

3.5.3 Discrete Cosine Transform (DCT)

- **2N-point extended DFT**

- 1-D DCT pair :

- $$C(u) = \alpha(u) \sum_{x=0}^{N-1} f(x) \cos\left[\frac{(2x+1)u\pi}{2N}\right]$$

- inverse ;

$$f(x) = \sum_{u=0}^{N-1} \alpha(u) C(u) \cos\left[\frac{(2x+1)u\pi}{2N}\right]$$

where $\alpha(u) = \begin{cases} \sqrt{\frac{1}{N}} & \text{for } u = 0 \\ \sqrt{\frac{2}{N}} & \text{for } u = 1, 2, \dots, N-1 \end{cases}$

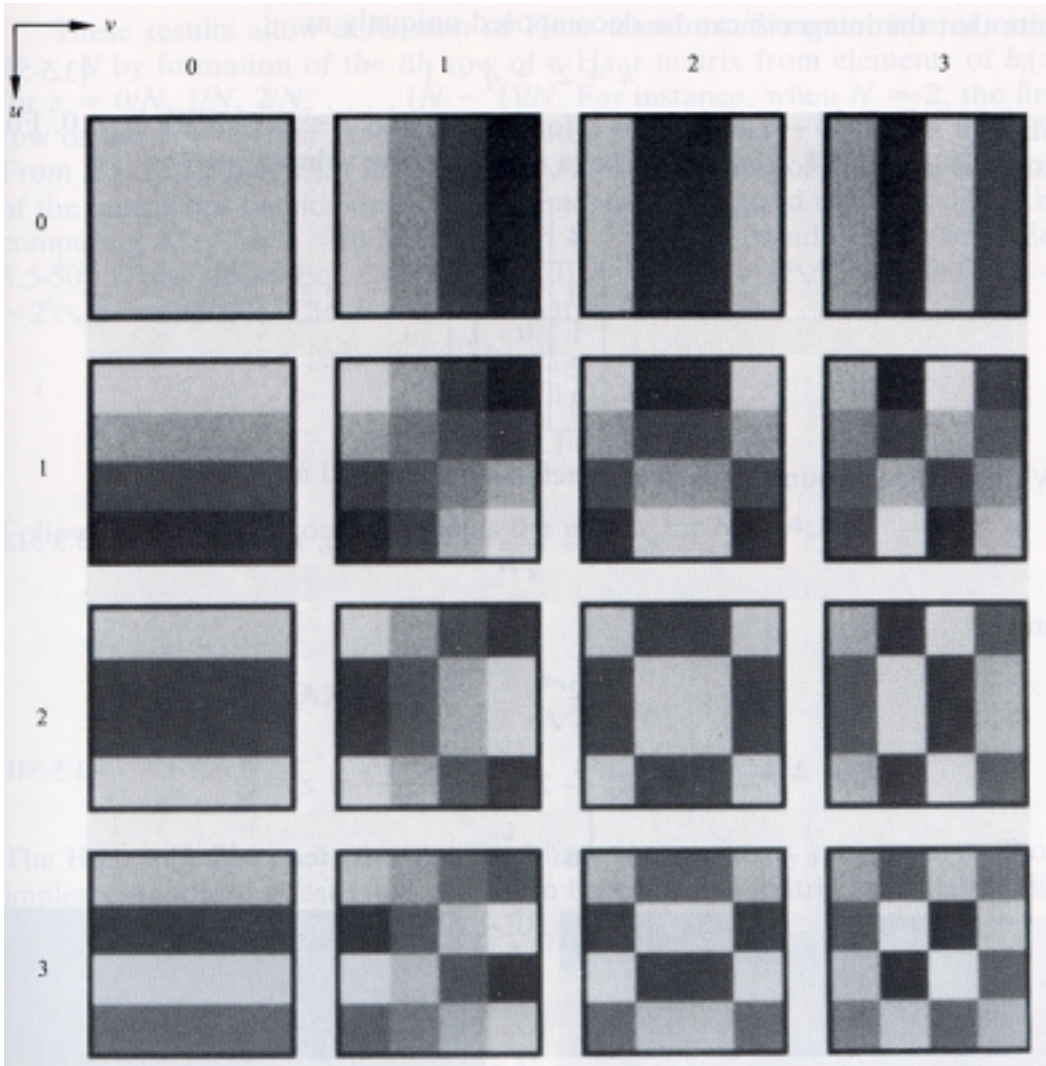
- 2-D DCT pair :

- $$C(u, v) = \alpha(u)\alpha(v) \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} f(x, y) \cos\left[\frac{(2x+1)u\pi}{2N}\right] \cos\left[\frac{(2y+1)v\pi}{2N}\right]$$

$$f(x, y) = \sum_{u=0}^{N-1} \sum_{v=0}^{N-1} \alpha(u)\alpha(v) C(u, v) \cos\left[\frac{(2x+1)u\pi}{2N}\right] \cos\left[\frac{(2y+1)v\pi}{2N}\right]$$

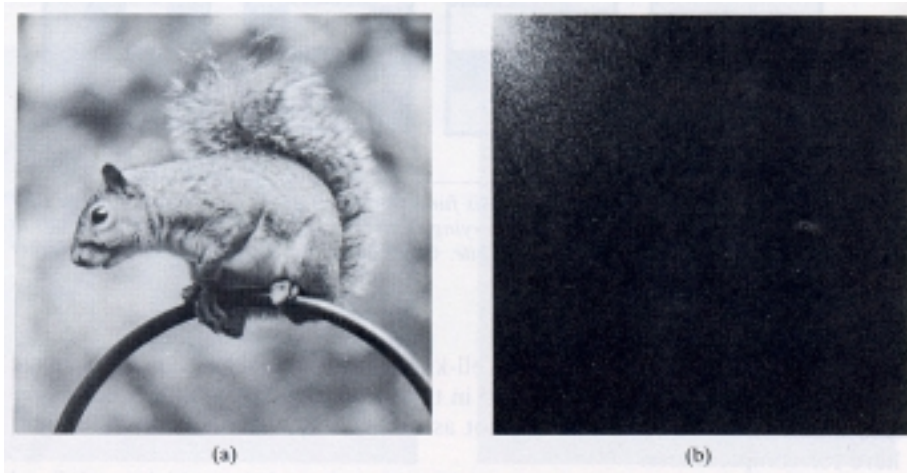
: mainly used in image compression (excellent energy compaction)

- DCT Basis Images (N=4) :



DCT basis function for $N=4$

- DCTed image (log. Mag.)



3.5.4 Harr Transform

- Based on Haar functions which are defined over continuous, closed interval
- 1st step in generating Haar Transform : (integer k decomposed uniquely)
k=0,..., N-1, N=2ⁿ

$$k = 2^p + q - 1 \quad (3.5-50)$$

where $0 \leq p \leq n - 1$, $q = 0$ or 1 for $p = 0$, and $1 \leq q \leq 2^p$ for $p \neq 0$. For example, if $N = 4$, k , q , and p have the following values:

k	p	q
0	0	0
1	0	1
2	1	1
3	1	2

With this background, the Haar functions are defined as

$$h_0(z) \triangleq h_{00}(z) = \frac{1}{\sqrt{N}} \quad \text{for } z \in [0, 1] \quad (3.5-51a)$$

and

$$h_k(z) \triangleq h_{pq}(z) = \frac{1}{\sqrt{N}} \begin{cases} 2^{p/2} & \frac{q-1}{2^p} \leq z < \frac{q-1/2}{2^p} \\ -2^{p/2} & \frac{q-1/2}{2^p} \leq z < \frac{q}{2^p} \\ 0 & \text{otherwise for } z \in [0, 1]. \end{cases} \quad (3.5-51b)$$

3.6 The Hotelling Transform (Karhunen-Loeve transform)

: based on statistical properties of vector representation

- a random vector :

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$$

- mean vector ;

$$\mathbf{m}_x = E\{\mathbf{x}\}$$

- covariance matrix ;

$$\mathbf{C}_x = E\{(\mathbf{x} - \mathbf{m}_x)(\mathbf{x} - \mathbf{m}_x)^T\}$$

: n×n matrix

- ✓ element c_{ii} : the variance of x_i
- ✓ element c_{ij} : covariance between x_i and x_j
- ✓ \mathbf{C}_x : real and symmetric ($c_{ij} = c_{ji}$)
- ✓ if x_i and x_j are uncorrelated
→ $c_{ij} = c_{ji} = 0$

- for M vector samples, approximately

$$\mathbf{m}_x = \frac{1}{M} \sum_{k=1}^M \mathbf{x}_k$$

$$\mathbf{C}_x = \frac{1}{M} \sum_{k=1}^M \mathbf{x}_k \mathbf{x}_k^T - \mathbf{m}_x \mathbf{m}_x^T$$

- \mathbf{C}_x : real, symmetric :

→ a set of n orthonormal eigenvectors : always exist

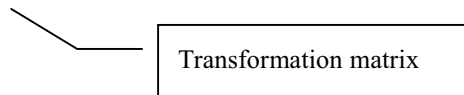
- \mathbf{e}_i : eigenvectors

- λ_i : eigenvalues $i=1,2,\dots,n$
 $\lambda_i \geq \lambda_{i+1}$
- $\mathbf{C}_x \mathbf{e}_i = \lambda_i \mathbf{e}_i$

- \mathbf{A} :
 - ✓ Matrix formed from the eigenvectors \mathbf{e}_i
 - ✓ the first row of \mathbf{A}
 : eigenvectors corresponding to the largest eigenvalue
 - ✓ the last row of \mathbf{A}
 : eigenvectors corresponding to the smallest eigenvalue

● Hotelling transform :

$$\mathbf{y} = \mathbf{A}(\mathbf{x} - \mathbf{m})$$



- mean of \mathbf{y} : $0 \rightarrow \mathbf{m}_y = 0$
- $\mathbf{C}_y = \mathbf{A} \mathbf{C}_x \mathbf{A}^T$; “similarity transformation”

$$= \begin{bmatrix} \lambda_1 & & & 0 \\ & \lambda_2 & & \\ & & \text{O} & \\ 0 & & & \lambda_n \end{bmatrix}$$

- ✓ element of \mathbf{y} vectors : uncorrelated
- $\mathbf{C}_x, \mathbf{C}_y$: the same eigenvalues, eigenvectors

$$\mathbf{x} = \mathbf{A}^{-1} \mathbf{y} + \mathbf{m}_x$$

ex) rotation of object (eigenvector 를 이용)

→ principal axes (or eigenvectors) 에 대하여 rotation

- rotation of axis;

$$y_1 = x_1 \cos \theta + x_2 \sin \theta$$

$$y_2 = -x_1 \sin \theta + x_2 \cos \theta$$

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

- for p pixels ;

$$\mathbf{m}_x \cong \frac{1}{p} \sum_{i=1}^p \mathbf{x}_i$$

$$\mathbf{C}_x \cong \frac{1}{p} \left[\sum_{i=1}^p \mathbf{x}_i \mathbf{x}_i^T \right] - \mathbf{m}_x \mathbf{m}_x^T$$

where \mathbf{x}_i : position (a,b) of pixels

$\mathbf{x}_i, \mathbf{m}_x$: 2×1 vectors

\mathbf{C}_x : 2×1 matrix

- eigenvectors of \mathbf{C}_x : $\mathbf{e}_1, \mathbf{e}_2$
 - ✓ direction : max variance
 - ⇒ the same as direction of eigenvectors ;

$$\mathbf{e}_1 = \begin{bmatrix} e_{11} \\ e_{12} \end{bmatrix}, \quad \mathbf{e}_2 = \begin{bmatrix} e_{21} \\ e_{22} \end{bmatrix}$$

$$\mathbf{A} = \begin{bmatrix} \mathbf{e}_1^T \\ \mathbf{e}_2^T \end{bmatrix} = \begin{bmatrix} e_{11} & e_{12} \\ e_{21} & e_{22} \end{bmatrix}$$

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} e_{11} & e_{12} \\ e_{21} & e_{22} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \rightarrow \mathbf{y} = \mathbf{A}(\mathbf{x} - \mathbf{m}_x)$$

$$\text{where } \mathbf{A} = \begin{bmatrix} e_{11} & e_{12} \\ e_{21} & e_{22} \end{bmatrix}$$

$$= \begin{bmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{bmatrix}$$

* \mathbf{m}_x 를 빼는것은 좌표축의 중심을 물체 영상의 중심에 놓는 역할을 한다.

● Reconstruction of \mathbf{x} from \mathbf{y} :

- $\mathbf{x} = \mathbf{A}^T \mathbf{y} + \mathbf{m}_x$

- \mathbf{A}_k : $k \times n$ matrix from the k eigenvectors corresponding to the k largest eigenvalues

- vector reconstructed by \mathbf{A}_k ;

$$\hat{\mathbf{x}} = \mathbf{A}_k \mathbf{y} + \mathbf{m}_x$$

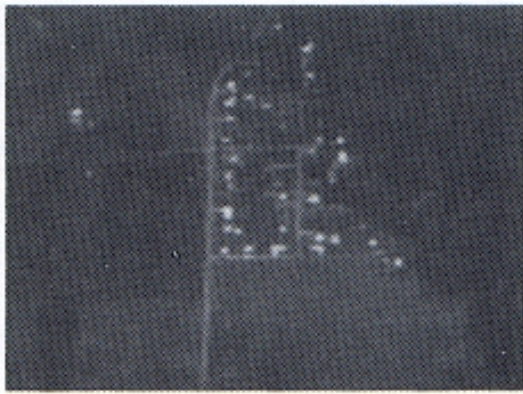
- mean square error between \mathbf{x} and $\hat{\mathbf{x}}$;

$$e_{ms} = \sum_{j=1}^n \lambda_j - \sum_{j=1}^k \lambda_j = \sum_{j=k+1}^n \lambda_j$$

→ “Hotelling Transform” is optimal in the sense that it minimizes the mean squared error

ex.) data compression (eigenvalue 를 이용)

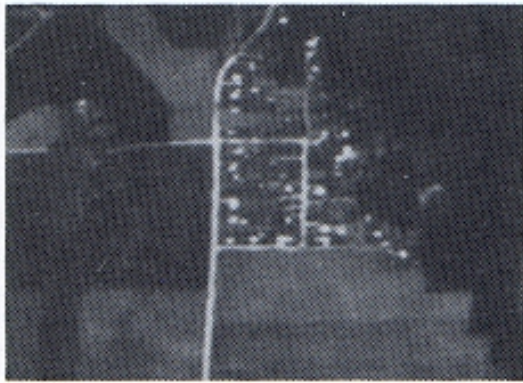
- 6 spectral images ; from 6-band multispectral scanner



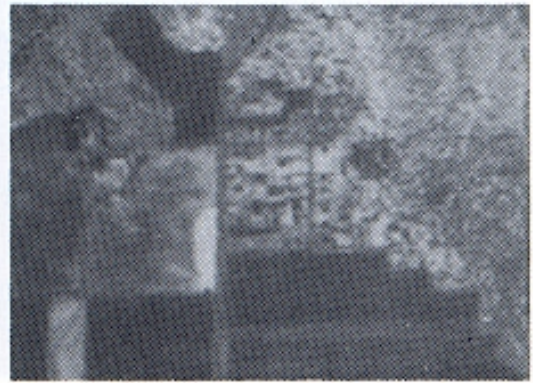
Channel 1



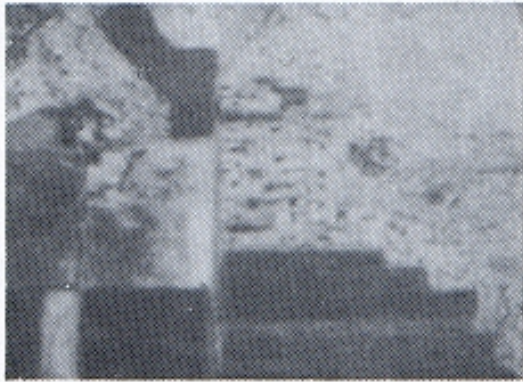
Channel 2



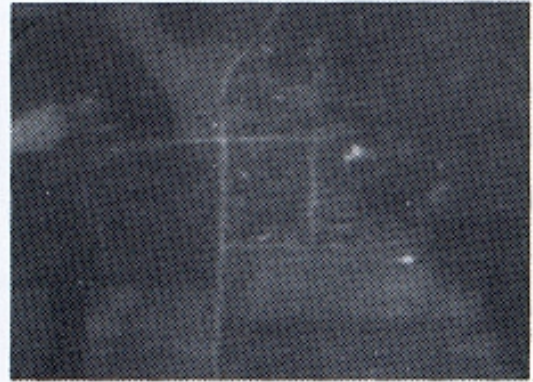
Channel 3



Channel 4



Channel 5



Channel 6

