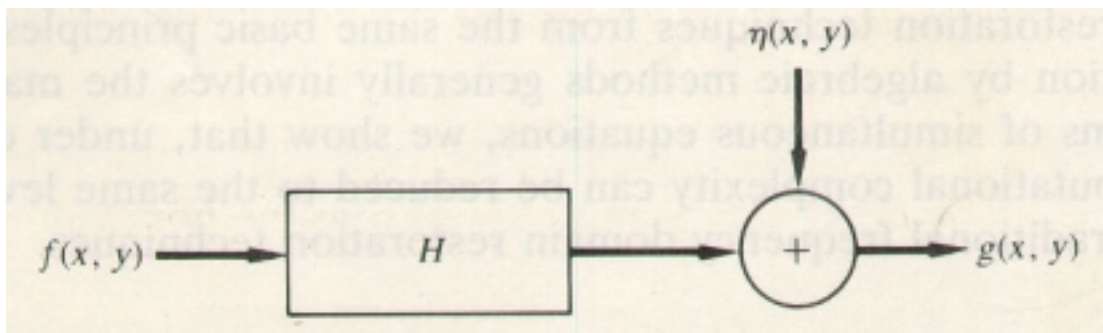


## Chapter 5. Image Restoration

- A process to reconstruct or recover an image that has been degraded by using some a priori knowledge of the degradation phenomenon
- Modeling of degradation  
Inverse process
- Example: Removal of image blur by applying a deblurring function

### 5.1 Degradation Model



$H$  : degradation operator

$\eta$  : noise

$f(x,y)$  : input image

$g(x,y)$  : degraded output

- Restoration
  - the process obtaining an approximation to  $f(x,y)$ , given  $g(x,y)$ ,  $H$  and  $\eta$

#### 5.1.1 Some Definitions

- $g(x, y) = H[f(x, y)] + \eta(x, y)$   
no noise case:  $\eta(x, y) = 0$
- $H$  : linear
  - $H[k_1 f_1 + k_2 f_2] = k_1 H[f_1] + k_2 H[f_2]$  : additivity and homogeneity
  - position (or space) invariant  
 $H[f(x - \alpha, y - \beta)] = g(x - \alpha, y - \beta)$

### 5.1.2 Degradation Model for Continuous Functions

- from the definition of impulse function

$$f(x, y) = \iint_{-\infty}^{\infty} f(\alpha, \beta) \delta(x - \alpha, y - \beta) d\alpha d\beta \quad ; \text{shifting property}$$

if  $\eta(x, y) = 0$

$$g(x, y) = H \left[ \iint_{-\infty}^{\infty} f(\alpha, \beta) \delta(x - \alpha, y - \beta) d\alpha d\beta \right]$$

from additive property

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

from homogeneity property

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

- Impulse response of H

$$H[\delta(x - \alpha, y - \beta)] = h(x, \alpha, y, \beta)$$

$$= h(x - \alpha, y - \beta) \quad : \text{position invariant}$$

- General model with noise

$$g(x, y) = \iint_{-\infty}^{\infty} f(\alpha, \beta) h(x - \alpha, y - \beta) d\alpha d\beta + \eta(x, y)$$

noise : independent of position in image

### 5.1.3 Discrete Formulation

- **Discrete, space-invariant degradation model**

- 1-D sampled function

$$f(x) : x=0, 1, 2, \dots, A-1$$

$$g(x) : x=0, 1, 2, \dots, B-1$$

- Convolution:

- period of sampled function : M

to avoid the overlap in convolution

$$M \geq A + B - 1 ; \text{zero paddings}$$

- Extending the function with zero  $\rightarrow f_e(x), h_e(x)$

$$g_e(x) = \sum_{m=0}^{M-1} f_e(m)h_e(x-m) \quad \text{for } x=0, 1, 2, \dots, M-1$$

- in matrix form ;

$$\mathbf{g} = \mathbf{H}\mathbf{f}$$

where

$$\mathbf{g} = \begin{bmatrix} g_e(0) \\ g_e(1) \\ \vdots \\ g_e(M-1) \end{bmatrix} \quad \mathbf{f} = \begin{bmatrix} f_e(0) \\ f_e(1) \\ \vdots \\ f_e(M-1) \end{bmatrix}$$

$$\mathbf{H} = \begin{bmatrix} h_e(0) & h_e(-1) & \Lambda & h_e(-M+1) \\ h_e(1) & h_e(0) & \Lambda & h_e(-M+2) \\ h_e(2) & h_e(1) & \Lambda & h_e(-M+3) \\ \vdots & \vdots & \vdots & \vdots \\ \mathbf{M} & \mathbf{M} & \mathbf{O} & \mathbf{M} \\ h_e(M-1) & h_e(M-2) & \Lambda & h_e(0) \end{bmatrix}; \text{ circulant matrix}$$

- By periodicity assumption of  $h_e(x)$

$$h_e(x) = h_e(M+x) ; \text{ modulo } M$$

$$\mathbf{H} = \begin{bmatrix} h_e(0) & h_e(M-1) & \Lambda & h_e(1) \\ h_e(1) & h_e(0) & \Lambda & h_e(2) \\ h_e(2) & h_e(1) & \Lambda & h_e(3) \\ \vdots & \vdots & \vdots & \vdots \\ \mathbf{M} & \mathbf{M} & \mathbf{O} & \mathbf{M} \\ h_e(M-1) & h_e(M-2) & \Lambda & h_e(0) \end{bmatrix}$$

- rows : circular shift to the right

ex.) if  $A=4$  and  $B=3$ ,  $M=6$

In this case  $\mathbf{f}$  and  $\mathbf{g}$  are 6-D vectors and  $\mathbf{H}$  is the  $6 \times 6$  matrix

$$\mathbf{H} = \begin{bmatrix} h_r(0) & h_r(5) & h_r(4) & \cdots & h_r(1) \\ h_r(1) & h_r(0) & h_r(5) & \cdots & h_r(2) \\ h_r(2) & h_r(1) & h_r(0) & \cdots & h_r(3) \\ \vdots & & & & \\ h_r(5) & h_r(4) & h_r(3) & \cdots & h_r(0) \end{bmatrix}$$

However, as  $h_r(x) = 0$  for  $x = 3, 4, 5$ , and  $h_r(x) = h(x)$  for  $x = 0, 1, 2$ ,

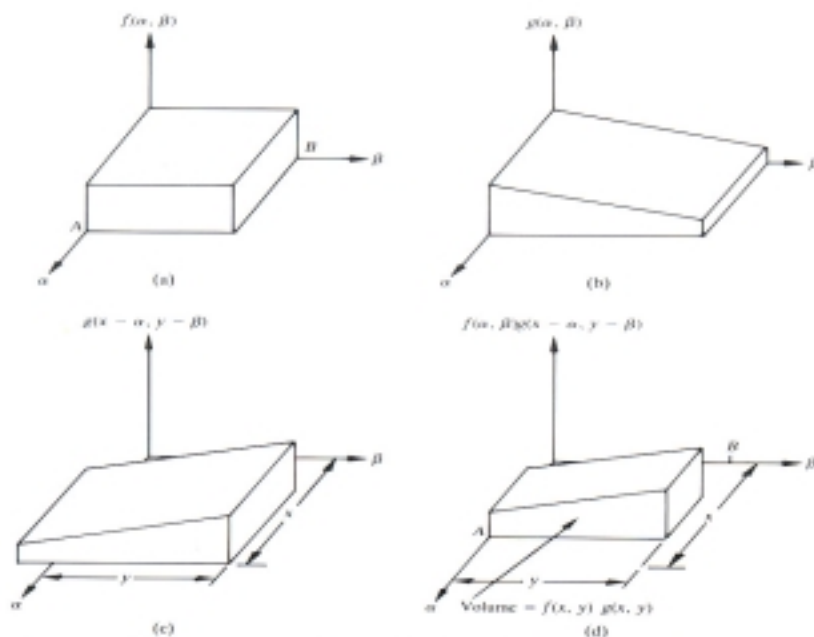
$$\mathbf{H} = \begin{bmatrix} h(0) & & & & h(2) & h(1) \\ h(1) & h(0) & & & & h(2) \\ h(2) & h(1) & h(0) & & & \\ & h(2) & h(1) & h(0) & & \\ & & h(2) & h(1) & h(0) & \\ & & & h(2) & h(1) & h(0) \end{bmatrix}$$

where all elements not indicated in the matrix are zero.

- 2-D case : straightforward extension of 1-D case

- $f(x,y) : A \times B$

- $h(x,y) : C \times D$



- Extended image of size  $M \times N$  by zero padding

$$f_e(x, y) = \begin{cases} f(x, y) & 0 \leq x \leq A-1 \quad \text{and} \quad 0 \leq y \leq B-1 \\ 0 & A \leq x \leq M-1 \quad \text{or} \quad B \leq y \leq N-1 \end{cases}$$

$$h_e(x, y) = \begin{cases} h(x, y) & 0 \leq x \leq C-1 \quad \text{and} \quad 0 \leq y \leq D-1 \\ 0 & C \leq x \leq M-1 \quad \text{or} \quad D \leq y \leq N-1 \end{cases}$$

where  $M \geq A+C-1$ ,  $N \geq B+D-1$

- Convolution, in general ;

$$g_e(x, y) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} f_e(m, n) h_e(x-m, y-n) + \eta_e(x, y)$$

for  $x=0, 1, \dots, M-1$

$y=0, 1, \dots, N-1$

- in matrix form ;

$\mathbf{g} = \mathbf{H}\mathbf{f} + \mathbf{n}$  ; linear, space-invariant degradation process

where  $\mathbf{f}, \mathbf{g}, \mathbf{n}$  :  $MN$ -dimensional column vectors

✓ the first  $N$  elements of  $\mathbf{f}$  : the element in the first row of  $f_e(x, y)$

the second  $N$  elements of  $\mathbf{f}$  : the element in the second row of  $f_e(x, y)$

$$\mathbf{g} = \begin{bmatrix} g_e(0,0) \\ g_e(0,1) \\ \text{M} \\ g_e(0,N-1) \\ \\ g_e(1,0) \\ g_e(1,1) \\ \text{M} \\ g_e(1,N-1) \\ \text{M} \\ g_e(M-1,0) \\ g_e(M-1,1) \\ \text{M} \\ g_e(M-1,N-1) \end{bmatrix} \quad \mathbf{f} = \begin{bmatrix} f_e(0,0) \\ f_e(0,1) \\ \text{M} \\ f_e(0,N-1) \\ \\ f_e(1,0) \\ f_e(1,1) \\ \text{M} \\ f_e(1,N-1) \\ \text{M} \\ f_e(M-1,0) \\ f_e(M-1,1) \\ \text{M} \\ f_e(M-1,N-1) \end{bmatrix}$$

$$\mathbf{H} = \begin{bmatrix} H_0 & H_{M-1} & \Lambda & H_1 \\ H_1 & H_0 & \Lambda & H_2 \\ H_2 & H_1 & \Lambda & H_3 \\ \text{M} & \text{M} & \text{O} & \text{M} \\ H_{M-1} & H_{M-2} & \Lambda & H_0 \end{bmatrix} : \text{MN} \times \text{MN} \text{ matrix, block circulant matrix}$$

$$\text{where } \mathbf{H}_j = \begin{bmatrix} h_e(j,0) & h_e(j,N-1) & \Lambda & h_e(j,1) \\ h_e(j,1) & h_e(j,0) & \Lambda & h_e(j,2) \\ h_e(j,2) & h_e(j,1) & \Lambda & h_e(j,3) \\ \text{M} & \text{M} & \text{O} & \text{M} \\ h_e(j,N-1) & h_e(j,N-2) & \Lambda & h_e(j,0) \end{bmatrix}$$

- computational complexity  
: reduced considerably by taking advantage of the circulant properties of  $\mathbf{H}$

## 5.2 Diagonalization of circulant and block-circulant matrices

### 5.2.1 circulant matrices

For  $M \times M$  circulant matrix :

$$\mathbf{H} = \begin{bmatrix} h_e(0) & h_e(M-1) & \Lambda & h_e(1) \\ h_e(1) & h_e(0) & \Lambda & h_e(2) \\ h_e(2) & h_e(1) & \Lambda & h_e(3) \\ \vdots & \vdots & \vdots & \vdots \\ h_e(M-1) & h_e(M-2) & \Lambda & h_e(0) \end{bmatrix}$$

- define a scalar

$$\lambda(k) = h_e(0) + h_e(M-1) \exp\left[j \frac{2\pi}{M} k\right] + h_e(M-2) \exp\left[j \frac{2\pi}{M} 2k\right] \Lambda + h_e(1) \exp\left[j \frac{2\pi}{M} (M-1)k\right]$$

- define a vector ;

$$\mathbf{w}(k) = \begin{bmatrix} 1 \\ \exp\left[j \frac{2\pi}{M} k\right] \\ \exp\left[j \frac{2\pi}{M} 2k\right] \\ \vdots \\ \exp\left[j \frac{2\pi}{M} (M-1)k\right] \end{bmatrix}$$

for  $k=0, 1, \dots, M-1$

- $\mathbf{H}\mathbf{w}(k) = \lambda(k)\mathbf{w}(k)$  ;

where  $\mathbf{w}(k)$  : eigenvector of  $\mathbf{H}$

$\lambda(k)$  : eigenvalue of  $\mathbf{H}$

$\lambda(k)$

- define  $M \times M$  matrix  $\mathbf{W}$  ;

$$\mathbf{W} = [\mathbf{w}(0) \quad \mathbf{w}(1) \quad \Lambda \quad \mathbf{w}(M-1)]$$

ki-th element of  $\mathbf{w}$

$$w(k, i) = \exp\left[j \frac{2\pi}{M} ki\right]$$

ki-th element of inverse matrix  $\mathbf{W}^{-1}$

$$w^{-1}(k, i) = \frac{1}{M} \exp\left[-j \frac{2\pi}{M} ki\right]$$

-  $\mathbf{W}\mathbf{W}^{-1} = \mathbf{W}^{-1}\mathbf{W} = \mathbf{I}$

because the column of  $\mathbf{W}$  are linearly independent

- From elementary matrix theory

$$\mathbf{H} = \mathbf{W}\mathbf{D}\mathbf{W}^{-1}$$

$$\Rightarrow \mathbf{D} = \mathbf{W}^{-1}\mathbf{H}\mathbf{W}$$

where  $\mathbf{D}$ : a diagonal matrix whose elements  $D(k,k)$  are the eigenvalue of  $\mathbf{H}$

### 5.2.2 Block-Circulant Matrix

-  $w_M(i, m) = \exp\left[j \frac{2\pi}{M} im\right]$

$$w_N(k, n) = \exp\left[j \frac{2\pi}{M} kn\right]$$

-  $\mathbf{W}$ : matrix of size  $MN \times MN$  and containing  $M^2$  partition of size  $N \times N$

-  $i$ m-th partition of  $\mathbf{W}$

$$\mathbf{W}(i, m) = \frac{1}{M} \mathbf{W}_N(m) \quad \text{for } i=0, 1, \dots, M-1$$

where  $\mathbf{W}_N$  is  $N \times N$  matrix with element of  $W_N(k, n) = w_N(k, n)$  for  $k, n=0, 1, \dots, N-1$

- for inverse matrix  $\mathbf{W}^{-1}$ : matrix of size  $MN \times MN$  and containing  $M^2$  partition of size  $N \times N$



$$\mathbf{W}^{-1}(i, m) = \frac{1}{M} w^{-1}(i, m) \mathbf{W}_N^{-1}$$

where  $\mathbf{W}_N^{-1}$  is  $N \times N$  matrix with element of  $W_N^{-1}(k, n) = \frac{1}{N} w_N^{-1}(k, n)$  for  $k, n=0, 1, \dots, N-1$

$$\text{and } w_N^{-1} i m = \left[ -j \frac{2\pi}{N} im \right] \text{ for } i, m=0, 1, \dots, N-1$$

$$- \quad \mathbf{W}\mathbf{W}^{-1} = \mathbf{W}^{-1}\mathbf{W} = \mathbf{I} \text{ (MN} \times \text{MN matrix)}$$

$$- \quad = \mathbf{W}\mathbf{D}\mathbf{W}^{-1}$$

$$= \mathbf{W}^{-1}\mathbf{H}\mathbf{W}$$

where  $\mathbf{D}$  : a diagonal matrix whose elements  $D(k, k)$  are related to the discrete FT of  $h_e(x, y)$

### 5.2.3 Effects of Diagonalization on the Degradation Model

$$\bullet \quad = \mathbf{f} = \mathbf{W}^{-1}\mathbf{f}$$

$$^{-1} = \mathbf{W}^{-1}\mathbf{f}$$

where  $\mathbf{W}^{-1}\mathbf{f}$  :  $M$ -dimensional column vector

$$\text{k-th element is } F(k) = \frac{1}{M} \sum_{i=0}^{M-1} f_e(i) \exp\left[-j \frac{2\pi}{M} ki\right]$$

for  $k=0, 1, \dots, M-1$

$\mathbf{W}^{-1}\mathbf{f}$  : Fourier Transform of  $\mathbf{f} \Rightarrow F(k)$

$^{-1}\mathbf{g}$  : Fourier Transform of  $\mathbf{g} \Rightarrow G(k)$

- For eigenvalue :

$$\lambda(k) = e^{-j\frac{2\pi}{M}k} + e^{-j\frac{2\pi}{M}(M-k)} \left[ e^{-j\frac{2\pi}{M}k} + e^{-j\frac{2\pi}{M}(M-k)} \right] \Lambda + e^{-j\frac{2\pi}{M}k} + e^{-j\frac{2\pi}{M}(M-k)}$$

$$\text{- by } \exp\left[j\frac{2\pi}{M}(M-i)k\right] = \exp\left[-j\frac{2\pi}{M}ki\right]$$

$$D(k, k) = \lambda(k) = \sum_{i=0}^{M-1} h_e(i) \exp\left[-j\frac{2\pi}{M}ki\right] = MH(k)$$

for  $k=0, 1, \dots, M-1$

- in other words, 1-D discrete Formulation of degradation model is 1D Fourier transform

$$G(k) = MH(k)F(k) \quad \text{for } k=0, 1, \dots, M-1$$

## 5.3 Algebraic Approach to Restoration

### 5.3.1 Unconstrained Restoration

- in absence of any knowledge about  $\mathbf{n}$

$\mathbf{n} = \mathbf{g} - \mathbf{H}\mathbf{f}$  ; noise term in degradation model

- Euclidean Norm

$$\|\mathbf{f}\| = \|\mathbf{f}\| \longrightarrow \hat{\mathbf{f}}$$

by definition, squared norm.

$$\|\mathbf{n}\|^2 = \mathbf{n}^T \mathbf{n}, \|\mathbf{g} - \mathbf{H}\mathbf{f}\|^2 = (\mathbf{g} - \mathbf{H}\hat{\mathbf{f}})^T (\mathbf{g} - \mathbf{H}\hat{\mathbf{f}})$$

- criterion function

$$\hat{\mathbf{f}} = \arg \min_{\mathbf{f}} \|\mathbf{H}\mathbf{f}\|^2$$

$$\frac{\partial}{\partial \hat{\mathbf{f}}} (\|\mathbf{g} - \mathbf{H}\hat{\mathbf{f}}\|^2) = 0 = \mathbf{H}^T (\mathbf{g} - \mathbf{H}\hat{\mathbf{f}})$$

$$\Rightarrow \hat{\mathbf{f}} = (\mathbf{H}^T \mathbf{H})^{-1} \mathbf{H}^T \mathbf{g} = \mathbf{H} (\mathbf{H}^T)^{-1} \mathbf{H}^T \mathbf{g}$$

- if  $\mathbf{H}$  is square matrix

$$\Rightarrow \hat{\mathbf{f}} = \mathbf{H}^{-1} \mathbf{g}$$

### 5.3.2 Constrained Restoration

- criterion function

- least squares restoration as one of minimizing  $\|\mathbf{Q}\hat{\mathbf{f}}\|^2$  subject to constraint

$$\|\mathbf{g} - \mathbf{H}\hat{\mathbf{f}}\|^2 = \|\mathbf{n}\|^2$$

- Using Lagrange multiplier

$$\mathbf{J}(\hat{\mathbf{f}}) = \|\mathbf{Q}\hat{\mathbf{f}}\|^2 + \alpha (\|\mathbf{g} - \mathbf{H}\hat{\mathbf{f}}\|^2 - \|\mathbf{n}\|^2)$$

where  $\alpha$  : Lagrange multiplier

- minimization

$$\frac{\partial \mathbf{J}(\hat{\mathbf{f}})}{\partial \hat{\mathbf{f}}} = 0 = 2\mathbf{Q}^T \mathbf{Q}\hat{\mathbf{f}} - 2\alpha \mathbf{H}^T (\mathbf{g} - \mathbf{H}\hat{\mathbf{f}})$$

$$\Rightarrow \hat{\mathbf{f}} = (\mathbf{H}^T \mathbf{H} + \gamma \mathbf{Q}^T \mathbf{Q})^{-1} \mathbf{H} \mathbf{g} \quad \text{where } \gamma = 1/\alpha$$