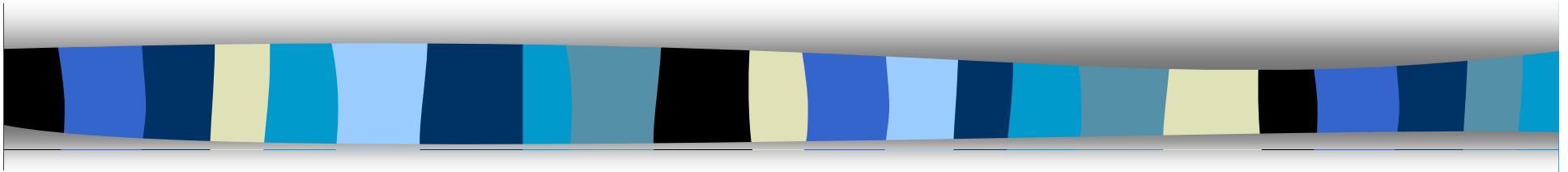
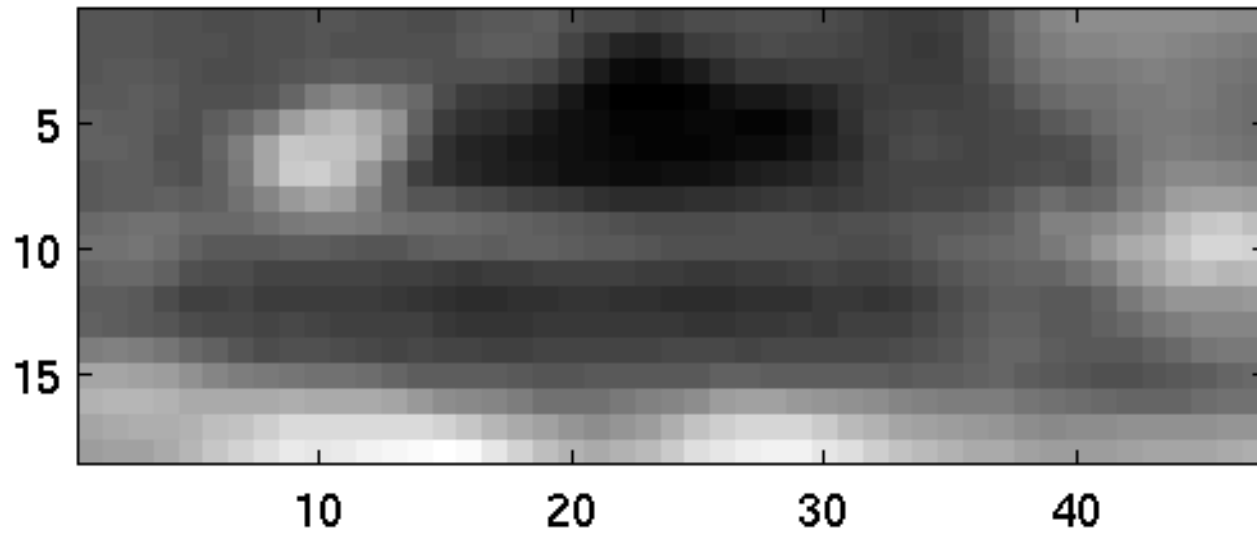
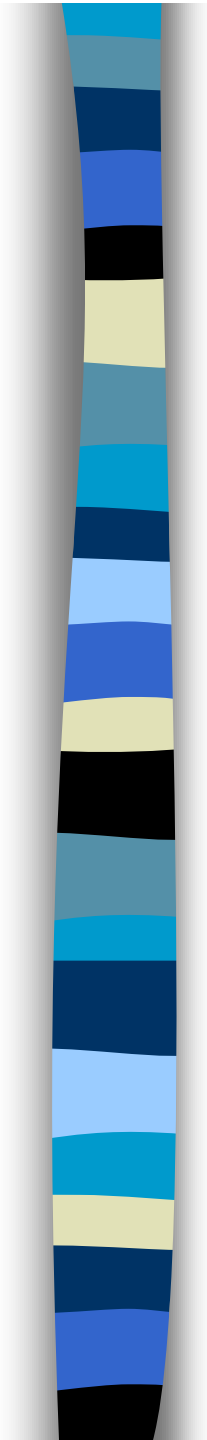


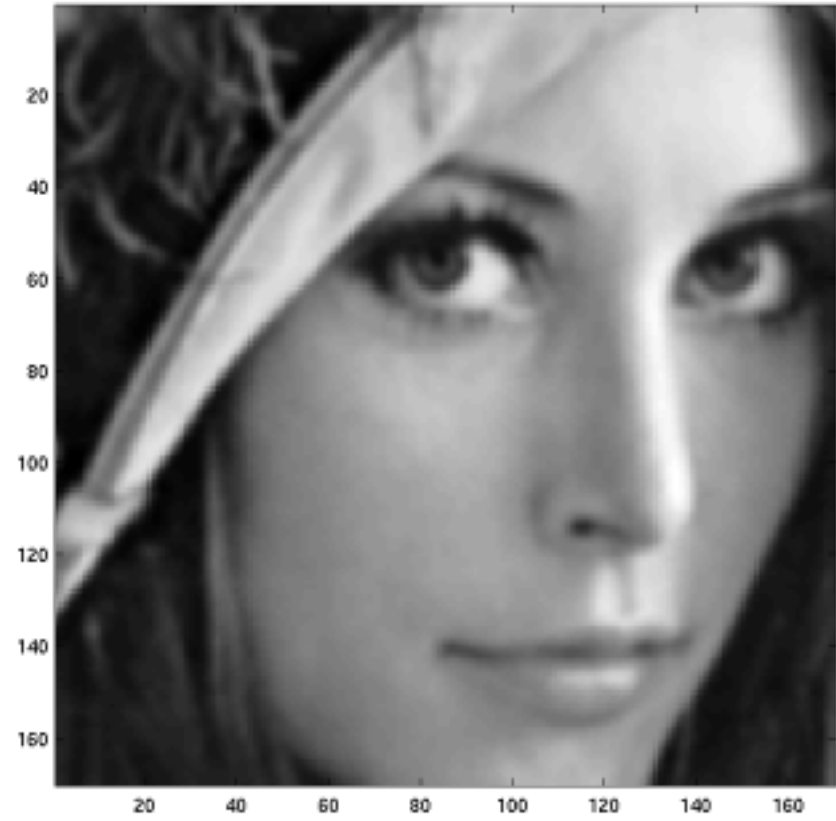
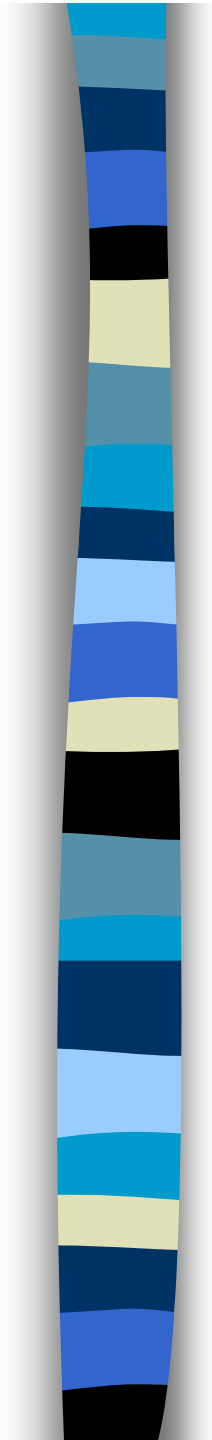
# Image Restoration



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# Degradation Model

- In noise-free cases, a blurred image can be modeled as

$$y = x * h$$

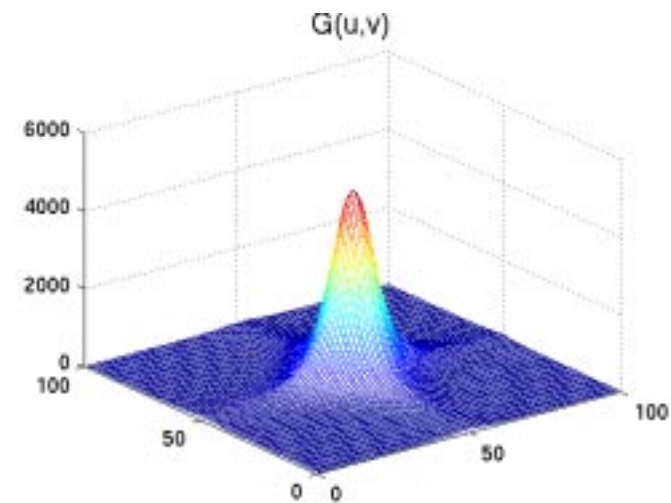
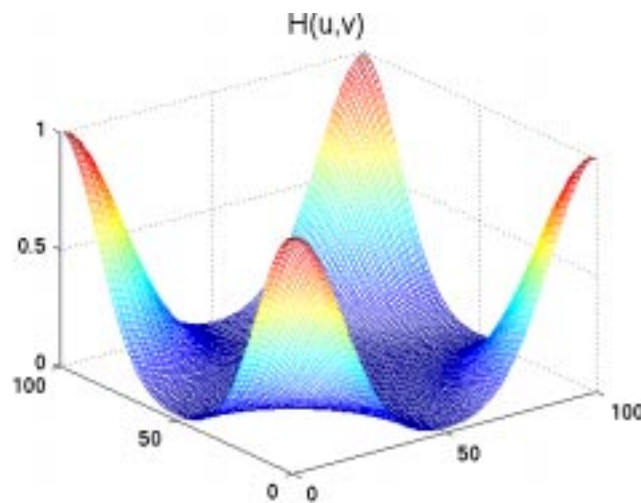
$h$ : linear space - invariant blur function

$x$ : original image

- In the DFT domain,  $Y(u,v) = X(u,v) H(u,v)$

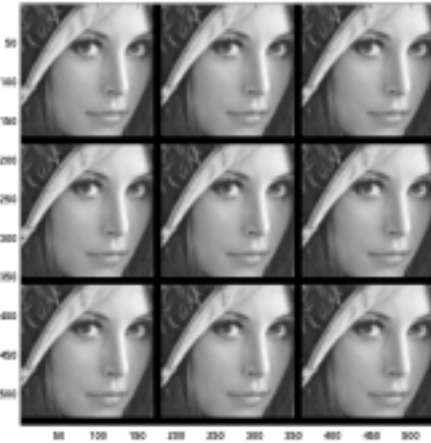
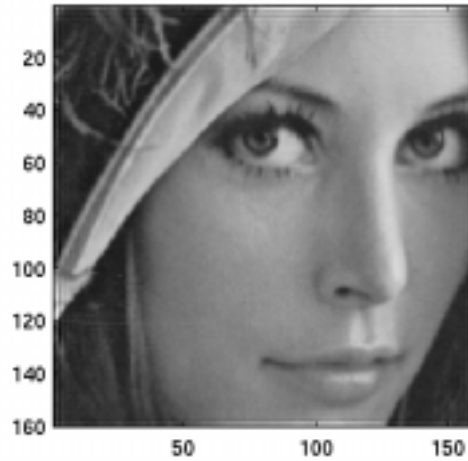
# Inverse Filtering

- Assume  $h$  is known (low-pass filter)
- Inverse filter  $G(u,v) = 1 / H(u,v)$
- $\tilde{X}(u, v) = Y(u, v) G(u, v)$

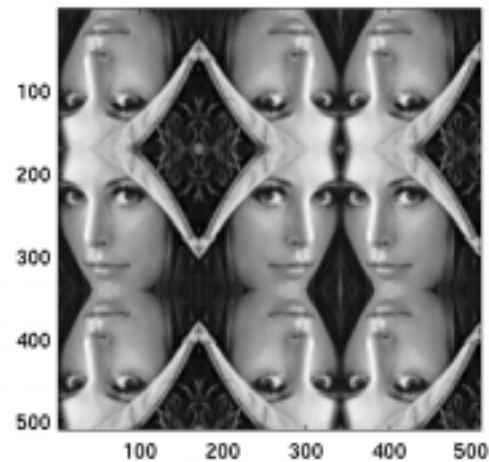
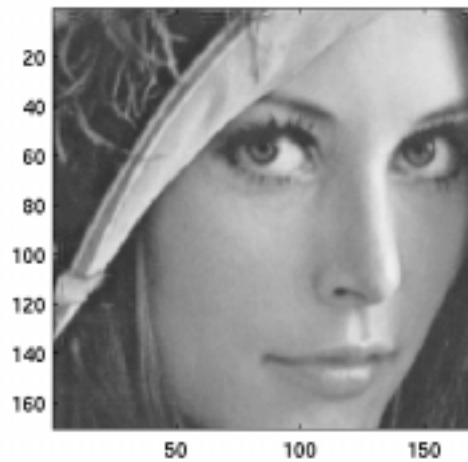


# Implementing Inverse Filtering

Linear Convolution

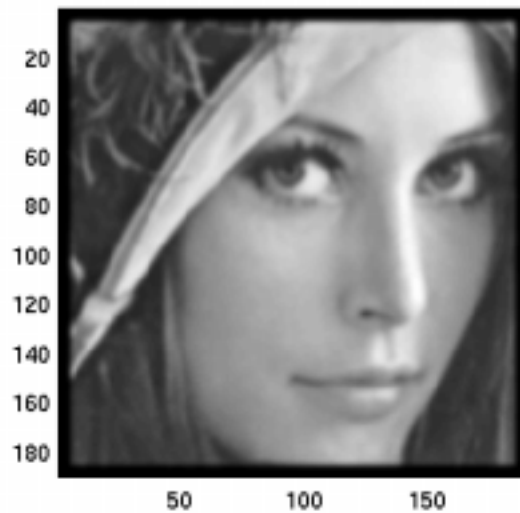


Boundary Reflection

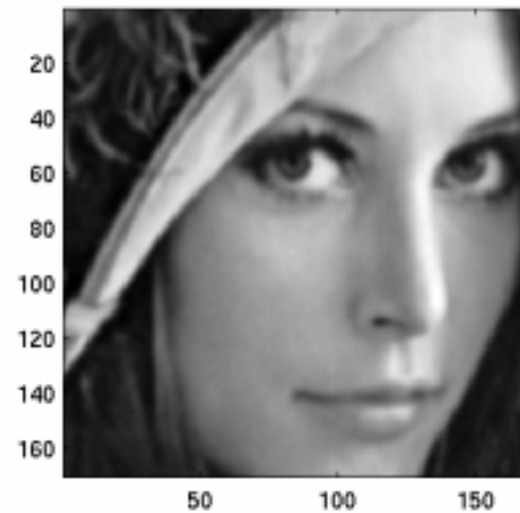


# Lost Information

What We Need



What We Have



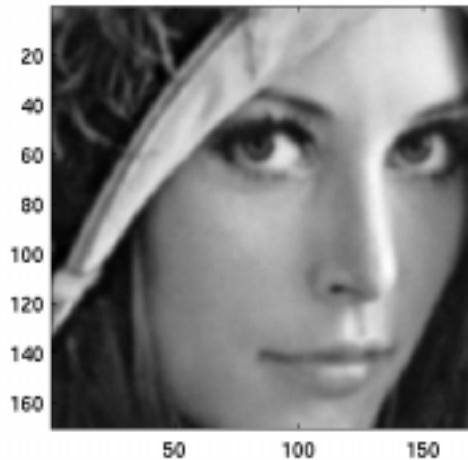
# Problems with Inverse Filtering

- $H(u,v) = 0$ , for some  $u, v$
- In noisy case,

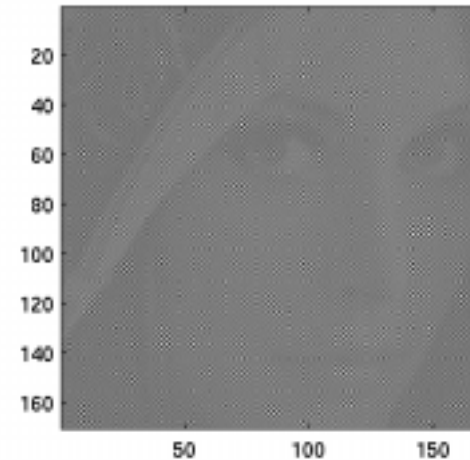
$$y = x * h + n$$

$n$  : additive noise

Gaussian Noise (zero mean,  $\sigma = 1$ )



Restored Image







# Wiener Filter Formulation

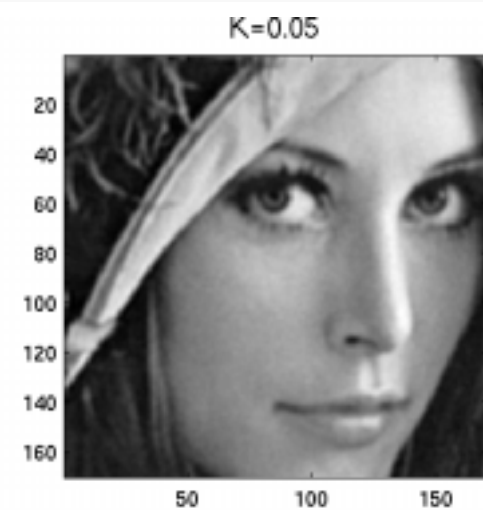
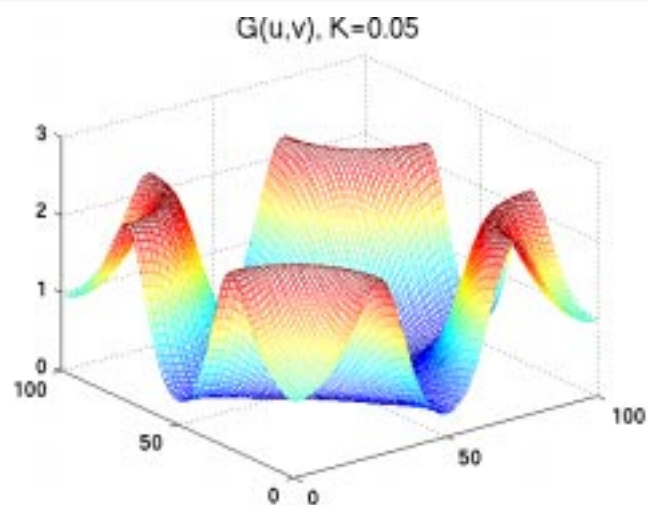
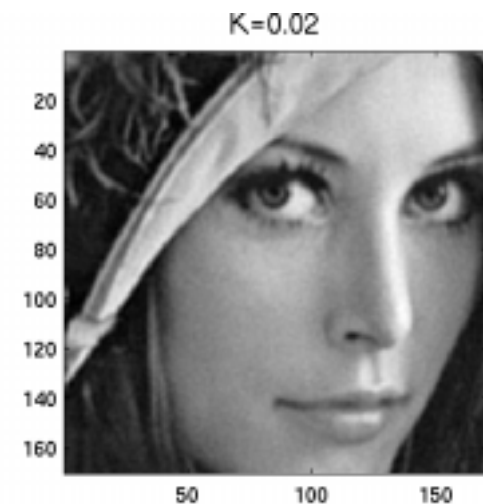
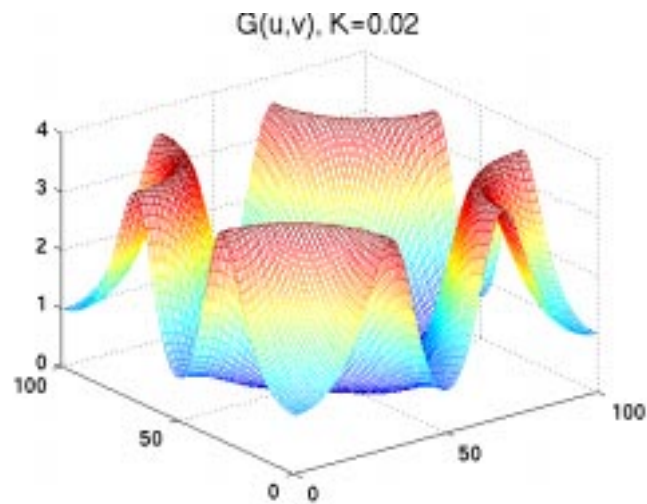
- Least Mean Square Filter

$$G(u, v) = \frac{H^*(u, v)}{|H(u, v)|^2 + [S_n(u, v)/S_x(u, v)]}$$

- In practice

$$G(u, v) = \frac{H^*(u, v)}{|H(u, v)|^2 + K}$$

# Wiener Filter Results





# Maximum-Likelihood (ML) Estimation

- $h$  is unknown
- Assume parametric models for the blur function, original image, and/or noise
- Parametric set  $\theta$  is estimated by

$$\theta_{ml} = \arg\{\max_{\theta} p(y | \theta)\}$$

- Solution is difficult



# Expectation-Maximization (EM) Algorithm

- Find *complete set*  $Z$ : for  $z \in Z$ ,  $f(z)=y$
- Choose an initial guess of  $\theta$
- Expectation-step

$$g(\theta \mid \theta^k) = E[p(z \mid \theta) \mid y, \theta^k]$$

- Maximization-step

$$\theta^{k+1} = \arg \max_{\theta} g(\theta \mid \theta^k)$$



# Subspace Methods

## ■ Observe

$$\begin{bmatrix} a_0 & a_1 & a_2 \\ a_1 & a_2 & a_3 \\ a_2 & a_3 & a_4 \end{bmatrix} \begin{bmatrix} b_0 \\ b_1 \\ b_2 \end{bmatrix} = \begin{bmatrix} b_0 & b_1 & b_2 & 0 & 0 \\ 0 & b_0 & b_1 & b_2 & 0 \\ 0 & 0 & b_0 & b_1 & b_2 \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ a_2 \\ a_3 \\ a_4 \end{bmatrix}$$

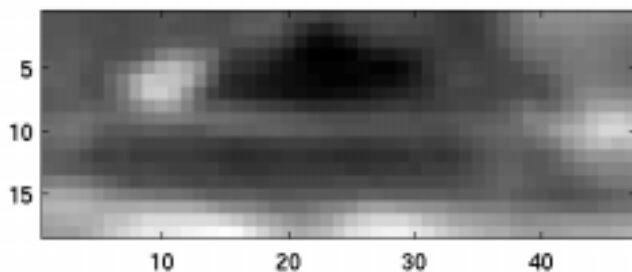


# Subspace Methods

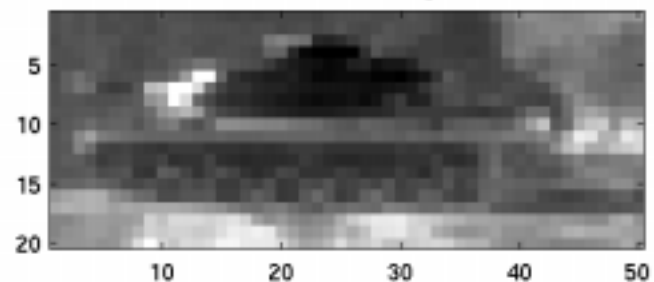
- Several blurred versions of original image are available
- Construct a block Hankel matrix  $X$  of blurred images
- $X = H \Sigma$ , where  $H$  is a block Toeplitz matrix of the blur functions and  $\Sigma$  is a block Hankel matrix of the original image

# Subspace Methods Results

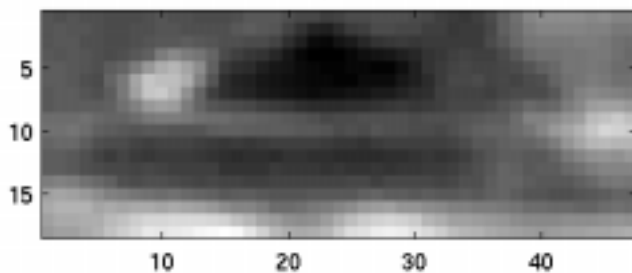
Noise-Free Case



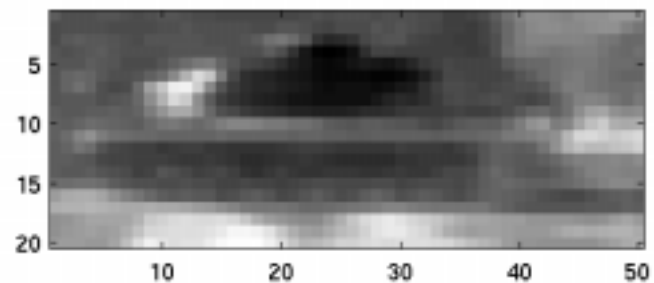
Restored Image



Noisy Case



Restored Image





# Conclusions

- Noise-free case: inverse filtering
- Noisy case: Wiener filter
- Blind case: Maximum-Likelihood approach using the Expectation-Maximization algorithm
- Multichannel blind case: subspace methods





## Further Reading

- M. R. Banham and A. K. Katsaggelos "Digital Image Restoration, " *IEEE Signal Processing Magazine*, vol. 14, no. 2, Mar. 1997, pp. 24-41.
- D. Kundur and D. Hatzinakos, "Blind Image Deconvolution," *IEEE Signal Processing Magazine*, vol. 13, no. 3, May 1996, pp. 43-64.