

Lecture 5 Recall

Separable image transformation ①

Given image f , transform f by ① to get g (coefficient matrix)

$$g = \mathcal{O}(f) = A f B$$

Let $\tilde{A} = A^{-1}$ and $\tilde{B} = B^{-1}$. Then:

$$f = A^{-1} g B^{-1} = \tilde{A} g \tilde{B}$$

Important formula:

$$f = \sum_{i=1}^N \sum_{j=1}^N g_{ij} \left[\begin{array}{c} | \\ | \\ \tilde{a}_i \\ | \\ | \end{array} \right] \left[\begin{array}{c} - \\ - \\ \tilde{b}_j \\ - \\ - \end{array} \right]$$

(Remove terms with)

Take away small $g_{ij} \leftarrow$ Image compression.

$$\tilde{A} = \begin{pmatrix} | & | & & | \\ \tilde{a}_1 & \tilde{a}_2 & \dots & \tilde{a}_N \\ | & | & & | \end{pmatrix}$$

$$\tilde{B} = \begin{pmatrix} - & \tilde{b}_1 & - \\ - & \tilde{b}_2 & - \\ & \vdots & \\ - & \tilde{b}_N & - \end{pmatrix}$$

$N \times N$ elementary image

Recall

Haar transformation

(From now on, we assume all images $S = (f_{ij})_{\substack{0 \leq i \leq N-1 \\ 0 \leq j \leq N-1}}$)

Definition: (Haar functions) The Haar functions are defined as follows

$$H_0(t) \equiv \begin{cases} 1 & \text{if } 0 \leq t < 1 \\ 0 & \text{elsewhere} \end{cases}$$

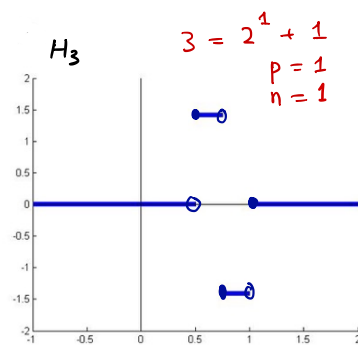
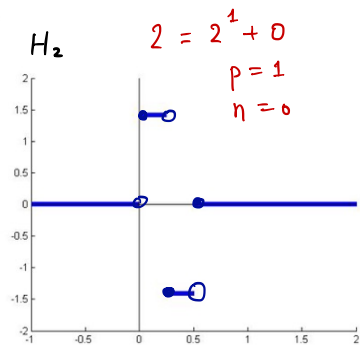
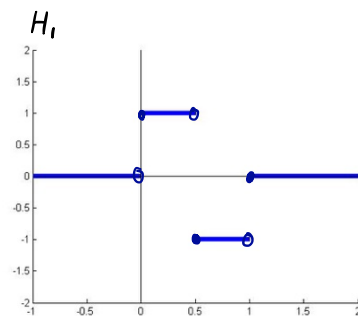
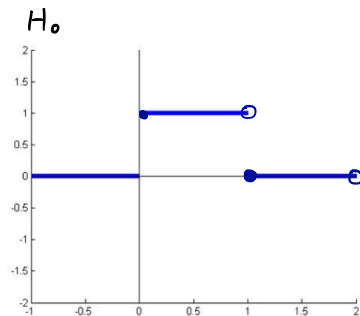
$$H_1(t) \equiv \begin{cases} 1 & \text{if } 0 \leq t < \frac{1}{2} \\ -1 & \text{if } \frac{1}{2} \leq t < 1 \\ 0 & \text{elsewhere} \end{cases}$$

$$H_{2^p+n} \equiv \begin{cases} \sqrt{2^p} & \text{if } \frac{n}{2^p} \leq t < \frac{n+0.5}{2^p} \\ -\sqrt{2^p} & \text{if } \frac{n+0.5}{2^p} \leq t < \frac{n+1}{2^p} \\ 0 & \text{elsewhere} \end{cases}$$

where $p=1, 2, \dots$, $n=0, 1, 2, \dots, 2^p-1$

Remark: If p is larger, H_{2^p+n} is compactly supported region

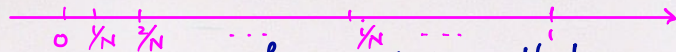
Examples of Haar functions:



Same wavefront
 Different locations
 $p \leftrightarrow$ wavefront
 $n \leftrightarrow$ location

Definition (Discrete Haar Transform)

The Haar Transform of a $N \times N$ image is done by dividing $[0, 1]$ into partitions



Let $H(k, i) \equiv H_k(\frac{i}{N})$ where $k, i = 0, 1, 2, \dots, N-1$

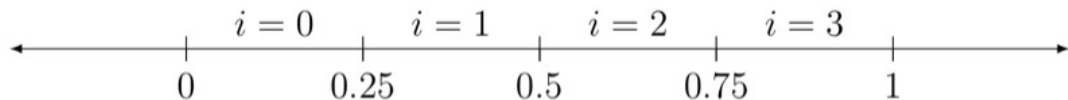
We obtain the Haar Transform matrix $\tilde{H} \equiv \frac{1}{\sqrt{N}} H$ where $H \equiv (H(k, i))_{0 \leq k, i \leq N-1}$

The Haar Transform of $f \in M_{N \times N}$ is defined as

$$g = \tilde{H} f \tilde{H}^T$$

Example Compute the Haar Transform matrix for a 4×4 image.

Solution: Divide $[0, 1]$ into 4 portions:



Example 2 Compute the Haar Transform of

$$f = \begin{pmatrix} 0 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 \end{pmatrix}$$

Solution:

$$g = \tilde{H} f \tilde{H}^T = \begin{pmatrix} 2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & -1 & 1 \\ 0 & 0 & 1 & -1 \end{pmatrix} \quad \left. \vphantom{\begin{pmatrix} 2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & -1 & 1 \\ 0 & 0 & 1 & -1 \end{pmatrix}} \right\} \text{More zeros}$$

Example 3 Suppose g in Example 2 is changed to:

$$g = \begin{pmatrix} 2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & -1 & 1 \\ 0 & 0 & 1 & 0 \end{pmatrix}$$

Reconstruct the original image.

Solution:

$$f = \tilde{H}^T g \tilde{H} = \begin{pmatrix} 0 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 \\ 1 & 0 & 0.5 & 0.5 \\ 0 & 1 & 0 & 0 \end{pmatrix} \quad \left. \vphantom{\begin{pmatrix} 0 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 \\ 1 & 0 & 0.5 & 0.5 \\ 0 & 1 & 0 & 0 \end{pmatrix}} \right\} \text{Localized error}$$

Remark:

1. Haar Transform usually produces coefficient matrix with more zeros!

2. Localized error in coefficient matrix causes localized error in the reconstructed image

Elementary images under Haar transform:

Using Haar transform, f can be written as:

$$f = \tilde{H}^T \underset{\substack{\uparrow \\ \text{transformed image}}}{g} \tilde{H}$$

Let $\tilde{H} = \begin{pmatrix} -\vec{h}_0^T \\ -\vec{h}_1^T \\ \vdots \\ -\vec{h}_{N-1}^T \end{pmatrix}$. Then: $f = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} g_{ij} \underbrace{\begin{pmatrix} \vec{h}_i & \vec{h}_j^T \end{pmatrix}}_{\substack{\text{"} \\ I_{ij}^H}}$

I_{ij}^T = elementary images under Haar Transform.

e.g. For 8×8 images, we have $64 = 8 \times 8$ elementary images :

$$\begin{array}{cccc} \vec{h}_0 & \vec{h}_0^T & \vec{h}_0 & \vec{h}_1^T & \dots & \vec{h}_0 & \vec{h}_7^T \\ \vec{h}_1 & \vec{h}_0^T & \vec{h}_1 & \vec{h}_1^T & \dots & \vec{h}_1 & \vec{h}_7^T \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \vec{h}_7 & \vec{h}_0^T & \vec{h}_7 & \vec{h}_1^T & \dots & \vec{h}_7 & \vec{h}_7^T \end{array} \quad (\text{each } \vec{h}_i, \vec{h}_j^T \in M_{8 \times 8}(\mathbb{R}))$$

Recall:

- Image decomposition f

$$f = \sum_{i=1}^N \sum_{j=1}^N g_{ij} \underbrace{I_{ij}}_{\text{elementary images}}$$

- ① Storage saving
 - ② Image processing by modifying transformed image (coefficient matrix)
(e.g. Removing coefficients associated to high-frequency elementary images)
- 2 Separable Image Transformation:
 - ① SVD (elementary images not universal and meaningless)
 - ② Haar (elementary images universal and meaningful) - unsmooth

Discrete Fourier Transform:

Definition:

The 2D DFT of a $M \times N$ image $g = (g(k, l))_{k, l}$, where $0 \leq k \leq M-1$, $0 \leq l \leq N-1$ is defined as:

$$\hat{g}(m, n) = \frac{1}{MN} \sum_{k=0}^{M-1} \sum_{l=0}^{N-1} g(k, l) e^{-j2\pi\left(\frac{km}{M} + \frac{ln}{N}\right)}$$

(where $j = \sqrt{-1}$, $e^{j\theta} = \cos \theta + j \sin \theta$)

Remark: The inverse of DFT is given by:

$$g(p, q) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} \hat{g}(m, n) e^{j2\pi\left(\frac{pm}{M} + \frac{qn}{N}\right)}$$

(no $\frac{1}{MN}!$)

DFT of g

(no -ve sign)

Proof of Inverse DFT:

$$\begin{aligned}
 \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} e^{j2\pi(\frac{pm}{M} + \frac{qn}{N})} \hat{g}(m, n) &= \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} e^{j2\pi(\frac{pm}{M} + \frac{qn}{N})} \frac{1}{MN} \sum_{k=0}^{M-1} \sum_{l=0}^{N-1} g(k, l) e^{-j2\pi(\frac{km}{M} + \frac{ln}{N})} \\
 &= \frac{1}{MN} \sum_{k=0}^{M-1} \sum_{l=0}^{N-1} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} g(k, l) e^{j2\pi(\frac{(p-k)m}{M} + \frac{(q-l)n}{N})} \\
 &= \frac{1}{MN} \underbrace{\sum_{k=0}^{M-1} \sum_{l=0}^{N-1} g(k, l) \sum_{m=0}^{M-1} e^{j2\pi(\frac{(p-k)m}{M})} \sum_{n=0}^{N-1} e^{j2\pi(\frac{(q-l)n}{N})}}_{(*)}
 \end{aligned}$$

Note that: $\sum_{m=0}^{M-1} e^{j2\pi(\frac{mt}{M})} = \underbrace{\frac{[e^{j2\pi(\frac{t}{M})}]^M - 1}{e^{j2\pi(\frac{t}{M})} - 1}}_{\substack{\text{if } t \neq 0 \\ = 0}} = M \delta(t) := \begin{cases} M & t=0 \\ 0 & t \neq 0 \end{cases}$

$\therefore (*)$ becomes: $\frac{1}{MN} \sum_{k=0}^{M-1} \sum_{l=0}^{N-1} g(k, l) M \delta(p-k) N \delta(q-l) = g(p, q).$

DFT in Matrix form

Theorem: Consider a $N \times N$ image g , the DFT of g can be written as:

$$\hat{g} = U g U \quad (\text{DFT in matrix form})$$

where $U = (U_{kl})_{0 \leq k, l \leq N-1} \in M_{N \times N}$ and $U_{kl} = \frac{1}{N} e^{-j \frac{2\pi k l}{N}}$.

Proof: Need to check $\hat{g}(k, l) = (U g U)(k, l)$

$$\text{LHS} = \hat{g}(k, l) = \frac{1}{N^2} \sum_{m=0}^{N-1} \sum_{n=0}^{N-1} g(m, n) e^{-j 2\pi \left(\frac{k m}{N} + \frac{l n}{N} \right)}$$

$$\text{RHS: } U g U = \sum_{m=0}^{N-1} \sum_{n=0}^{N-1} g(m, n) \begin{pmatrix} 1 \\ \vec{u}_m \\ 1 \end{pmatrix} \begin{pmatrix} 1 & -\vec{u}_n \end{pmatrix}$$

$$\begin{pmatrix} \frac{1}{N} & \frac{1}{N} & \dots & \frac{1}{N} \\ \vec{u}_1 & \vec{u}_2 & \dots & \vec{u}_N \\ 1 & 1 & \dots & 1 \end{pmatrix} \begin{pmatrix} 1 \\ -\vec{u}_1 \\ -\vec{u}_2 \\ \vdots \\ -\vec{u}_N \\ 1 \end{pmatrix}$$

$$U g U(k, l) = \sum_{m=0}^{N-1} \sum_{n=0}^{N-1} g(m, n) \frac{e^{-j 2\pi \frac{k m}{N}}}{N} \cdot \frac{e^{-j 2\pi \frac{l n}{N}}}{N}$$

$$= \text{LHS}$$

(k -th row, l -th col of $U g U$)

$$\vec{u}_m = \begin{pmatrix} u_{0m} \\ u_{1m} \\ \vdots \\ u_{N-1,m} \end{pmatrix} = \frac{1}{N} \begin{pmatrix} e^{-j \frac{2\pi(0)m}{N}} \\ \vdots \\ e^{-j \frac{2\pi(k)m}{N}} \\ \vdots \\ e^{-j \frac{2\pi(N-1)m}{N}} \end{pmatrix}$$

$$\vec{u}_n = (u_{n0}, u_{n1}, \dots, u_{nN})$$

$$= \frac{1}{N} (e^{-j \frac{2\pi(0)n}{N}}, \dots, e^{-j \frac{2\pi(l)n}{N}}, \dots)$$

Theorem: $U^* U = \frac{1}{N} I$ where $U^* = (\overline{U})^T$ (conjugate transpose)

$U U^* = \frac{1}{N} I$

$\therefore U^{-1} = (NU)^*$

($\overline{a+jb} = a-jb$)

($\overline{e^{j\theta}} = \overline{\cos\theta + j\sin\theta} = \cos\theta - j\sin\theta = e^{-j\theta}$)

Proof: Later "

Image decomposition by DFT

$$\text{Suppose } \hat{g} = \text{DFT}(g) = U g U$$

$$\text{Then: } U U^* = \frac{1}{N} I = U^* U$$

$$\therefore g = (N U)^* \hat{g} (N U)$$

$$\therefore g = \sum_{k=0}^{N-1} \sum_{l=0}^{N-1} \hat{g}_{kl} \vec{w}_k \vec{w}_l^T$$

← Elementary image of DFT

$$\text{where } \vec{w}_k = k^{\text{th}} \text{ col of } (N U)^*$$