Image Transforms and Compression

Jayanta Mukhopadhyay Dept. of CSE, IIT Kharagpur



Image Transform

$$f(x,y) = \sum_{j} \sum_{i} \lambda_{ij} b_{ij}(x,y)$$

□ Image in continuous form: f(x,y): A 2-D function, where (x,y) in R^2 . Properties of basis functions

- □ Let *B* be a set of basis functions: $B = \{b_i(x,y) \mid i=..,-1,0,1,2,3,...\}, b_i(x,y) \text{ in } R \text{ or } C.$
- Let f(x,y) be expanded using *B* as follows:

 $f(x,y) = \sum_{i} \lambda_{i} b_{i}(x,y)$ Coefficients of transform The **transform** of f w.r.t. B is given by $\{\lambda_{i} | i = \dots -1, 0, 1, 2, 3, \dots\}$.

Indexing may be multidimensional say, λ_{ij} .

Orthogonal Expansion and 1-D Transforms

$$f(x) = \sum_{i} \lambda_{i} b_{i}(x)$$

• Inner product: $\langle f, g \rangle = \int f(x)g^*(x)dx$

• Orthogonal expansion: If B satisfies : $\langle b_i, b_i \rangle = 0$, for $i \neq j$ $= c_i$ Otherwise (for i = j), where $c_i > 0$ Transform coefficients in O.E.: $\lambda_i = \frac{1}{C_i} \langle f, b_i \rangle$ • $c_i = 1 \rightarrow$ orthonormal expansion. Forward transform $f(x) = \int_{i=-\infty}^{\infty} \lambda_i b_i(x) di$ • Inverse transform:

Fourier transform

Complete base $B = \{e^{-ij\omega x} | -\infty < \omega < \infty\}$

Unit impulse function

Orthogonality:
$$\int_{-\infty}^{\infty} e^{j\omega x} dx = \begin{cases} 2\pi \delta(x), & \text{for } \omega = 0\\ 0, & \text{otherwise.} \end{cases}$$

Fourier Transform: $\mathcal{F}(f(x)) = \hat{f}(j\omega) = \int_{-\infty}^{\infty} f(x)e^{-j\omega x} dx$ Inverse Transform: $f(x) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \hat{f}(j\omega) e^{j\omega x} d\omega$ Full reconstruction $e^{-j\omega x} = \cos(\omega x) - j\sin(\omega x)$ $\hat{f}(j\omega) = \int_{-\infty}^{\infty} f(x)(\cos(\omega x) - j\sin(\omega x)) dx$ $= \{ \cos(\omega x) | -\infty < \omega < \infty \} \qquad S = \{ \sin(\omega x) | -\infty < \omega < \infty \}$ Orthogonal \checkmark But not complete!

Fourier transform of a square pulse

• f(t) = A, $-B/2 \le t \le B/2$





Fourier transform of a Gaussian Pulse

$$g(t) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{t^2}{2\sigma^2}} \qquad \qquad G(\omega) = e^{-\frac{\omega^2 \sigma^2}{2}}$$

- Transform is also a Gaussian function.
- Standard deviation in the Fourier domain (angular frequency) is reciprocal of that in the time domain.



Convolution and Fourier Transform



• Convolved output: Sum of scaled and shifted impulse responses.

$$F(f(t) * h(t)) = \int \left(\int f(\tau) h(t - \tau) d\tau \right) e^{-j\omega t} dt = \int f(\tau) \int h(t - \tau) e^{-j\omega t} dt d\tau$$
$$= \int f(\tau) H(j\omega) e^{-j\omega \tau} d\tau$$
$$= H(j\omega) F(j\omega)$$

Fourier transform of unit impulse

• Definition and properties of unit infinite impulse

$$\delta(t) = \infty, t = 0$$

= 0, otherwise
$$\int_{-\infty}^{\infty} \delta(t) dt = 1 \int_{-\infty}^{\infty} f(t) \delta(t - t_0) dt = f(t_0)$$

$$F(\delta(t)) = \int_{-\infty}^{\infty} \delta(t) e^{-j\omega t} dt = e^{-j\omega .0} = 1$$

$$F(\delta(t-T)) = e^{-j\omega T} \quad \bigoplus_{\text{Duality}} F(e^{j\omega_0 t}) = \delta(\omega - \omega_0)$$

Train of impulses: $\sum \delta(t - n\Delta T) \quad \bigoplus_{n=-\infty}^{\mathcal{F}} \frac{1}{\Delta T} \sum_{n=-\infty}^{\infty} \delta(\omega - \frac{2\pi n}{\Delta T})$
Fourier series of a period ΔT
with unit impulse in a period

Fourier transform of a sampled function



Even and odd functions

- Even: f(-x)=f(x) for all x.
- Odd: f(-x) = -f(x) for all x. $\rightarrow f(0) = 0$.
- For even f(x) :

$$\int_{-\infty}^{\infty} f(x)(\sin(\omega x)) \, dx = 0$$

 $\cos(\theta) = \frac{e^{j\theta} + e^{-j\theta}}{2}$ $\sin(\theta) = \frac{e^{j\theta} - e^{-j\theta}}{2j}$

• For odd f(x) :

$$\int_{-\infty}^{\infty} f(x)(\cos(\omega x)) \, dx = 0$$

• Full reconstruction possible with cosines (sines) only if it is even (odd).



Discrete representation

Discrete representation of a function:

$$f(n) = \{f(nX_0) | n \in \mathbb{Z}\}$$
 Set of integers
Sampling interval

- Can be considered as a vector in an infinite dimensional vector space.
- In our context, it is of a finite dimensional space, e.g. {f(n), n=0,1,..N-1}, or
- $f=[f(0) f(1) \dots f(N-1)]^T$.



Discrete Linear Transform: A general form

- For *n*-dimensional vector *X* any linear transform,
 - e.g. $Y_{mxl} = B_{mxn} X_{nxl}$
 - X_{nxl} : A column vector of dimension n.
 - Y_{mx1} : A column vector of dimension m.
 - B_{mxn} : A matrix of dimension mxn.
- Has inverse transform if *B* is a square matrix and invertible.



Basis vectors

- *B* is the transformation matrix.
- Rows of *B* are called basis vectors.

•
$$Y(i) = \langle \boldsymbol{b}_i^{*T}, X \rangle$$

• $Y(i) = \langle \boldsymbol{b}_i^{*T}, X \rangle$
• dot product or inner product.

Orthogonality condition:

$$< \boldsymbol{b}_i^{*T} \cdot \boldsymbol{b}_j > = 0 \ if \ i \neq j$$

= c_i , otherwise



Discrete Fourier Transform (DFT)

$$b_k(n) = \frac{1}{\sqrt{N}} e^{j2\pi \frac{k}{N}n}, \text{ for } 0 \le n \le N-1, \text{ and } 0 \le k \le N-1.$$

$$F(k) \iff \hat{f}(k) = \sum_{n=0}^{N-1} f(n) e^{-j2\pi \frac{k}{N}n} \text{ for } 0 \le k \le N-1. \qquad \hat{f}(N+k) = \hat{f}(k)$$

$$f(n) = \frac{1}{N} \sum_{k=0}^{N-1} \hat{f}(k) e^{j2\pi \frac{k}{N}n} \text{ for } 0 \le n \le N-1.$$

Fundamental frequency: 1/(NX₀)

f(n+N)=f(n)

DFT: Fourier series of a periodic function

A single period

$\begin{aligned} \mathbf{DFT} \ \mathbf{as} \\ \mathbf{F}(n) &= \frac{1}{N} \sum_{k=0}^{N-1} \hat{f}(k) e^{j2\pi \frac{k}{N}n} \ \text{for} \ 0 \leq n \leq N-1. \\ \mathbf{Fourier Series} \quad \hat{f}(k) &= \sum_{n=0}^{N-1} f(n) e^{-j2\pi \frac{k}{N}n} \ \text{for} \ 0 \leq k \leq N-1. \end{aligned}$

- For a periodic sequence of period *N*: *f*(*n*+*N*)=*f*(*n*)
- Sampling interval: X_0
- Period: $N \cdot X_0$
 - Fundamental period: 1/ (NX₀)
 - Fourier series: Components of k/(NX₀), k=0,1,2,...

$$F\left(\frac{k}{NX_{0}}\right) = \frac{1}{NX_{0}} \sum_{n=0}^{N-1} f(nX_{0}) e^{-j2\pi \frac{k}{NX_{0}}nX_{0}} \Delta x$$

In the DFT
$$F(k) = \frac{1}{N} \sum_{n=0}^{N-1} f(n) e^{-j2\pi \frac{k}{N}n}$$

is adjusted.

For any integer k, $e^{j2\pi k} = 1$

DFT properties

- Linearity: DFT(a.f(n) + b(g(n))) = aF(k) + bG(k)
- Circular time shifting $DFT(f(\langle n n_0 \rangle_N) = e^{-j2\pi \frac{k}{N}n_0}F(k)$
- Periodicity:

$$F(k+N) = \sum_{n=0}^{N-1} f(n) e^{-j2\pi \frac{k+N}{N}n} = \sum_{n=0}^{N-1} f(n) e^{-j2\pi (\frac{k}{N}+1)n} = \sum_{n=0}^{N-1} f(n) e^{-j2\pi \frac{k}{N}n} = F(k)$$

• Symmetry

$$F(N-k) = F(-k) = \sum_{n=0}^{N-1} f(n) e^{j2\pi \frac{k}{N}n} = F^*(k)$$
 $F\left(\frac{N}{2} + m\right) = F^*(\frac{N}{2} - m)$
Putting. $k = N/2 + m$

- Duality
 - *DFT* of *DFT* of x(n) = N. $x(\langle -k \rangle_N)$
- Energy preservation

$$\vec{x}. \vec{y}^* = \frac{1}{N} \vec{\hat{x}}. \vec{\hat{y}}^* \implies \|\vec{x}\|^2 = \vec{x}. \vec{x}^* = \frac{1}{N} \vec{\hat{x}}. \vec{\hat{x}}^* = \frac{1}{N} \|\vec{\hat{x}}\|^2$$

• Freq. Shifting $DFT(f(n)e^{j2\pi \frac{k_0}{N}n}) = F(\langle k - k_0 \rangle_N)$

$$DFT(f(n)e^{j2\pi \frac{k_0}{N}n}) = F(\langle k - k_0 \rangle_N)$$

- Multiplying k_0 th sinusoid shifts transform to k_0 .
- Let $k_0 = N/2$
 - $\rightarrow f(n) (-1)^n$
 - $\rightarrow F(\langle k N/2 \rangle_N)$
 - Centers the Fourier transform bringing the 0 th freq. component in the center.
- A useful trick to center the transform
 - Multiply by $(-1)^n$ and then compute DFT.



Fast Fourier Transform (FFT)

$$F(k) = \sum_{n=0}^{N-1} f(n) e^{-j2\pi \frac{k}{N}n}$$
Assume N even

$$F(k) = \sum_{m=0}^{\frac{N}{2}-1} f(2m) e^{-j2\pi \frac{k}{N}(2m)} + \sum_{m=0}^{\frac{N}{2}-1} f(2m+1) e^{-j2\pi \frac{k}{N}(2m+1)}$$

$$F(k) = \sum_{m=0}^{\frac{N}{2}-1} f(2m) e^{-j2\pi \frac{k}{N/2}(m)} + \sum_{m=0}^{\frac{N}{2}-1} f(2m+1) e^{-j2\pi \frac{k}{N}(m+1/2)}$$

$$F(k) = \sum_{m=0}^{\frac{N}{2}-1} f(2m) e^{-j2\pi \frac{k}{N/2}(m)} + e^{-j2\pi \frac{k}{N}(1/2)} \sum_{m=0}^{\frac{N}{2}-1} f(2m+1) e^{-j2\pi \frac{k}{N}(m)}$$

$$F(k) = \sum_{m=0}^{\frac{N}{2}-1} f(2m) e^{-j2\pi \frac{k}{N/2}(m)} + e^{-j2\pi \frac{k}{N}} \sum_{m=0}^{\frac{N}{2}-1} f(2m+1) e^{-j2\pi \frac{k}{N}(m)}$$

$$F(k) = \sum_{m=0}^{\frac{N}{2}-1} f(2m) e^{-j2\pi \frac{k}{N/2}(m)} + e^{-j2\pi \frac{k}{N}} \sum_{m=0}^{\frac{N}{2}-1} f(2m+1) e^{-j2\pi \frac{k}{N}(m)}$$

$$F(k) = \sum_{m=0}^{\frac{N}{2}-1} f(2m) e^{-j2\pi \frac{k}{N/2}(m)} + e^{-j2\pi \frac{k}{N}} \sum_{m=0}^{\frac{N}{2}-1} f(2m+1) e^{-j2\pi \frac{k}{N}(m)}$$

$$F(k) = \sum_{m=0}^{\frac{N}{2}-1} f(2m) e^{-j2\pi \frac{k}{N/2}(m)} + e^{-j2\pi \frac{k}{N}} \sum_{m=0}^{\frac{N}{2}-1} f(2m+1) e^{-j2\pi \frac{k}{N}(m)}$$

$$F(k) = \sum_{m=0}^{\frac{N}{2}-1} f(2m) e^{-j2\pi \frac{k}{N/2}(m)} + e^{-j2\pi \frac{k}{N}} \sum_{m=0}^{\frac{N}{2}-1} f(2m+1) e^{-j2\pi \frac{k}{N}(m)}$$

$$F(k) = \sum_{m=0}^{\frac{N}{2}-1} f(2m) e^{-j2\pi \frac{k}{N/2}(m)} + e^{-j2\pi \frac{k}{N}} \sum_{m=0}^{\frac{N}{2}-1} f(2m+1) e^{-j2\pi \frac{k}{N}(m)}$$

Fast Fourier Transform (FFT) (Cooley and Tukey (1965))

$$F(k) = \sum_{n=0}^{N-1} f(n) e^{-j2\pi \frac{k}{N}n}$$

Assume N even

Divide and conquer strategy Exploiting other properties of DFT can be reduced to O(N log(N))

$$F(k) = \sum_{m=0}^{\frac{N}{2}-1} f(2m) e^{-j2\pi \frac{k}{N/2}(m)} + e^{-j2\pi \frac{k}{N}} \sum_{m=0}^{\frac{N}{2}-1} f(2m+1) e^{-j2\pi \frac{k}{N}(m)}$$

$$f(2m+1) e^{-j2\pi \frac{k}{N}(m)}$$

Danielson-Lanczos lemma



Danielson, G.C. and Lanczos, C., "Some Improvements In Practical Fourier Analysis and Their Application to X-Ray Scattering from Liquids," J. Franklin Institute, vol. 233, pp. 365-380 and 435-452, 1942.



- Periodic convolution: Convolution between two finite sequences with periodic extension.
- It is defined if both have the same period, providing a periodic sequence with the same period.

Circular Convolution

$$\begin{array}{lll} f \circledast h(n) &=& \sum_{m=0}^{N-1} f(m) h(n-m), \\ &=& \sum_{m=0}^{n} f(m) h(n-m) + \sum_{m=n+1}^{N-1} f(m) h(n-m+N). \end{array}$$

Circular Cross Correlation

• Cross correlation with periodic extensions of both the functions.





$$\widehat{f \odot h}(k) = \widehat{f}(k).\,\widehat{h}(k)^*$$

22

Filtering in the transform domain



- Use sufficient 0 padding at the both end to make circular convolution equivalent to linear convolution
 - To take care of boundary effect.
 - The length of f(n) and h(n) should be the same.
- H(k) usually provided as symmetric about the center.
 - 0th freq. at the N/2 th element.
- Center F(k) as $F_c(k)$ by multiplying f(n) with (-1)ⁿ



Obtain $G(k) = H(k) \cdot F_c(k)$

Multiply G(k) by $(-1)^k$ and perform IDFT to get g(n).

DFT: A linear transform $F(k) = \sum_{n=0}^{N-1} f(n)e^{-j2\pi \frac{kn}{N}}$ for $0 \le k \le N-1$



Generalized Discrete Fourier Transform (GDFT)

$$\mathbf{F}_{\alpha,\beta} = \left[e^{-j2\pi \frac{k+\alpha}{N}(n+\beta)} \right]_{0 \le (k,n) \le N-1}$$

 $\begin{array}{rclcrcrcrc} \mathbf{F}_{0,0}^{-1} & = & \frac{1}{N}\mathbf{F}_{0,0}^{H} & = & \frac{1}{N}\mathbf{F}_{0,0}^{*}, \\ \mathbf{F}_{\frac{1}{2},0}^{-1} & = & \frac{1}{N}\mathbf{F}_{\frac{1}{2},0}^{H} & = & \frac{1}{N}\mathbf{F}_{0,\frac{1}{2}}^{*}, \\ \mathbf{F}_{0,\frac{1}{2}}^{-1} & = & \frac{1}{N}\mathbf{F}_{0,\frac{1}{2}}^{H} & = & \frac{1}{N}\mathbf{F}_{\frac{1}{2},0}^{*}, \text{and} \\ \mathbf{F}_{\frac{1}{2},\frac{1}{2}}^{-1} & = & \frac{1}{N}\mathbf{F}_{\frac{1}{2},\frac{1}{2}}^{H} & = & \frac{1}{N}\mathbf{F}_{\frac{1}{2},\frac{1}{2}}^{*}. \end{array}$

 $b_{k}^{(\alpha,\beta)}(n) = \frac{1}{\sqrt{N}} e^{j2\pi \frac{k+\alpha}{N}(n+\beta)}, \text{ for } 0 \le n \le N-1, \text{ and } 0 \le k \le N-1$ $\hat{f}_{\alpha,\beta}(k) = \sum_{n=0}^{N-1} f(n) e^{-j2\pi \frac{k+\alpha}{N}(n+\beta)}, \text{ for } 0 \le k \le N-1$

$$f(n) = \frac{1}{N} \sum_{k=0}^{N-1} \hat{f}_{\alpha,\beta}(k) e^{j2\pi \frac{k+\alpha}{N}(n+\beta)}, \text{ for } 0 \le n \le N-1$$

α	β	Transform name	Notation
0	0	Discrete Fourier Transform (DFT)	$\hat{f}(k)$
0	$\frac{1}{2}$	Odd Time Discrete Fourier Transform $(OTDFT)$	$\hat{f}_{0,\frac{1}{2}}(k)$
$\frac{1}{2}$	0	Odd Frequency Discrete Fourier Transform $(OFDFT)$	$\hat{f}_{\frac{1}{2},0}(k)$
$\frac{1}{2}$	$\frac{1}{2}$	Odd Frequency Odd Time Discrete Fourier Transform $({\cal O}^2 DFT)$	$\hat{f}_{\frac{1}{2},\frac{1}{2}}(k)$

Symmetric / Antisymmetric extension of a finite sequence



Discrete Cosine / Sine Transforms $\alpha(p) = \begin{cases} \sqrt{\frac{1}{2}}, & \text{for } p = 0 \text{ or } N, \\ 1, & \text{otherwise.} \end{cases}$

 Types of symmetric / antisymmetric extensions at the two ends of a sequence and a type of GDFT→ DCTs / DSTs







Ô

There exist 16 different types of DCTs and DSTs. Type-II Even DCT is used in signal, image, and video compression.

Matrix form of Type-II DCT

$$\alpha(p) = \begin{cases} \sqrt{\frac{1}{2}}, & \text{for } p = 0 \text{ or } N, \\ 1, & \text{otherwise.} \end{cases}$$

- Matrix form: N-point DCT $C_N = \left[\sqrt{\frac{2}{N}} \cdot \alpha(k) \cos(\frac{\pi k(2n+1)}{2N})\right]_{0 \le (k,n) \le N-1}$
- Each row is either symmetric (even row) or antisymmetric (odd row).

$$C_N(k, N-1-n) = \begin{cases} C_N(k, n) & \text{for } k \text{ even} \\ -C_N(k, n) & \text{for } k \text{ odd} \end{cases}$$

$$X = C_N \cdot \mathbf{x} \qquad \qquad C_N^{-1} = C_N^T$$



Antiperiodic extension and skew-circular convolution

- Antiperiodic function with an antiperiod N, if f(x+N)=-f(x).
- An antiperiodic function of antiperiod $N \rightarrow a$ periodic function of period 2N.
- Skew-circular convolution: convolution between two antiperiodic extended sequences of the same antiperiod.

$$f(s)h(n) = \sum_{m=0}^{N-1} f(m)h(n-m),$$

= $\sum_{m=0}^{n} f(m)h(n-m) - \sum_{m=n+1}^{N-1} f(m)h(n-m+N)$

$$u(n) = x(n) \circledast y(n)$$
$$w(n) = x(n) \circledast y(n)$$

CMPs tor DU

- $= \sqrt{2NC_{1e}(x(l))C_{1e}(y(m))}$ $C_{1e}\left(u(n)\right)$
- $= \sqrt{2NC_{2e}(x(l))C_{1e}(y(m))}$ $C_{2e}\left(u(n)\right)$

 $= \sqrt{2NC_{3e}} \left(x(l) \right) C_{3e} \left(y(m) \right)$ $C_{3e}\left(w(n)\right)$



2-D Transforms

 $f(x,y) = \sum_{i} \sum_{j} \lambda_{ij} b_{ij}(x,y)$

 Easily extendable if basis functions are separable, i.e. B={ b_{ij}(x,y)=g_i(x).g_j(y)}.

They could be from two different sets, say b(x,y)=g(x).h(y).

1-D basis function

- *B*: Orthogonal if *G*={*g_i*(*x*), *i*=1,2,..} is orthogonal.
- *B*: Orthogonal and complete if G is so.
- Reuse of 1-D transform computation.

$$\lambda_{ij} = \sum_{j} g_j^*(y) \left(\sum_{i} f(x, y) g_i^*(x) \right)$$



2D Discrete Transform

- Use of separability:
 - Transform columns.
 - Transform rows.
- Input: X_{mxn} 1-D Transform Matrix: B
- Transform columns: $[Y_1]_{m \ge n} = B_{m \ge m} X_{m \ge n}$
- Transform rows: $Y_{mxn} = [B_{nxn}Y_1^T]^T$

$$=Y_1 B_{n \times n}^{T}$$
$$=B_{m \times m} X_{m \times n} B_{n \times n}^{T}$$

 $Y_{m \times n} = B_{m \times m} X_{m \times n} B_{n \times n}^{T}$



Image Transform: DFT

Image: f(m,n), of size $M \ge N$ $F(k,l) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} f(m,n)e^{-j2\pi \frac{km}{M}}e^{-j2\pi \frac{ln}{N}}$ $f(m,n) = \frac{1}{MN} \sum_{k=0}^{M-1} \sum_{l=0}^{N-1} F(k,l)e^{j2\pi \frac{km}{M}}e^{j2\pi \frac{ln}{N}}$ Property of separability

$$\mathbf{F} = \mathcal{F}_m \mathbf{f} \mathcal{F}_N^T \qquad F(k,l) = \sum_{m=0}^{M-1} e^{-j2\pi \frac{km}{M}} \sum_{n=0}^{N-1} f(m,n) e^{-j2\pi \frac{ln}{N}}$$

DFT Examples:

Magnitude







Phase

Magnitudes and phases are shown by bringing them into displayable range, and shifting the origin at the center of image.



$$\alpha(p) = \begin{cases} \sqrt{\frac{1}{2}}, & \text{for } p = 0 \text{ or } N, \\ 1, & \text{otherwise.} \end{cases}$$
• Type-I:

 $X_{I}(k,l) = \frac{2}{N} \cdot \alpha^{2}(k) \cdot \alpha^{2}(l) \cdot \sum_{m=0}^{M} \sum_{n=0}^{N} (x(m,n)\cos(\frac{m\pi k}{M})\cos(\frac{n\pi l}{N})), \\ 0 \le k \le M, 0 \le l \le N.$

- Type-II
- Matrix Representation:

 $\begin{array}{lll} X_{II}(k,l) &=& \frac{2}{N} . \alpha(k) . \alpha(l) . \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} (x(m,n) \cos(\frac{(2m+1)\pi k}{2M}) \cos(\frac{(2n+1)\pi l}{2N})), \\ & & 0 \le k \le M-1, 0 \le l \le N-1. \end{array}$

$$X = DCT(x) = C_M . \mathbf{x} . C_N^T$$





Input image

Discrete Cosine Transform





Wavelets

- Functions to have *ideally* finite support in both its original domain (say, time or space) and also in the transform domain (i.e., the frequency domain).
 - No such function exists truly satisfying it.
 - Attempts to match these properties as far as possible.
- Acts as basis functions.
- Good localization property in both domain.







An interesting function

Same form in time and frequency domain

 $\sigma_t^2 \sigma_f^2 \ge \frac{1}{\Lambda}$

- Gaussian
- Analogy from Heisenberg's uncertainty principle

 $\omega^2 \sigma^2$

 $G(\omega) =$

Variance of *t* weighted by $g^2(t)$. Similarly for *f*. For any function it holds !!

$$g(t) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{t^2}{2\sigma^2}}$$

Designing wavelet: An intuitive approach

- Time limited signal:
 - Square pulse
- Band limited signal:
 - Sinusoidal signal

- Wavelet to satisfy both?
 - Multiply them!!



Gabor wavelet (1-D)





Shannon wavelet





Haar Wavelet





Family of wavelets

• Translate and dilate a mother wavelet



Continuous wavelet transform

• Forward transform

From 1-D
representation to
$$W(s,\tau) = \int f(t) \frac{1}{\sqrt{s}} \psi^* \left(\frac{t-\tau}{d}\right) dt$$

2-D representation.

 $C_{\psi} =$

How correlated at that instance with the wavelet fn.

Reveals structure of function at multiple resolution.

$$f(t) = \frac{1}{C_{\psi}} \int_0^{\infty} \int_{-\infty}^{\infty} W(s,\tau) \frac{\psi(t)}{s^2} ds d\tau$$

 $\stackrel{\sim}{\longrightarrow} \frac{|\hat{\psi}(\omega)|}{|\omega|}$

 $d\omega$

Fourier transform



where

Multiresolution representation

• Gaussian Pyramid



Gaussian Pyramid: Wavelet analysis



Haar Wavelet transform



nily of translated and dilated functions from the both forms the basis.

Discrete wavelet transform (DWT)

- Translated only at discrete grid points.
 - $k=0, \pm 1, \pm 2, \dots$
 - Finite sequence: A finite number of basis functions.
- Scaled by powers of 2: 2^{j} , j=0,1,...
 - Downsampling takes care of dilation of wavelets and allows to use the same function at that level.
- Family of scaling and wavelet functions:

$$\varphi_{j,k}(n) = 2^{-\frac{j}{2}} \varphi \left(2^{-j}n - k \right), \ j = 0, 1, \dots, k = 0, 1, \dots, M$$

$$\psi_{j,k}(n) = 2^{-\frac{j}{2}} \psi \left(2^{-j}n - k \right), \ j = 0, 1, \dots, k = 0, 1, \dots, M$$

$$\underset{M < N \text{ (length of sequence)}}{M < N \text{ (length of sequence)}}$$

Haar wavelets in discrete grid

• N=8 φ(r	ı) =	$\frac{1}{\sqrt{2}}$	(1,	1,0	,0,0	,0,	0,0)			
$\psi(n$) =	$\frac{1}{\sqrt{2}}$	(1, •	-1	,0,0	,0,0	0,0,0))		
		1	1	0	0	0	0	0	0	
ransformation matrix:		0	0	$1 \\ 0$	1 0	0 1	0 1	0	0	
	$\frac{1}{\sqrt{2}}$	$\begin{vmatrix} 0\\ 1 \end{vmatrix}$	$0 \\ -1$	0 0	0 0	0 0	0 0	$\begin{array}{c} 1 \\ 0 \end{array}$	$\begin{array}{c} 1 \\ 0 \end{array}$	
		0	0	1	-1	0	0	0	0	
		0	0	0 0	0 0	$\frac{1}{0}$	$^{-1}_{0}$	$0 \\ 1$	$0 \\ -1$	

courtesy: "Image and video processing in the compressed domain", J. Mukhopadhyay, CRC Press, 2011.

DWT

- Translated only at discrete grid points.
- Scaled by powers of 2: 2^{j} , j=0,1,...
 - Downsampling takes care of dilation of wavelets and allows to use the same function at that level.
 - Filtering by the filter of same impulse response.
- Filtering banks.



Dyadic decomposition



- At each level sample size is halved
 - Equivalent of scaling by 2.
- Total number of samples remain the same.



Typical wavelet filters

Daubechies 9/7 filters

	Analysi	is filter bank	Synthesis filter bank			
\boldsymbol{n}	h(n)	g(n-1)	h'(n)	g'(n+1)		
0	0.603	1.115	1.115	0.603		
± 1	0.267	-0.591	0.591	-0.267		
± 2	-0.078	-0.058	-0.058	-0.078		
± 3	-0.017	0.091	-0.091	0.017		
± 4	0.027			0.027		

Le Gall 5/3 filters ^{_}

	Analy	sis filter bank	Synthesis filter bank			
n	h(n)	g(n-1)	h'(n)	g'(n+1)		
0	68	1	1	6 8		
± 1	2 8,	$-\frac{1}{2}$	$\frac{1}{2}$	$-\frac{2}{8}$		
± 2	$-\frac{1}{8}$			$-\frac{1}{8}$		



ourtesy: "Image and video processing in the compressed domain", J. Mukhopadhyay, CRC Press, 2011.

2-D DWT

- Separable filters.
- Transform rows, then transform columns.



Applications:

- o Compression
- Denoising
- Feature representation
- \circ Image fusion





Image compression

- An alternative representation requiring less storage compared to in original original space.
 - An analogy with representation of a circle:
 - A set of all points in its periphery.
 - Only three (non-collinear) points.
 - Center and radius
- Decompression: Reconstruction from a compressed image in the original space.
- Lossy compression: Approximate reconstruction.



Lossless compression: Exact reconstruction

Desirable features

- Good reconstructibility
 - Visual quality of decompressed image should be high.
- Low redundancy
 - Spatial correlation, Channel (color) correlation, Symbol representation,
- Factorization in substructures
 - Frequency components, Space-frequency decomposition,
 - DCT, DWT



Generic pipeline of compression and decompression





Courtesy: J. Mukhopadhyay, Image and video processing in the compressed domain, CRC Press, 2011.

JPEG: Baseline scheme



Color encoding in JPEG

• Y-Cb-Cr color space:

Y = 0.520G + 0.098 B + 0.256R Cb = -0.290G + 0.438 B - 0.148R + 128Cr = -0.366G - 0.071 B + 0.438R + 128





Courtesy: J. Mukhopadhyay, Image and video processing in the compressed domain, CRC Press, 2011.

Courtesy: J. Mukhopadhyay, Image and video processing in the compressed domain, CRC Press, 2011.

V=B-G

JPEG 2000



- Lossy: Daubechies 9/7 filters
- Lossless: Le Gall 5/3 filters
- Color Transformation:
 - Lossy: Y-Cb-Cr (w/o downsampling)

Lossless:
$$Y = \left\lfloor \frac{R + 2G + B}{4} \right\rfloor$$
 $U=R-G$

$$G = Y - \left[\frac{U+V}{4}\right]$$
$$R = U + G$$
$$B = V + G$$

JPEG 2000: Quantization

• Each sub-band independently quantized with a uniform quantization threshold.

$$\Delta = 2^{n-\epsilon} \left(1 + \frac{\mu}{2^{11}}\right)$$

- n: Nominal dynamic range of the sub-band, e.g. 10 for HH₁
- ϵ , μ : the number of bits allotted to the exponent and mantissa respectively, of its coefficients.
- Quantized coefficient (of X(u,v))

$$X_q(u,v) = sign(X(u,v)) \left[\frac{|X(u,v)|}{\Delta} \right]$$

- For lossless compression: $\Delta = 1$
- Implicit quantization: Lowest level (LL): ϵ_0 , μ_0
 - For the *i* th sub-band at level *k*: $\mu_i = \mu_0$ and $\epsilon_i = \epsilon_0 + i k$

JPEG2000: Code Structure

- Every sub-band partitioned into a set of non-overlapping codeblocks.
- Each codeblock independently coded by a schema called Embedded Block Coding on Truncation (EBCOT).
- each bit-plane of wavelet coefficients is processed by three passes, namely, significant propagation, magnitude refinement, and clean-up.
- The resulting bit-stream encoded using Arithmetic Encoding.
- A layer formed with the output of similar passes from a group of code blocks.
- In a layer, packets formed by grouping corresponding code blocks of subbands at the same level of decomposition.

also known as precincts

Precincts



Courtesy: J. Mukhopadhyay, Image and video processing in the compressed domain, CRC Press, 2011.

64

Summary

- Image transforms involve representation of images as a linear combination of a given set of basis functions.
- For a finite discrete sequence, this is treated as a linear combination of a given set of basis vectors.
- Orthogonal set of basis functions (vectors) simplifies computation of forward and inverse transforms
 - Inner product of the function with the basis function.
 - Examples: Fourier Transform, Wavelet Transforms (may be also non-orthogonal)
- A set of basis functions may be orthogonal but not complete for exactly representing any arbitrary function.
 - Cosine and Sine Transforms in continuous domain.



For finite discrete sequences several orthogonal and complete 65 transforms available: DFT, GDFTs, DCTs, DSTs, etc.

Summary

- Alternative representation provides other insights of structure of images.
 - low frequency and high frequency components.
- May become useful for providing more compact representation.
 - A few transform coefficients.
 - Selective quantization of components, considering their effect on our perception.
 - Image compression: JPEG

Sometimes convenient for processing.

Filtering, enhancement,

Summary

- Wavelets represent the scale of features in an image, as well as their positions.
 - Time-scale, Space-Scale representation
- Fast computation of forward and inverse transform
- Provides multiresolution representation.
 - Enables progressive and scalable processing
- Lossy and lossless reconstruction possible.
- useful for a number of applications including image compression.



JPEG2000

Thank You

