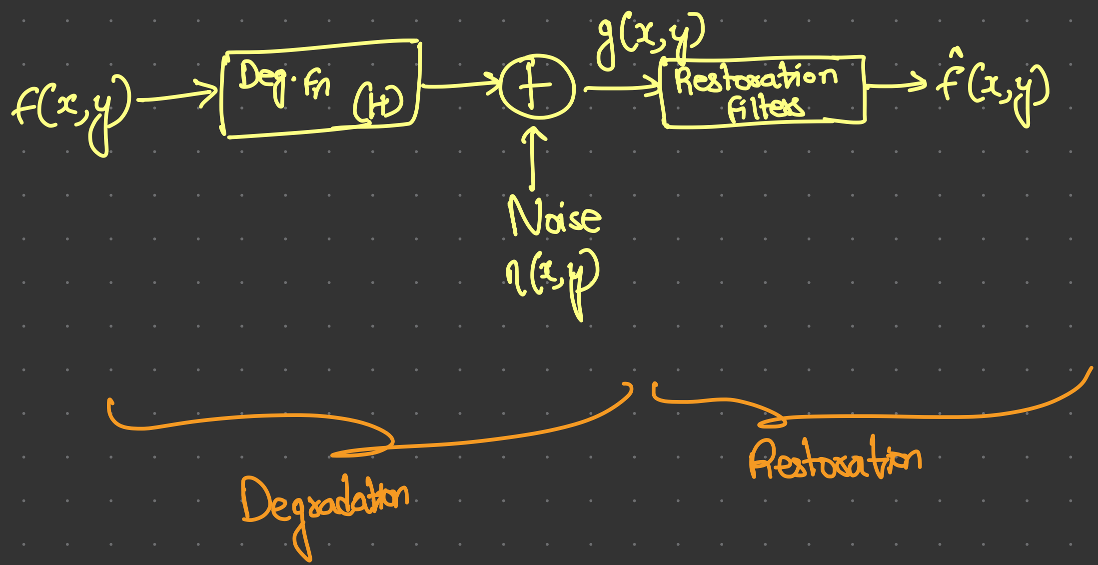
Lec 20

Image Restoration



$$G(u,v) = F(u,v) + N(u,v)$$

$$g(x,y) = f(x,y) + \eta(x,y)$$

Estimation of degradation function:

→ Observations: → Iterate

→ Experimentation → Imp idea for calibration

→ Mathematical modelling

Recovering Image:

→ Direct inverse filtering:

Assume H is know by above 3 methods:

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

Problems:

1) $N(u,v)$ is rand. whose $F(\,)$ isn't known

2) If deg has 0 or small values → $N(u,v)/H(u,v)$ will dominate

Weiner Filter:

$$e^2 = E\{(f-\hat{f})^2\}$$ → Assuming image & noise as R.Vs

→ Explicitly incorporate both degradation

$$\hat{F}(u,v) = \left[\frac{H^*(u,v)S_f(u,v)}{S_f(u,v)|H(u,v)|^2 + S_n(u,v)}\right]G(u,v)$$

$S_n(u,v) = |N(u,v)|^2$ = Power spectrum of noise (auto correlation of noise)

$S_f(u,v) = |F(u,v)|^2$ = Power spectrum of undegraded image

SNR Ratio → To quantify how much we have recovered

Higher → Good recovery/restoration

$$f \longrightarrow \boxed{H} \longrightarrow g$$

Inverse Problems

Known	Problem
H, g	Recovery
g	Blind Recovery
g, H partially	Semi-Blind Recovery
f, g	System Identification

Geometric Distortion

① Thick lens

② Vignetting → Causes radial darkening in frame corners

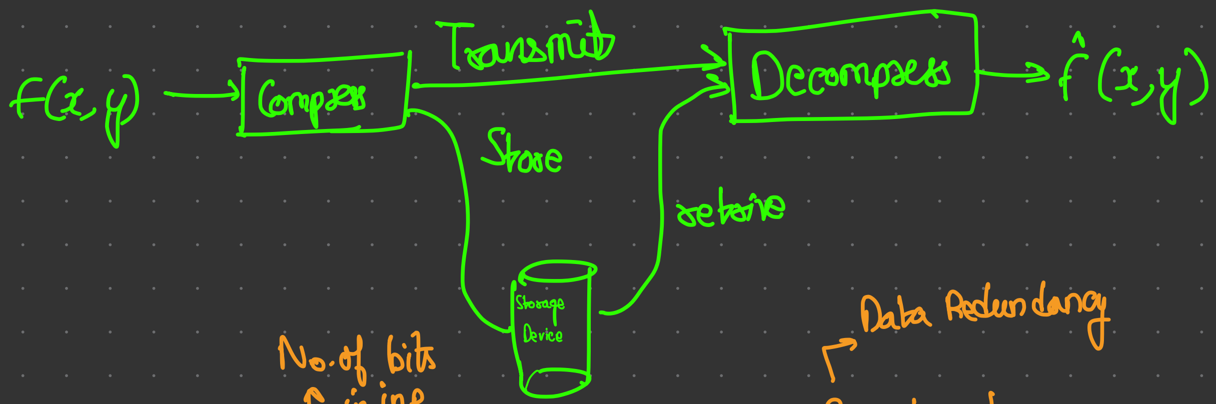
③ Chromatic Aberration → Not able to focus all wavelengths at same focal length
- ↳ Longitudinal
- ↳ Transverse

④ Radial and Tangential Distortion → lens & screen aren't parallel
- ↳ unequal bending of light (bend more near edges)

Lens Glare → Very bright source in same frame

Image Compression

→ Data comp aims to reduce amount of data while preserving as much info as possible



No. of bits in inp

$C_R = \frac{n_1}{n_2}$

↳ No. of bits used in compr. img

Data Redundancy

$R_D = 1 - \frac{1}{C_R}$

when $n_2 = n_1 \Rightarrow C_R = 1, R_D = 0$

$n_2 \ll n_1 \Rightarrow C_R = \infty$, $R_D = 1$

Type of redundancy:

→ Coding

→ Spatial

→ Irrelevant

Optimal Information Coding

$$L_{avg} = \sum_{k=0}^{L-1} l(r_k) p_r(r_k)$$

$p_r(r_k) \rightarrow \frac{n_k}{MN}, k = 0, 1, 2 \ldots L-1$

r_k ↳ Discrete R.V in range $[0, L-1]$ i.e. k^{th} intensity level

Total no. of bits to rep. image:

$$MNL_{avg}$$

Cases:

1. $l(r_k)$ = constant length
2. $l(r_k)$ = Variable length

Spatial Redundancy:

→ Maximally corelated horizontal direction. Each col has const. intensity

→ Run-length pairs

→ All 256 I's are independant

Reduce interpixel red, use transformations like thresholding, DFT

Psychovisual:

→ Change not visible to eyes

→ Quantisation

Entropy:

$$H = -\sum_{i=0}^{L-1} p_i \log(p_i)$$

$$I = \log_2(1/p) \Rightarrow -\log_2 p$$

Shannon Noiseless Coding Thm

$$H(z) \leq \frac{L'_{avg}}{n} < H(z) + 1/n$$

Efficiency: entropy/L'_{avg}