




Enhancement v.s. Restoration

- **Image Enhancement:**
 - A process which aims to improve bad images so they will “look” better.
- **Image Restoration:**
 - A process which aims to invert known degradation operations applied to images.

Enhancement vs. Restoration

- "Better" visual representation 
 - Subjective 
 - No quantitative measures 
- Remove effects of sensing environment
 - Objective
 - Mathematical, model dependent quantitative measures

Typical Degradation Sources

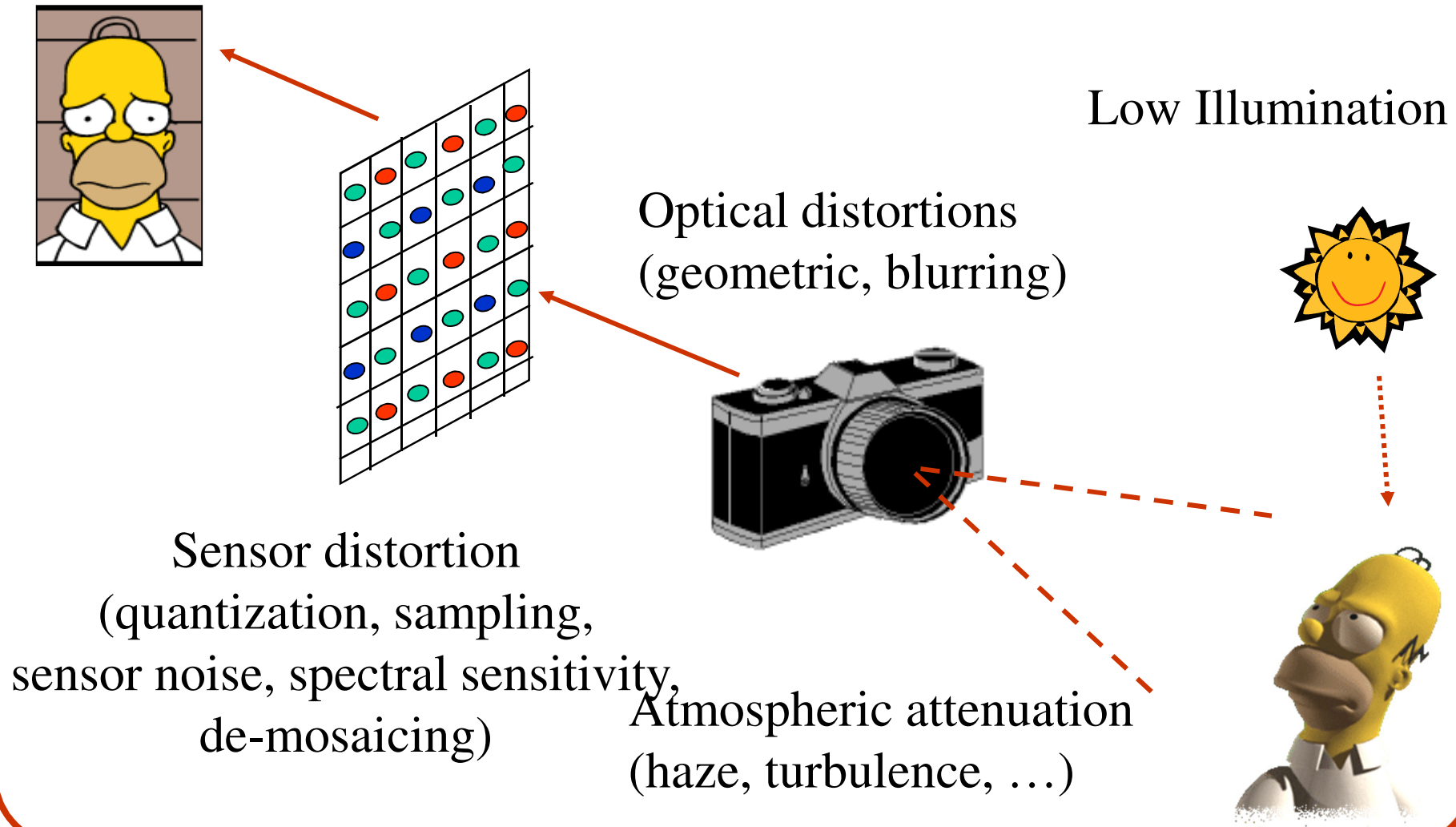
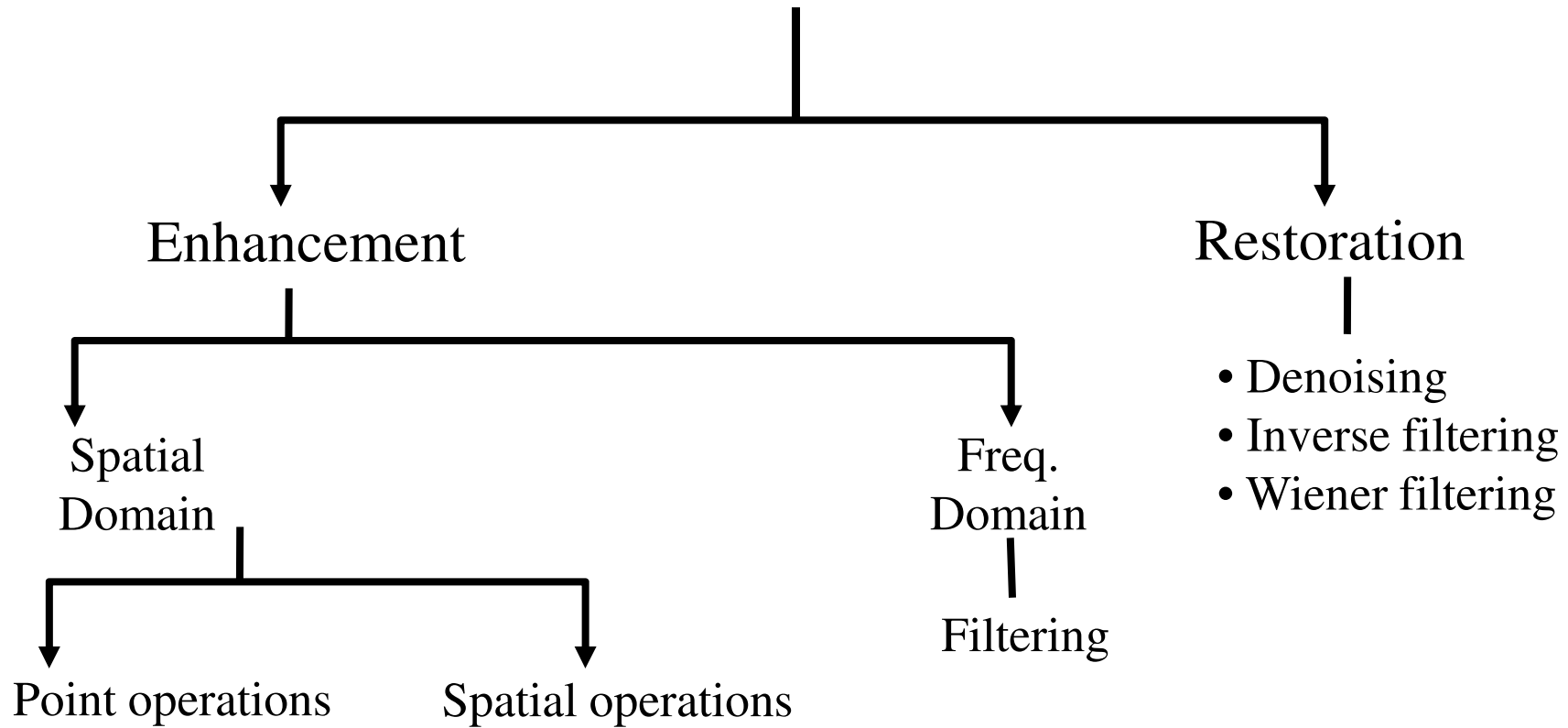
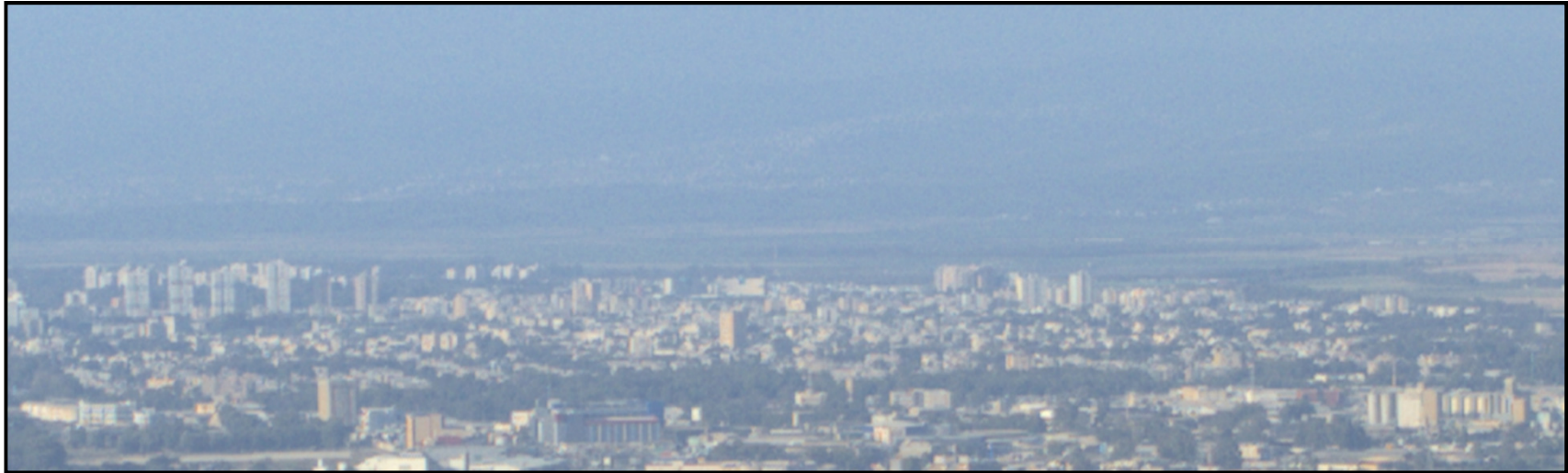


Image Preprocessing



Examples



Hazing



Echo image



Motion Blur

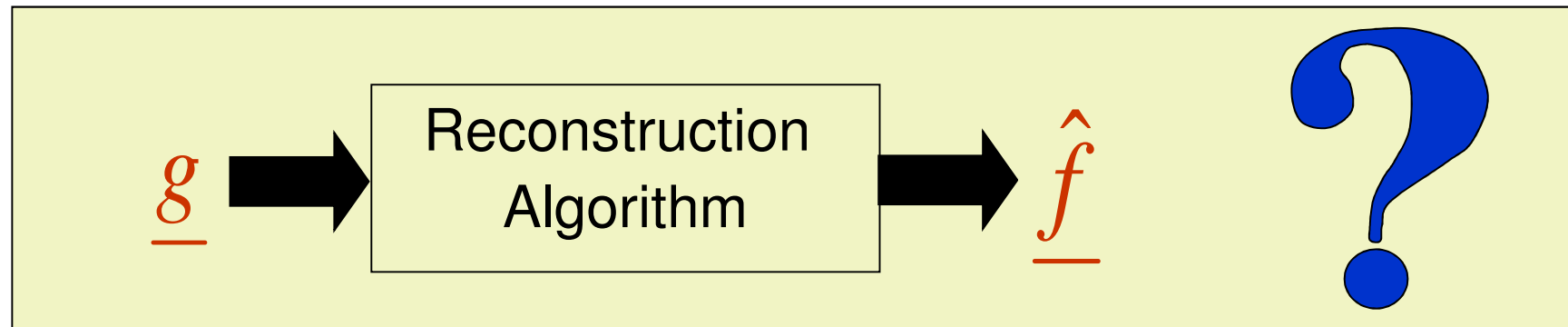
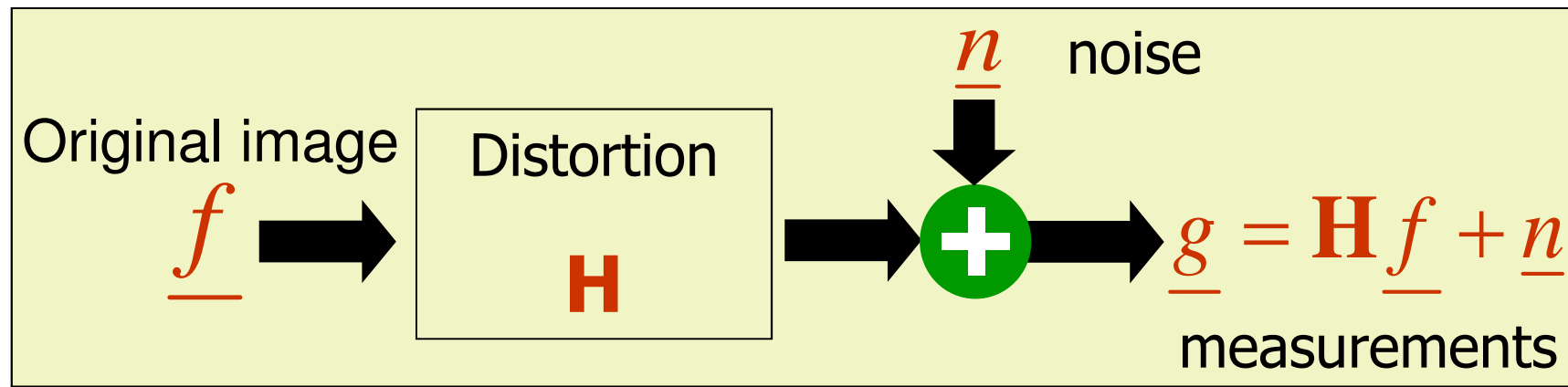


Blurred image

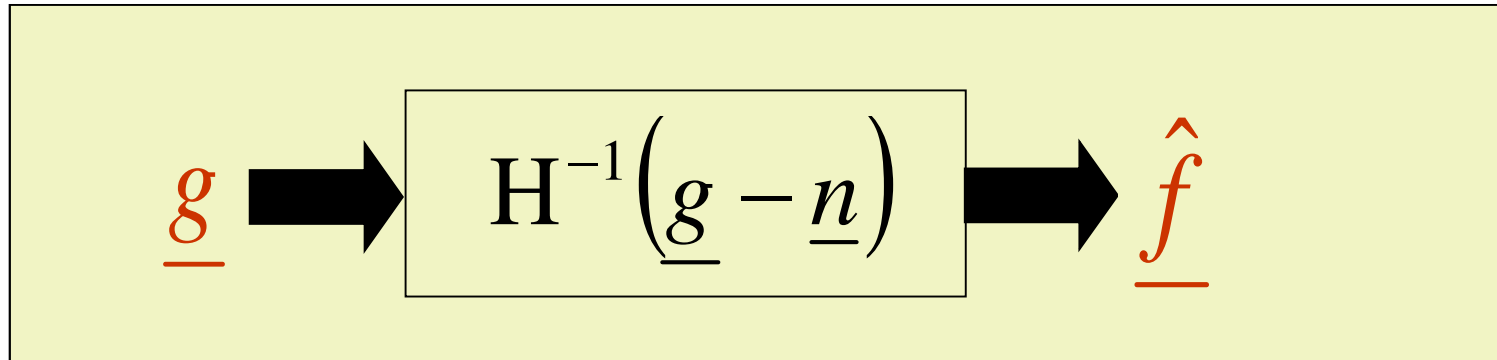


Blurred image + additive white noise

Reconstruction as an Inverse Problem



So what is the problem?



- Typically:
 - The distortion H is singular or ill-posed.
 - The noise n is unknown, only its statistical properties can be learnt.

Key point: Stat. Prior of Natural Images



MAP (Max A-posteriori) estimation: likelihood prior

$$\underline{\hat{f}} = \arg \max_x P(f|g) \propto \arg \max_x P(g|f)P(f)$$

Bayesian Denoising

- Assume an additive noise model :

$$g = f + n$$

- A MAP estimate for the original f :

$$\hat{f} = \arg \max_f P(f | g)$$

- Using Bayes rule and taking the log likelihood :

$$\hat{f} = \arg \max_f \frac{P(g | f)P(f)}{P(g)} = \arg \min_f \{-\log P(g | f) - \log P(f)\}$$

Bayesian Denoising

If noise component is white Gaussian distributed:

$$g = f + n \quad \text{where } n \text{ is distributed } \sim N(0, \sigma)$$

$$P(g | f) = e^{-(g-f)^2 / \sigma}$$

$$-\log P(g | f) = (g - f)^2 / \sigma$$

$$\hat{f} = \arg \min_f \left\{ \underbrace{(g - f)^2}_{\text{data term}} + \underbrace{\lambda R(f)}_{\text{prior term}} \right\}$$

$R(f)$ is a penalty for non probable f


Inverse Filtering

- Degradation model:

$$g(x,y) = h(x,y)*f(x,y)$$



$$G(u,v)=H(u,v)\cdot F(u,v)$$

 $\hat{F}(u,v)=G(u,v)/H(u,v)$

Inverse Filtering (Cont.)

Two problems with the above formulation:

1. $H(u,v)$ might be zero for some (u,v) .
2. In the presence of noise the noise might be amplified:

$$\hat{F}(u,v) = G(u,v)/H(u,v) + N(u,v)/H(u,v)$$

Solution: Use prior information

$$\hat{F} = \arg \min_F \underbrace{(HF - G)^2}_{\text{data term}} + \underbrace{\lambda R(F)}_{\text{prior term}}$$

Option 1: Prior Term

- Use penalty term that restrains high F values:

$$\hat{F} = \arg \min_F E(F)$$

where $E(F) = (HF - G)^2 + \lambda F^2$

- Solution:

$$\frac{\partial E(F)}{\partial F} = 2H^*(HF - G) + 2\lambda F = 0$$

$$\hat{F} = \frac{H^*}{H^*H + \lambda} G$$

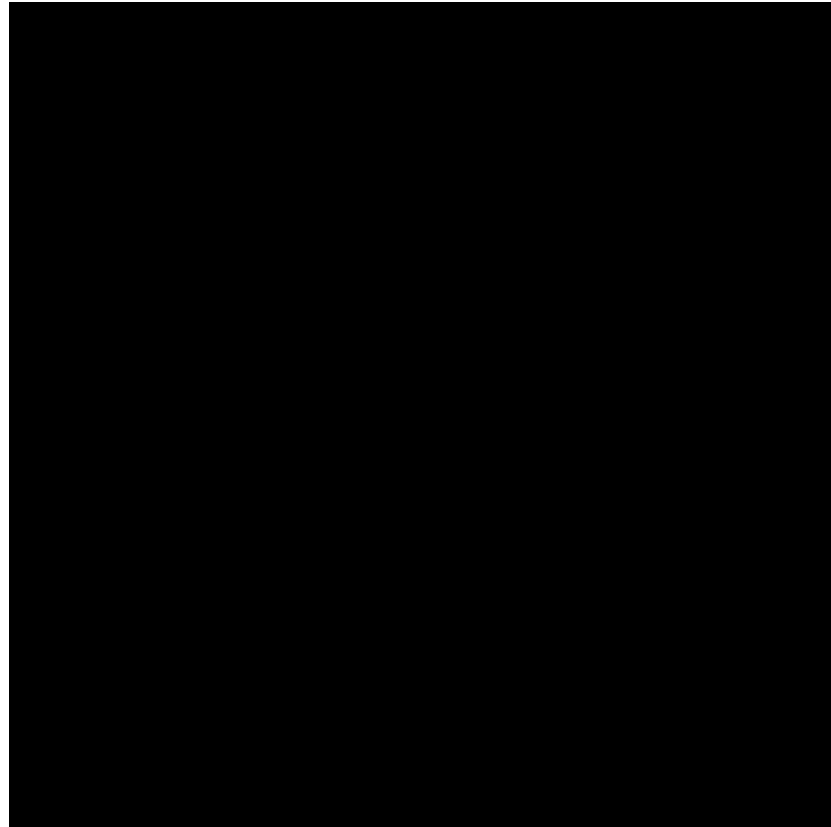
$$H(u, v) \gg 1 \Rightarrow \hat{F} = G/H$$

$$H(u, v) \ll 1 \Rightarrow \hat{F} = 0$$

Degraded Image (echo)



$$\hat{F} = G/H$$



$$\hat{F} = \frac{H^*}{H^*H + \lambda} G$$



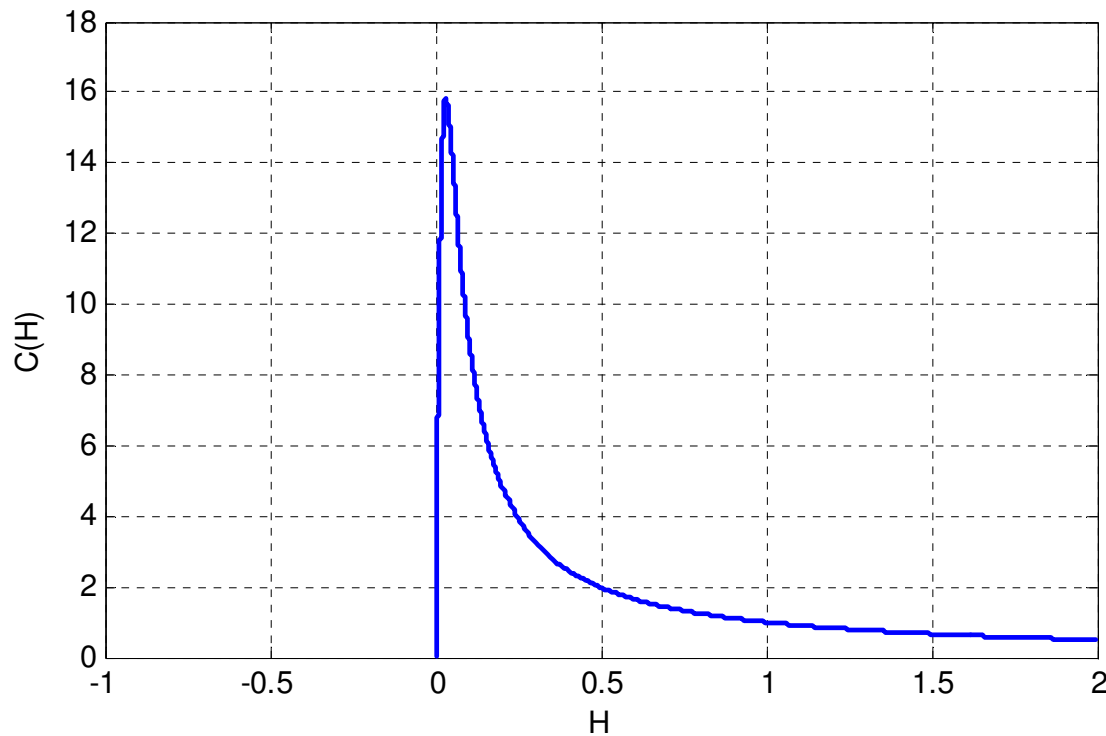
Degraded Image (echo+noise)



$$\hat{F} = \frac{H^*}{H^*H + \lambda} G$$



- The inverse filter is $C(H) = H^*/(H^*H + \lambda)$
- At some range of (u,v) :
 $S(u,v)/N(u,v) < 1 \Rightarrow$ noise amplification.



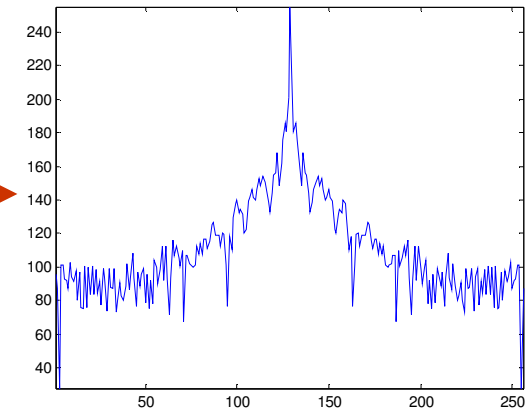
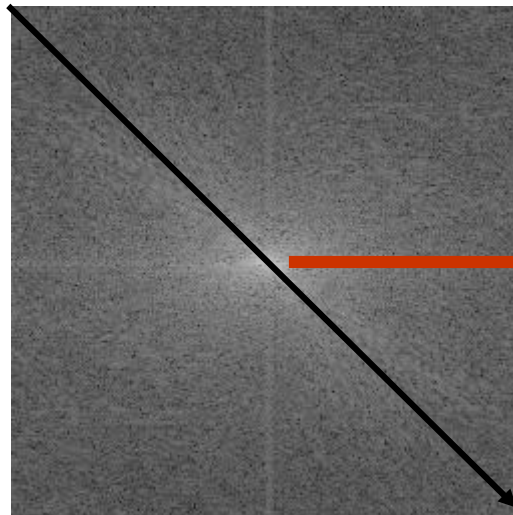
$$\lambda = 10^{-3}$$

Option 2: Prior Term

1. Natural images tend to have low energy at high frequencies
2. White noise tend to have constant energy along freq.

where $\hat{F} = \arg \min_F E(F)$

$$E(F) = (HF - G)^2 + \lambda(u^2 + v^2)F^2$$



- Solution: $\frac{\partial E(F)}{\partial F} = 2H^*(HF - G) + 2\lambda(u^2 + v^2)F = 0$

$$\hat{F} = \frac{H^*}{H^*H + \lambda(u^2 + v^2)} G$$

- This solution is known as the *Wiener Filter*
- Here we assume $N(u,v)$ is constant.
- If $N(u,v)$ is not constant:

$$\hat{F} = \frac{H^*}{H^*H + \lambda(u^2 + v^2) \cdot N(u,v)} G$$

Degraded Image (echo+noise)



Wiener Filtering



Wiener



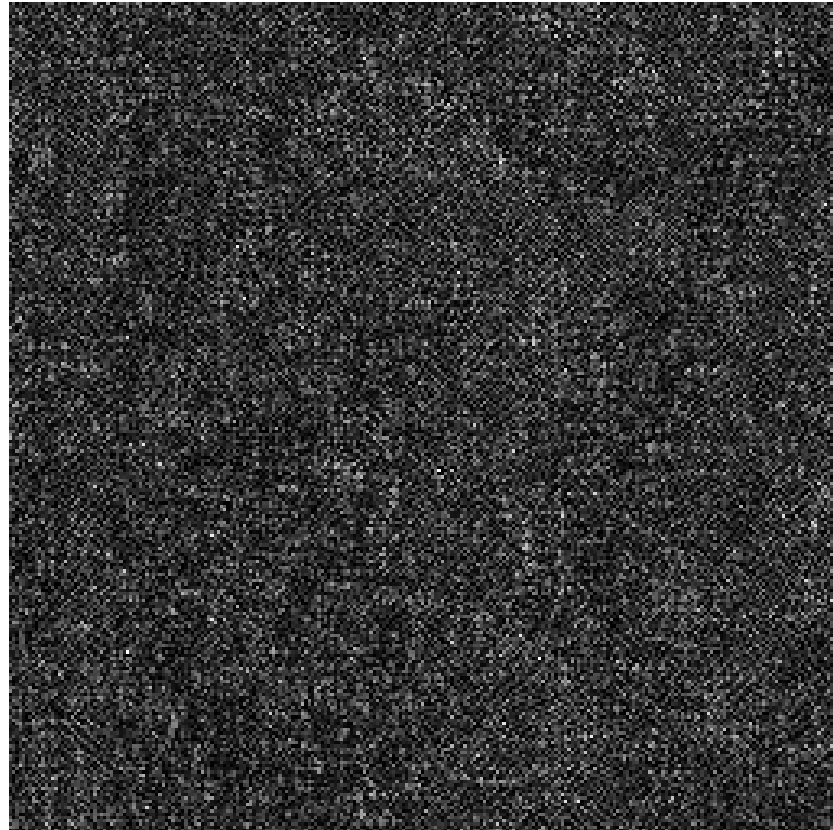
Previous



Degraded Image (blurred+noise)



Inverse Filtering



Using Prior (Option 1)



Wiener Filtering

