

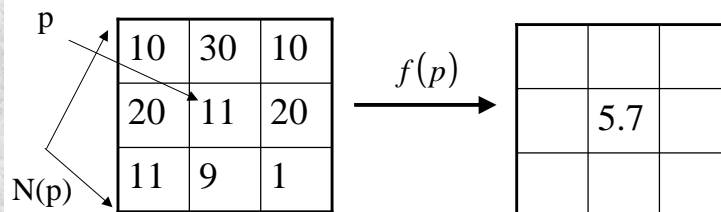
CAP5415 Computer Vision
Spring 2003

Khurram Hassan-Shafique



Image Filtering

- Modifying the pixels in an image based on some function of a local neighborhood of the pixels

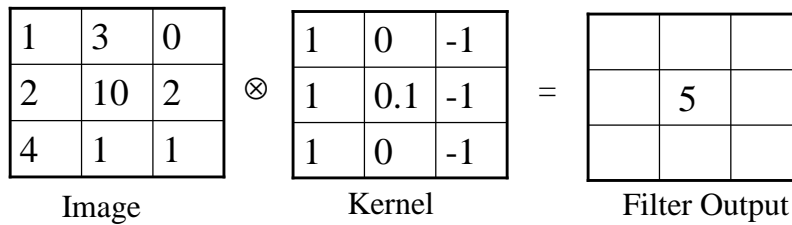


Linear Filtering

- The output is the linear combination of the neighborhood pixels

$$f(p) = \sum_{q_i \in N(p)} a_i q_i$$

- The coefficients of this linear combination combine to form the “filter-kernel”

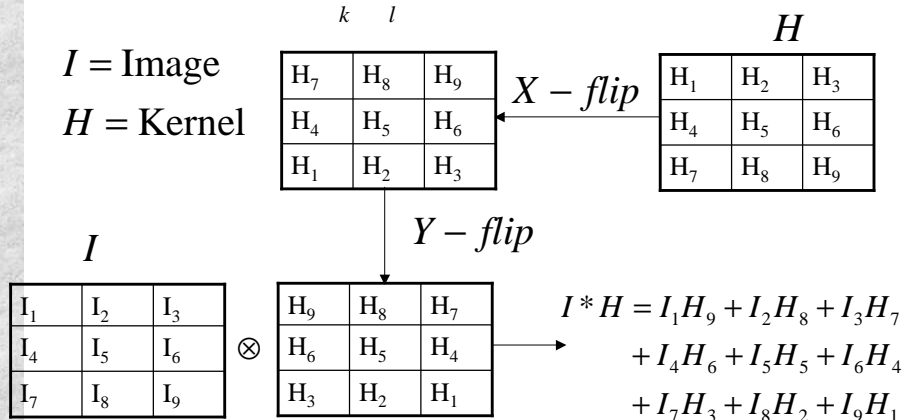


Convolution

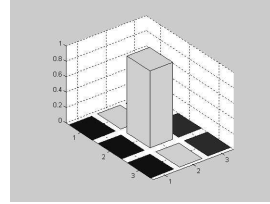
$$f(i, j) = I * H = \sum_k \sum_l I(k, l) H(i - k, j - l)$$

I = Image

H = Kernel



Linear Filtering



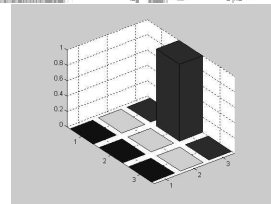
*

0	0	0
0	1	0
0	0	0

=



Linear Filtering



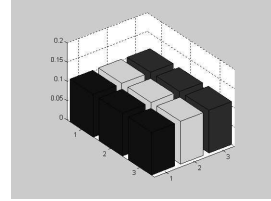
*

0	0	0
0	0	1
0	0	0

=



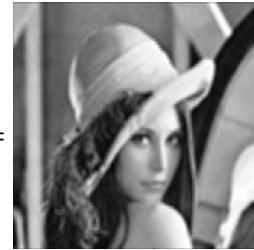
Linear Filtering



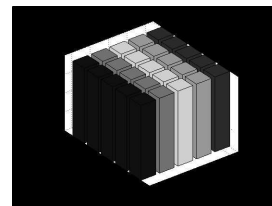
$\ast \frac{1}{9}$

1	1	1
1	1	1
1	1	1

=



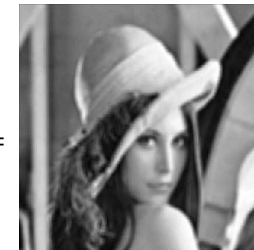
Linear Filtering



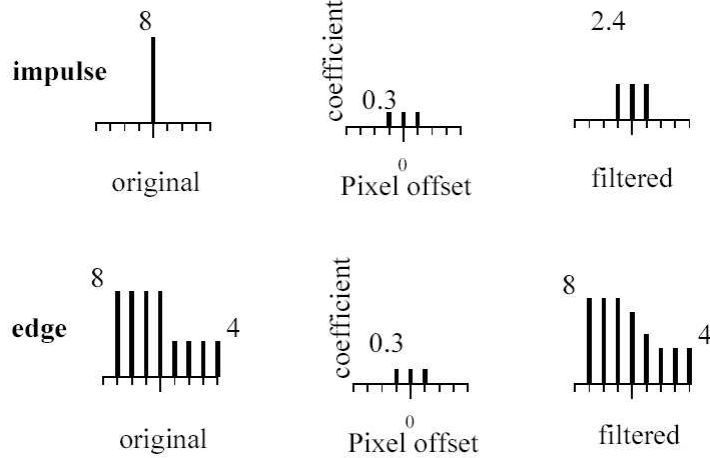
$\ast \frac{1}{25}$

1	1	1	1	1
1	1	1	1	1
1	1	1	1	1
1	1	1	1	1
1	1	1	1	1

=

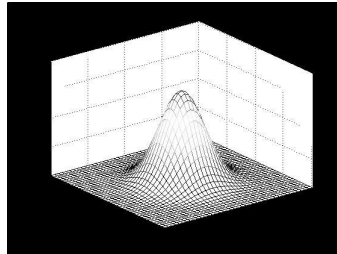


Blur examples



Gaussian Filter

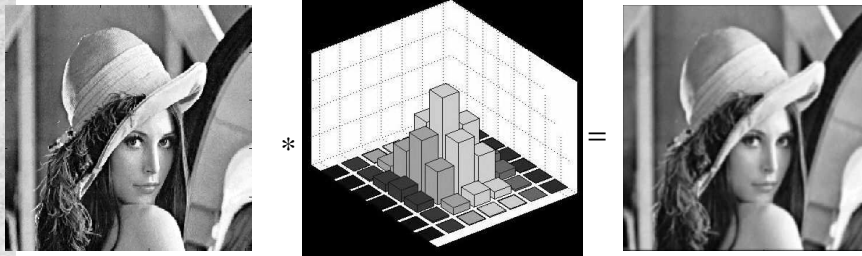
$$G_{\sigma}(x, y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{(x^2 + y^2)}{2\sigma^2}\right)$$



$$H(i, j) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{((i-k-1)^2 + (j-k-1)^2)}{2\sigma^2}\right)$$

where $H(i, j)$ is $(2k+1) \times (2k+1)$ array

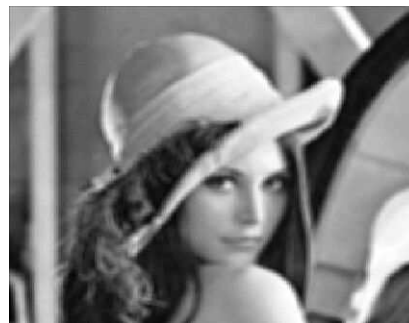
Linear Filtering(Gaussian Filter)



Gaussian Vs Average



Gaussian Smoothing



Smoothing by Averaging

Noise Filtering



Gaussian Noise



After Averaging



After Gaussian Smoothing

Noise Filtering



Salt & Pepper Noise



After Averaging



After Gaussian Smoothing

Shift Invariant Linear Systems

- Superposition

$$R(f + g) = R(f) + R(g)$$

- Scaling

$$R(kf) = kR(f)$$

- Shift Invariance

Linear image transformations

- In analyzing images, it's often useful to make a change of basis.

transformed image \vec{F} ← $\vec{F} = U\vec{f}$ ← Vectorized image

↑
Fourier transform, or
Wavelet transform, or
Steerable pyramid transform

Self-inverting transforms

Same basis functions are used for the inverse transform

$$\begin{aligned}\vec{f} &= U^{-1} \vec{F} \\ &= U^+ \vec{F}\end{aligned}$$

↑
U transpose and complex conjugate

Fourier Transform

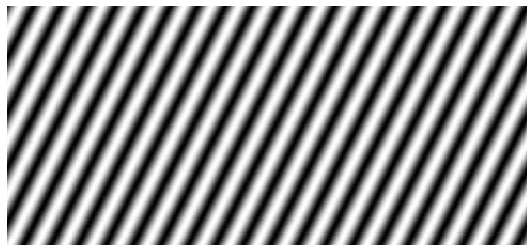
Continuous : $F(g(x, y))(u, v) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x, y) e^{-i2\pi(ux+vy)} dx dy$

Discrete $F[m, n] = \sum_{k=0}^{M-1} \sum_{l=0}^{N-1} f[k, l] e^{-\pi i \left(\frac{km}{M} + \frac{ln}{N} \right)}$

To get some sense of what basis elements look like, we plot a basis element --- or rather, its real part --- as a function of x,y for some fixed u, v . We get a function that is constant when $(ux+vy)$ is constant. The magnitude of the vector (u, v) gives a frequency, and its direction gives an orientation. The function is a sinusoid with this frequency along this frequency along the direction, and constant perpendicular to the direction.



Here u & v are larger than the previous slide



Larger than the upper example

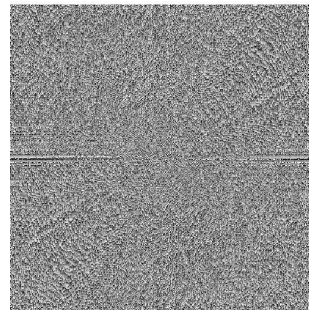


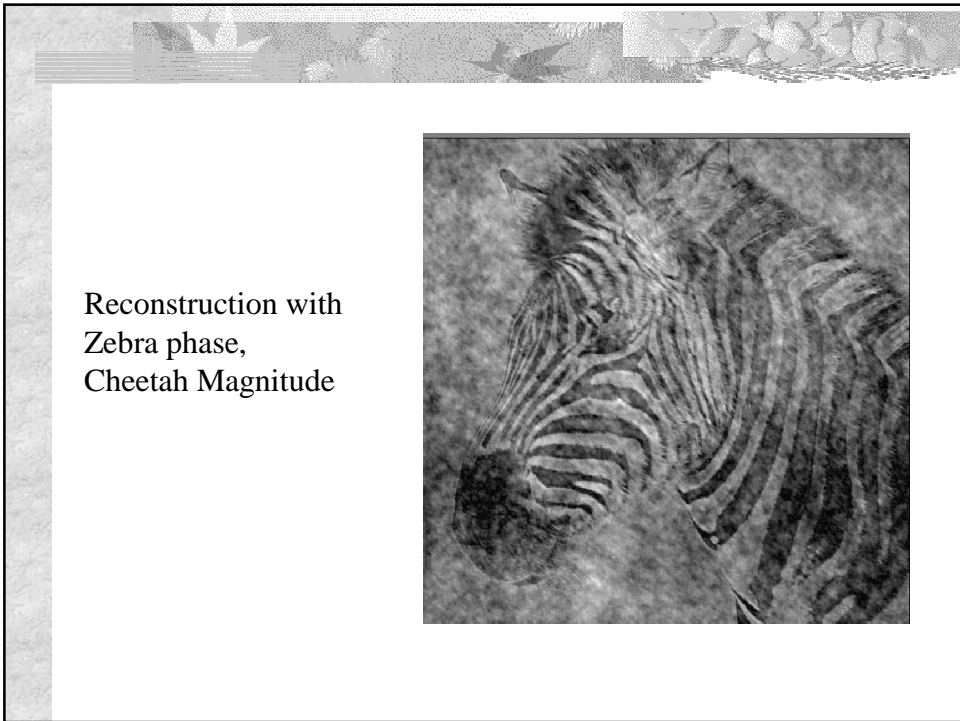
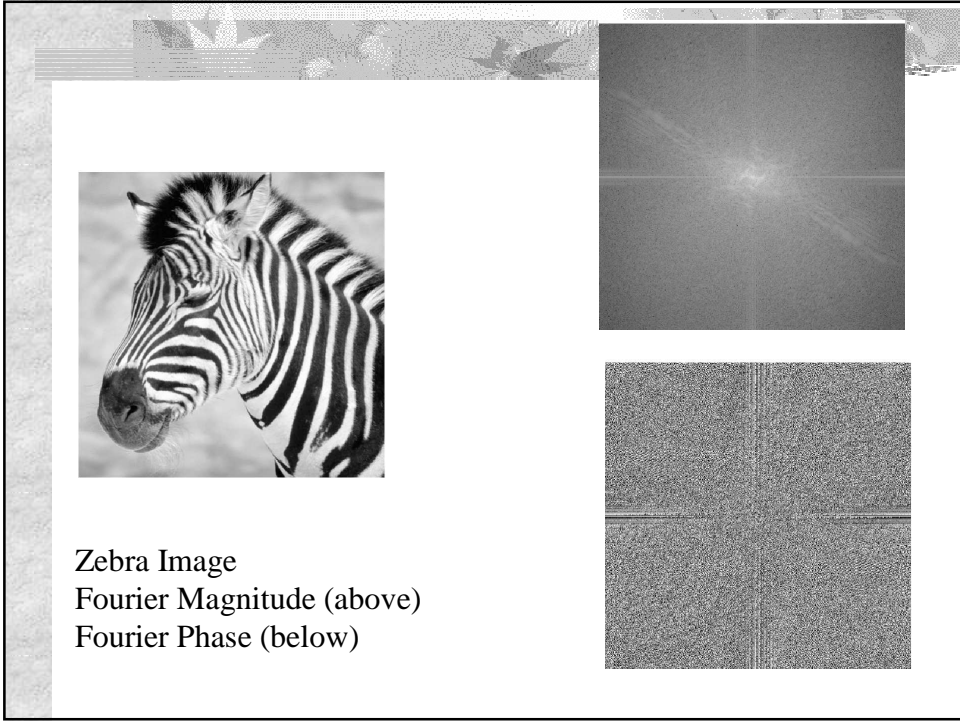
Phase and Magnitude

- Fourier transform of a real function is complex
 - difficult to plot, visualize
 - instead, we can think of the phase and magnitude of the transform
- Phase is the phase of the complex transform
- Magnitude is the magnitude of the complex transform
- Curious fact
 - all natural images have about the same magnitude transform
 - hence, phase seems to matter, but magnitude largely doesn't
- Demonstration
 - Take two pictures, swap the phase transforms, compute the inverse - what does the result look like?

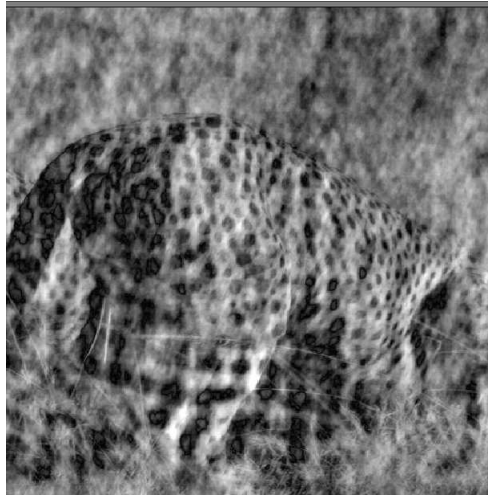


Cheetah Image
Fourier Magnitude (above)
Fourier Phase (below)





Reconstruction with
Cheetah phase,
Zebra Magnitude



Suggested Reading

- Chapter 7, David A. Forsyth and Jean Ponce, "Computer Vision: A Modern Approach"