

## Image restoration

→ Pointed Noise :-

→ Band reject filters :-

(1) Ideal

$$H_{\text{Ibr}}(u,v) = \begin{cases} 1 & \text{if } D(u,v) < D_0 - \frac{w}{2} \\ 0 & \text{if } D_0 - \frac{w}{2} \leq D(u,v) \leq D_0 + \frac{w}{2} \\ 1 & \text{if } D(u,v) > D_0 + \frac{w}{2} \end{cases}$$

(2) Butterworth

$$H_{\text{Btr}}(u,v) = \frac{1}{1 + \left[ \frac{\omega(u,v) w}{D^2(u,v) - D_0^2} \right]^{2n-\text{order}}}$$

(3) Gaussian

$$H_{\text{Gtr}}(u,v) = 1 - e^{-\frac{1}{2} \left[ \frac{D^2(u,v) - D_0^2}{\omega(u,v) w} \right]^2}$$

→ Bandpass filter :-

$$H_{\text{bp}}(u,v) = 1 - H_{\text{Btr}}(u,v)$$

→ Notch reject filter :-

$$H(u,v) = \begin{cases} 0 & \text{if } D(u,v) \leq D_0 \\ & \text{or } D_2(u,v) \leq D_0 \\ 1 & \text{otherwise} \end{cases}$$

where  $D_0 \rightarrow$  centre of the notch

$$D_2(u,v) = \left[ \left\{ \left( u - \frac{M}{2} \right) - u_0 \right\}^2 + \left\{ \left( v - \frac{N}{2} \right) - v_0 \right\}^2 \right]^{\frac{1}{2}}$$

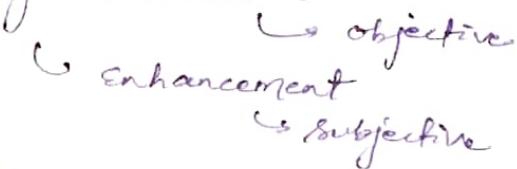
$$\Rightarrow H(u, v) = \frac{T}{\pi(u_a + v_b)} \sin(\pi(u_a + v_b)) \times e^{-j\pi(u_a + v_b)}$$

12/04/14

$$\text{for } x_o(t) = \frac{at}{T} \quad \text{and } y_o(t) = \frac{bt}{T}$$

### Tutorial

Image Restoration



SSIM → Standard static Index measurement

PSNR

imnoise(A, type of noise)

Gaussian, salt & pepper, speckle

Eg:

$$F(z) = \begin{cases} 1 - e^{-(z-a)^2/b} & ; z \geq a \\ 0 & ; z < a \end{cases} \quad b > 0$$

let  $w$  be random variable (use hand for)

$$F(z) = w \Rightarrow 1 - e^{-(z-a)^2/b} = w$$

$$\Rightarrow e^{-(z-a)^2/b} = 1-w$$

$$\Rightarrow -(z-a)^2/b = \ln(1-w)$$

$$\Rightarrow (z-a)^2 = -b \ln(1-w)$$

$$\Rightarrow z = a + \sqrt{-b \ln(1-w)}$$

Eg:  $F(z) = \begin{cases} 1 - e^{-az^2} & ; z \geq 0 \\ 0 & ; z < 0 \end{cases}$

Eg:  $F(z) = w$  (rand variable)

$$1 - e^{-az} = \omega$$

$$\Rightarrow e^{-az} = 1 - \omega \Rightarrow -az = \ln(1 - \omega)$$

$$\Rightarrow z = -\frac{1}{a} \ln(1 - \omega)$$

Spatial filtering

margin  $\rightarrow$  no. of input arguments.

16/04/14

$\rightarrow$  Inverse filtering :-

$$\begin{aligned}\hat{F}(u, v) &= \frac{G(u, v)}{H(u, v)} \\ &= \frac{H(u, v) F(u, v) + N(u, v)}{H(u, v)} \\ &= F(u, v) + \frac{N(u, v)}{H(u, v)}\end{aligned}$$

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

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

$$H(u, v) = e^{jK[(u - \frac{M}{2})^2 + (v - \frac{N}{2})^2]^{\frac{1}{2}}}$$

const. (turbulence)

$\rightarrow$  Weiner filtering :-

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

where,  $H(u, v) \rightarrow$  degradation fn.  $|H(u, v)|^2 = H^*(u, v) \cdot H(u, v)$

$$S_\eta(u, v) = |N(u, v)|^2 \rightarrow \text{Noise power}$$

$$S_f(u, v) = |f(u, v)|^2 \rightarrow \text{Undegradable image power}$$

Based on minimum mean square error (MMSE) i.e.

$$e^2 = E \left\{ (\hat{F} - F)^2 \right\}$$

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

$$= \left[ \frac{1}{H(u, v)} \times \frac{|H(u, v)|^2}{|H(u, v)|^2 + K} \right] G(u, v)$$

where  $K = \frac{S_n(u, v)}{S_f(u, v)} = (SNR)^{-1}$

→ If  $S_n(u, v) = 0$ , then

$$\hat{F}(u, v) = \frac{1}{H(u, v)} \cdot G(u, v) = H^{-1}(u, v) \cdot G(u, v).$$

$$D_0(u, v) = \left[ \left\{ (u - \frac{M}{2}) + u_0 \right\}^2 + \left\{ (v - \frac{N}{2}) + v_0 \right\}^2 \right]^{1/2}$$

→ Notch pass filter:

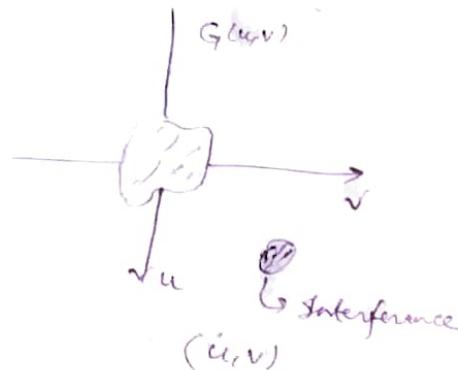
→ Optimum notch filtering:

We need to isolate particular pattern and then subtract a variable which is weighted for of pattern from the

It minimizes the local variance restore

$$\begin{aligned} g(x, y) &= f(x, y) + \eta(x, y) \\ &\quad \text{↓ } f(x) \\ g(u, v) &= \text{N}(u, v) \end{aligned}$$

$$\begin{aligned} N(u, v) &= H(u, v) \cdot G(u, v) \\ &\quad \text{↓ } \text{notch pass} \end{aligned}$$



$$\hat{f}(x, y) = g(x, y) - \eta(x, y)$$

↓  
extreme

For optimum

$$\hat{f}(x, y) = g(x, y) - \underbrace{\omega(x, y)}_{\text{to find}} \underbrace{\eta(x, y)}_{\text{weighted}}$$

Local Variance

$$\sigma_L^2(x, y) = \frac{1}{(2a+1)(2b+1)} \sum_{s=-a}^{+a} \sum_{t=-b}^{+b} \left\{ \hat{f}(x+s, y+t) - \bar{\hat{f}}(x, y) \right\}^2$$

l'mean

$$\bar{\hat{f}}(x, y) = \frac{1}{(2a+1)(2b+1)} \sum_{s=-a}^{+a} \sum_{t=-b}^{+b} \hat{f}(x+s, y+t)$$

$$\Rightarrow \sigma_L^2(x, y) = \frac{1}{(2a+1)(2b+1)} \sum_s \sum_t \left\{ [g(x+s, y+t) - w(x+s, y+t) \eta_{x+s, y+t}] \right. \\ \left. - [\bar{g}(x, y) - \bar{w}(x, y) \bar{\eta}(x, y)] \right\}^2$$

Assumption,

$$w(x+s, y+t) = w(x, y)$$

$$\Rightarrow \sigma_L^2(x, y) = \frac{1}{(2a+1)(2b+1)} \sum_s \sum_t \left\{ [g(x+s, y+t) - w(x, y) \eta_{x+s, y+t}] \right. \\ \left. - [\bar{g}(x, y) - w(x, y) \bar{\eta}(x, y)] \right\}^2$$

for optimization or to achieve min. value of  $\sigma_L^2$

$$\frac{\partial \sigma_L^2}{\partial w(x, y)} = \frac{\partial}{\partial w(x, y)} \left[ \quad \right] = \left[ \quad \right] = 0$$

$$\Rightarrow \boxed{w(x, y) = \frac{g(x, y) \eta(x, y) - \bar{g}(x, y) \cdot \bar{\eta}(x, y)}{\bar{\eta}^2(x, y) - (\bar{\eta}(x, y))^2}}$$

$$\hat{f}_{opt.}(x, y) = g(x, y) - w_{opt.}(x, y) \cdot \eta(x, y)$$

04/04/18

Assignment → Q (submit to 513EC1007@nitkkl.ac.in by 12/04/18)

- ① Take any gray image where spatial dependent noise is visible and name it Fig-a.
- ② Present the spectrum corresponding to Fig-a in Fig-1
- ③ comment on Fig-b, particularly about the actual image information and possible noise.
- ④ extract the noise using a suitable bandpass/notch filter. Present its spatial and spectral appearance.

in gray image naming Fig.-c and Fig.-d respectively

- ⑤ Find the histogram of Fig.-c.
- ⑥ Find the local variance and mean.
- ⑦ Finally, find the optimum filtering weight for  $w_{opt}(x,y)$ .

→ Linear, position-invariant degradation :-

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

degradation fn. (operator)

① Linearity :-

$$H[af_1(x,y) + bf_2(x,y)] = aH[f_1(x,y)] + bH[f_2(x,y)]$$

say  $a=1, b=1$

②  $\Rightarrow$  additivity property

(b) say,  $f_2(x,y) = 0$

$$H[f_1(x,y) + b f_2(x,y)] = aH[f_1(x,y)]$$

$\Rightarrow$  Homogeneity property

② Position / space invariant :-

$g(x,y) = H[f(x,y)]$ , is said to be p/s invariant

if  $g(x-\alpha, y-\beta) = H[f(x-\alpha, y-\beta)]$

→ Now we take

$$g(x,y) = H[f(x,y)] \rightarrow \text{for simplicity}$$

$$f(x,y) = \iint_{-\infty}^{\infty} f(\alpha, \beta) \delta(x-\alpha, y-\beta) d\alpha d\beta$$

$$\begin{aligned}
 g(x,y) &= H[f(x,y)] \\
 &= H \iint f(\alpha, \beta) \delta(x-\alpha, y-\beta) d\alpha d\beta \\
 &= \iint H[f(\alpha, \beta) \delta(x-\alpha, y-\beta)] d\alpha d\beta \quad (\text{linearity}) \\
 &= \iint f(\alpha, \beta) H[\delta(x-\alpha, y-\beta)] d\alpha d\beta \quad (\text{opposite})
 \end{aligned}$$

Let  $h(x, \alpha, y, \beta) = H[\delta(x-\alpha, y-\beta)] = h(x-\alpha, y-\beta)$   
     • "point spreading function"

$$\begin{aligned}
 \therefore g(x,y) &= \iint f(\alpha, \beta) h(x-\alpha, y-\beta) d\alpha d\beta \\
 &= \iint f(\alpha, \beta) h(x-\alpha, y-\beta) d\alpha d\beta \quad \beta: \text{spreading} \\
 &= \iint_{-\infty}^{\infty} f(\alpha, \beta) h(x-\alpha, y-\beta) d\alpha d\beta + \eta(x, y)
 \end{aligned}$$

$$\boxed{g(x,y) = f(x,y) * h(x,y) + \eta(x,y)}$$

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

$$\Rightarrow G(u,v) \overset{?}{=} H(u,v) = \frac{F(u,v)}{H(u,v)} \overset{?}{=} \tilde{H}(u,v) + N(u,v) \tilde{H}(u,v)$$

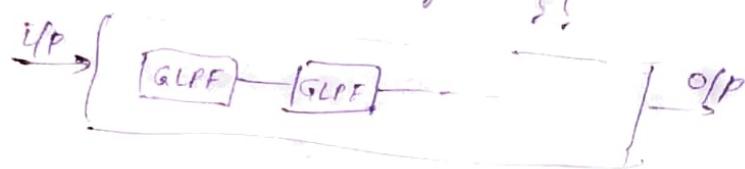
Identify pr

07/04/14

Tutorial

1) Given an image of size  $m \times n$ . you are asked to perform an exp. that consist of a repeatedly low pass filtering the image using one Gaussian RPF. cut-off freq.  $\nu_0$ . Let  $k_{\min}$  be the smallest positive no. representable in the machine. you are going to perform the exp.

Let  $K$  denotes the no. of application of the filter. Can you predict without doing the exp., what is the result of the system ??



$$\begin{aligned} \rightarrow G(u, v) &= H(u, v) \cdot F(u, v) \\ &= e^{-D^2(u, v)/2\nu_0^2} \cdot F(u, v) \end{aligned}$$

$$G_K(u, v) = e^{-KD^2(u, v)/2\nu_0^2} \cdot F(u, v)$$

$$H_K(u, v) = e^{-KD^2(u, v)/2\nu_0^2}$$

Yes, we can predict the result  
for  $K \rightarrow \text{large}$

$$\begin{aligned} H_K(u, v) &= e^{-KD^2(u, v)/2\nu_0^2} \\ &= \begin{cases} 1 & \text{if } (u, v) = (0, 0) \\ 0 & \text{otherwise} \end{cases} \end{aligned}$$

2) Derive an expression for the min of  $K$  that will guarantee ~~that~~ gives

$$H_K(u, v) = \begin{cases} 1 & ; (u, v) = (0, 0) \\ 0 & \text{otherwise} \end{cases}$$

$$e^{-K D^2(u,v) / 2D_0^2} < K_{min}$$

$$\Rightarrow K > - \frac{\ln(K_{min})}{D^2(u,v) / 2D_0^2}$$

$$\Rightarrow K > \frac{2D_0^2 \ln(K_{min})}{D^2(u,v)}$$

37. Consider a set of images generated by an exp in dealing with stellar event. In this exp each image contains a set of bright widely scattered dots corresponding to these dots are barely visible due to superimpose illumination resulting from atmospheric. If these images are noted as product of convolution with a set of impulses then given enhancement procedure based on homomorphic design to bring component due to the

→ For one star

$$K_1 \delta(x_0, y_0) K_2 \delta(x_1, y_1)$$

$$f(x, y) = K \delta(x_0, y_0)$$

$$\begin{aligned} \ln f(x, y) &= \text{dark} + \ln \{\delta(x_0, y_0)\} \\ &= K' + \delta'(x_0, y_0) \end{aligned}$$

$$E[\ln f(x, y)] = K' 2\pi \delta(0, 0) + e^{-J2\pi} (\quad)$$

4).

i/p 2.I.P

(i)

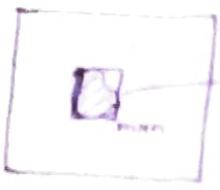
o/p 9.I.Q

(ii)

11/04/13

→ Estimation of degradation function :

- (1) Estimation by image observation
- (2) " " Experimentation
- (3) " " Mathematical modeling.

① 

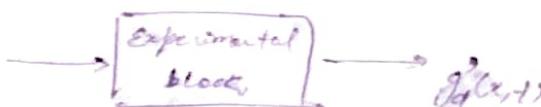
$$g_d(x,t) = h_d(x,y) * f(x,y)$$

$\Rightarrow G(u,v) = H_d(u,v) \cdot F(u,v)$

$$\Rightarrow H_d(u,v) = \frac{G(u,v)}{F(u,v)}$$

Degradation fn

- ② design a system for the exp.  
collect reference image of some type



$$H(u,v) = \frac{G(u,v)}{F[A \cdot S(x,y)]}$$

↑ Inverse of light

$$\Rightarrow H(u,v) = \frac{G(u,v)}{A}$$

③  $H(u,v) = e^{-k(u^2+v^2)^{1/2}}$  → Hufnagel & Stanley [1964]  
Atmospheric turbulence  
It is almost like a Gaussian LPF eqn.

① Example : Modeling an occurrence

Let us consider an image has been blurred by uniform linear motion b/w the image & sensor during acquisition.

$x_0(t)$  &  $y_0(t)$   $\rightarrow$  spatial movement for  $T$  seconds.

$$g(x, y) = \int_0^T [f(x - x_0(t), y - y_0(t))] dt$$

↳ degraded image

$$\begin{aligned} G(u, v) &= \iint_{-\infty}^{+\infty} g(x, y) e^{-j2\pi(ux+vy)} dx dy \\ &= \iint_{-\infty}^{+\infty} \left[ \int_0^T f(x - x_0(t), y - y_0(t)) dt \right] e^{-j2\pi(ux+vy)} dx dy \\ &= \int_0^T \left[ \iint f(x - x_0(t), y - y_0(t)) e^{-j2\pi(ux+vy)} dx dy \right] dt \\ &= \int_0^T \left[ \iint f(\underline{x - x_0(t)}, \underline{y - y_0(t)}) e^{-j2\pi\{u\underline{(x - x_0(t))} + v\underline{(y - y_0(t))}\}} dx dy \right] dt \\ &= \int_0^T \left[ F(u, v) e^{-j2\pi\{u\underline{x_0(t)} + v\underline{y_0(t)}\}} \right] dt \\ &= F(u, v) \left[ \int_0^T e^{-j2\pi(u\underline{x_0(t)} + v\underline{y_0(t)})} dt \right] \\ &= F(u, v) \cdot H(u, v) \end{aligned}$$

where,  $H(u, v) = \int_0^T e^{-j2\pi(u\underline{x_0(t)} + v\underline{y_0(t)})} dt$