bmatrix}
0 & 0 & 0 \\
0 & A & 0 \\
0 & 0 & 0
\end{bmatrix} + \begin{pmatrix}
0 & 0 & 0 & 0
\end{pmatrix}$$

0	0	0
0	CI	0
0	0	0

0	0 1	
1	1	1
0	1	0

$$= \frac{1}{A} \begin{vmatrix} 0 & -1 & 0 \\ -1 & A+4 & -1 \\ 0 & -1 & 0 \end{vmatrix}$$









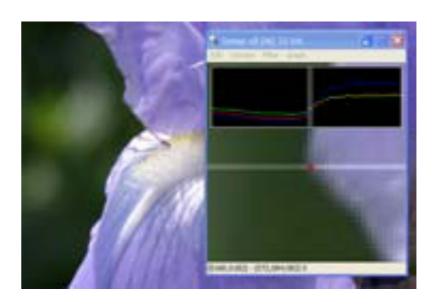
Tradeoff

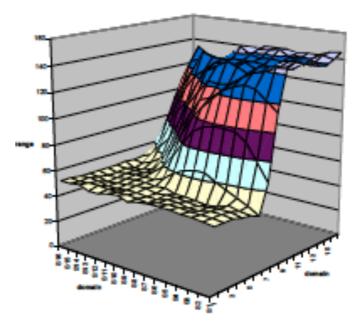
- Blurring:
 - Reduces noise
 - Causes blur

- Sharpening:
 - Reduces blur
 - Strengthens noise

Edge Detection

- Edges between objects in images are often places where there are strong changes
- Find these using (approximations to) image derivatives





Approximating Derivatives

• Can approximate derivatives with *finite differences*

$$\frac{d}{dt}f(t) = \lim_{h \to 0} \frac{f(t+h) - f(t)}{h}$$

- Can choose
 - Forward (right)
 - Backward (left)
 - Central

$$\frac{d}{dt}f(t) \approx \frac{f(t+1) - f(t)}{1}$$

$$\frac{d}{dt}f(t) \approx \frac{f(t) - f(t-1)}{1}$$

$$\frac{d}{dt}f(t) \approx \frac{f(t+1) - f(t-1)}{2}$$

Approximating Derivatives

- Simplest:
 Just take central differences
 horizontally and vertically
- Approximates <u>partial derivatives</u>

0	0	0
-1	0	1
0	0	0

$$\frac{\partial}{\partial x}$$

$$\frac{\partial}{\partial y}$$

Prewitt Kernels

- Better still: Average in other direction
- More robust since you're reducing noise in one direction while taking derivative in the other

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

∂	
∂x	r

$$\frac{\partial}{\partial y}$$

Sobel Kernels

- More common:
 Use a center-weighted
 average in other direction
- More robust to noise

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

$$\frac{\partial}{\partial x}$$

$$\frac{\partial}{\partial y}$$

2nd Derivatives

- Can also do second derivatives
- Differences of differences
- Can still combined with smoothing in other direction

0	0	0
1	-2	1
0	0	0

0	1	0
0	-2	0
0	1	0

1	-2	1
1	-2	1
1	-2	1

1	1	1
-2	-2	-2
1	1	1

Gradients

- The gradient is a vector of partial derivatives (one per dimension)
- The *direction* of the gradient is the *direction of greatest increase*
- The magnitude of the gradient is the amount of increase in that direction

$$\nabla f = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \\ \vdots \end{bmatrix}$$

$$\|\nabla f\|$$

Gradient Magnitude

 The magnitude of the local gradient is the most common form of edge detector

$$\nabla I = \left[\begin{array}{c} \frac{\partial I}{\partial x} \\ \frac{\partial I}{\partial y} \end{array} \right]$$





Lab #7

- Brightness / contrast (level operations)
- Noise removal (uniform averaging)
- Noise removal (median filter)
- Sharpening (unsharp masking)
- Edge detection (gradient magnitude)

Coming up...

- Interpolation
- Geometric operations:
 - resizing, rotating, warping