

Image Coding, JPEG, and JPEG2000



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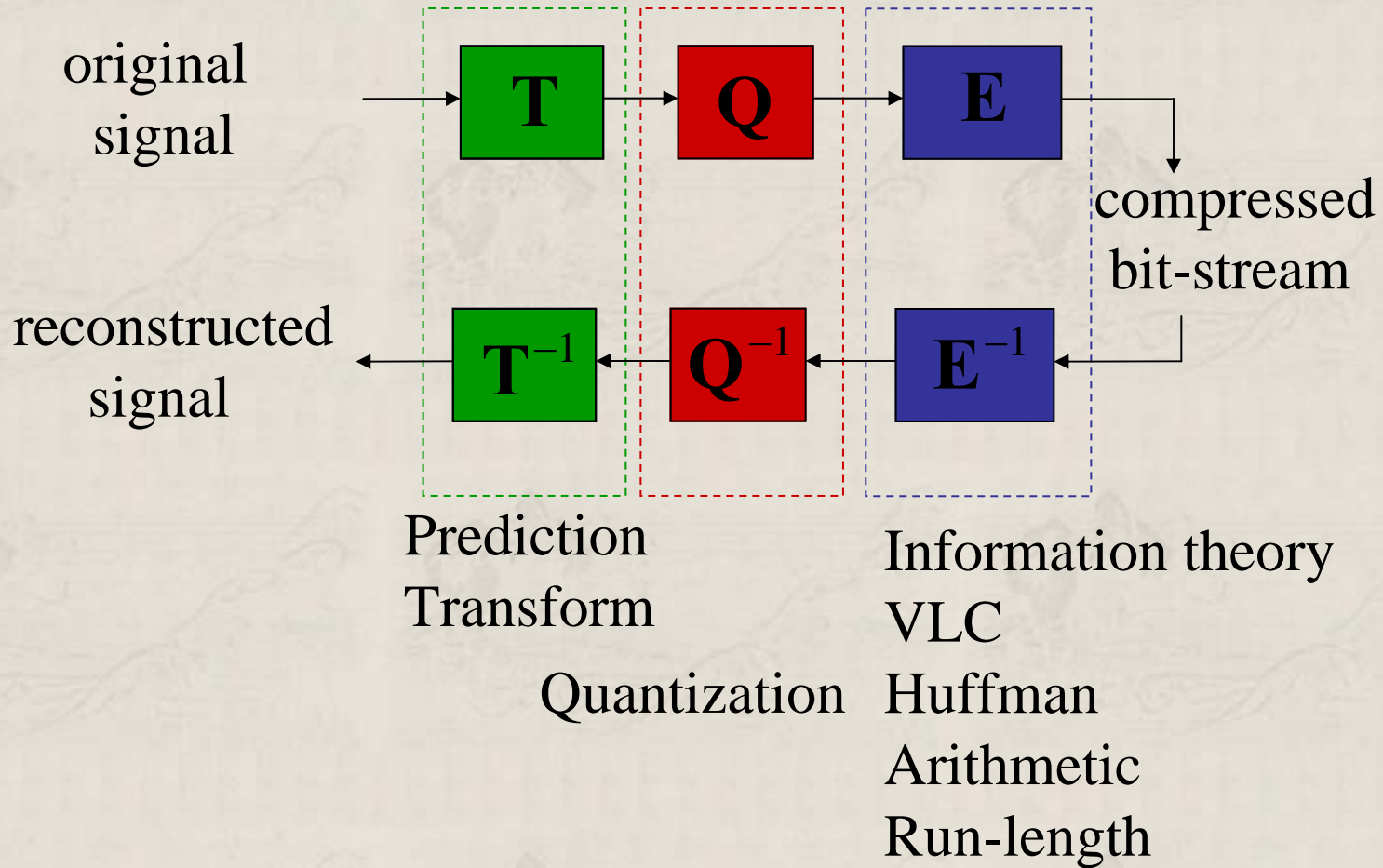
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Outline

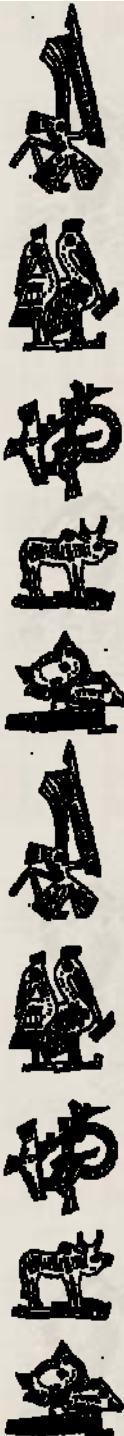
- ◆ Prediction
 - Open-loop differential pulse-code modulation (DPCM)
 - Closed-loop DPCM
 - Optimal linear prediction
- ◆ Transformation
 - Transform fundamentals
 - Karhunen-Loeve Transform (KLT): optimal linear transform
 - Discrete Cosine Transform (DCT)
- ◆ Putting everything together
 - JPEG: DCT – Quantization – Run-length – Huffman
- ◆ Latest development
 - JPEG2000 and scalable, progressive coding

Reminder

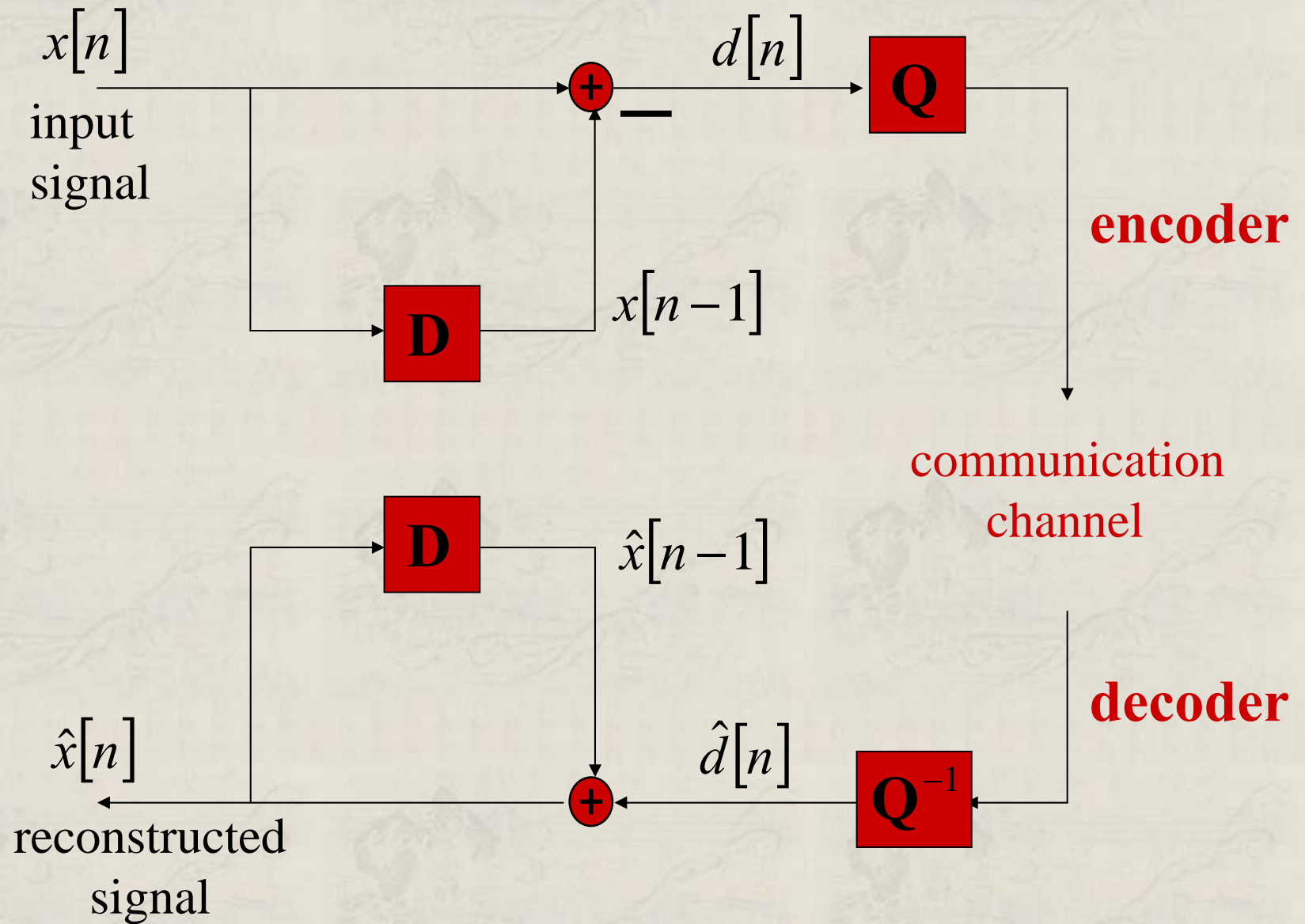


Predictive Coding

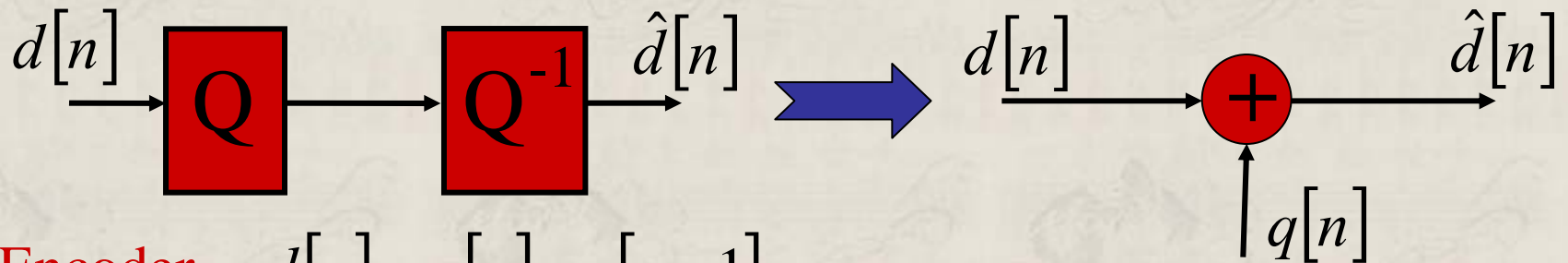
- ◆ We have only dealt with memory-less model so far
 - Each symbol/sample is quantized and/or coded without much knowledge on previous ones
- ◆ There is usually a strong correlation between neighboring symbols/samples in multimedia signals
- ◆ Simplest prediction scheme: take the difference!
- ◆ If the difference between two adjacent symbols/samples is quantized and encoded instead, we can achieve the same level of compression performance using fewer bits – the range of the differences should be a lot smaller.



Open-Loop DPCM



Open-Loop DPCM: Analysis



Encoder $d[n] = x[n] - x[n-1]$

Decoder $\hat{x}[n] = \hat{d}[n] + \hat{x}[n-1]$

$$\hat{d}[n] = d[n] + q[n]$$

$$\hat{d}[0] = d[0] + q[0]$$

$$\hat{x}[0] = \hat{d}[0] = d[0] + q[0] = x[0] + q[0]$$

$$\hat{d}[1] = d[1] + q[1]$$

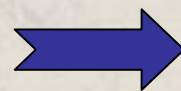
$$\hat{x}[1] = \hat{d}[1] + \hat{x}[0] = d[1] + q[1] + x[0] + q[0]$$

$$= x[1] - x[0] + q[1] + x[0] + q[0]$$

$$= x[1] + q[0] + q[1]$$

**Quantization Error
Accumulation**

$$\hat{x}[n] = x[n] + \sum_{i=0}^n q[i]$$



$$|e[n]| = |\hat{x}[n] - x[n]| = \left| \sum_{i=0}^n q[i] \right|$$

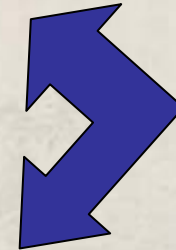
Open-Loop DPCM: Analysis

- ◆ There seems to be a **model mismatch**

- **Encoder:** $d[n] = x[n] - x[n-1]$

- **Decoder:** $\hat{x}[n] = \hat{d}[n] + \hat{x}[n-1]$

$$\Rightarrow \hat{d}[n] = \hat{x}[n] - \hat{x}[n-1]$$



- ◆ How about using the reconstructed sample for the difference?

$$d[n] = x[n] - \hat{x}[n-1]$$

Closed-Loop DPCM: Analysis

Modified prediction scheme $d[n] = x[n] - \hat{x}[n-1]$

Decoder remains the same $\hat{x}[n] = \hat{d}[n] + \hat{x}[n-1]$
 $\overbrace{d[n] + q[n]}$

$$\hat{d}[0] = d[0] + q[0]$$

$$\hat{x}[0] = \hat{d}[0] = d[0] + q[0] = x[0] + q[0]$$

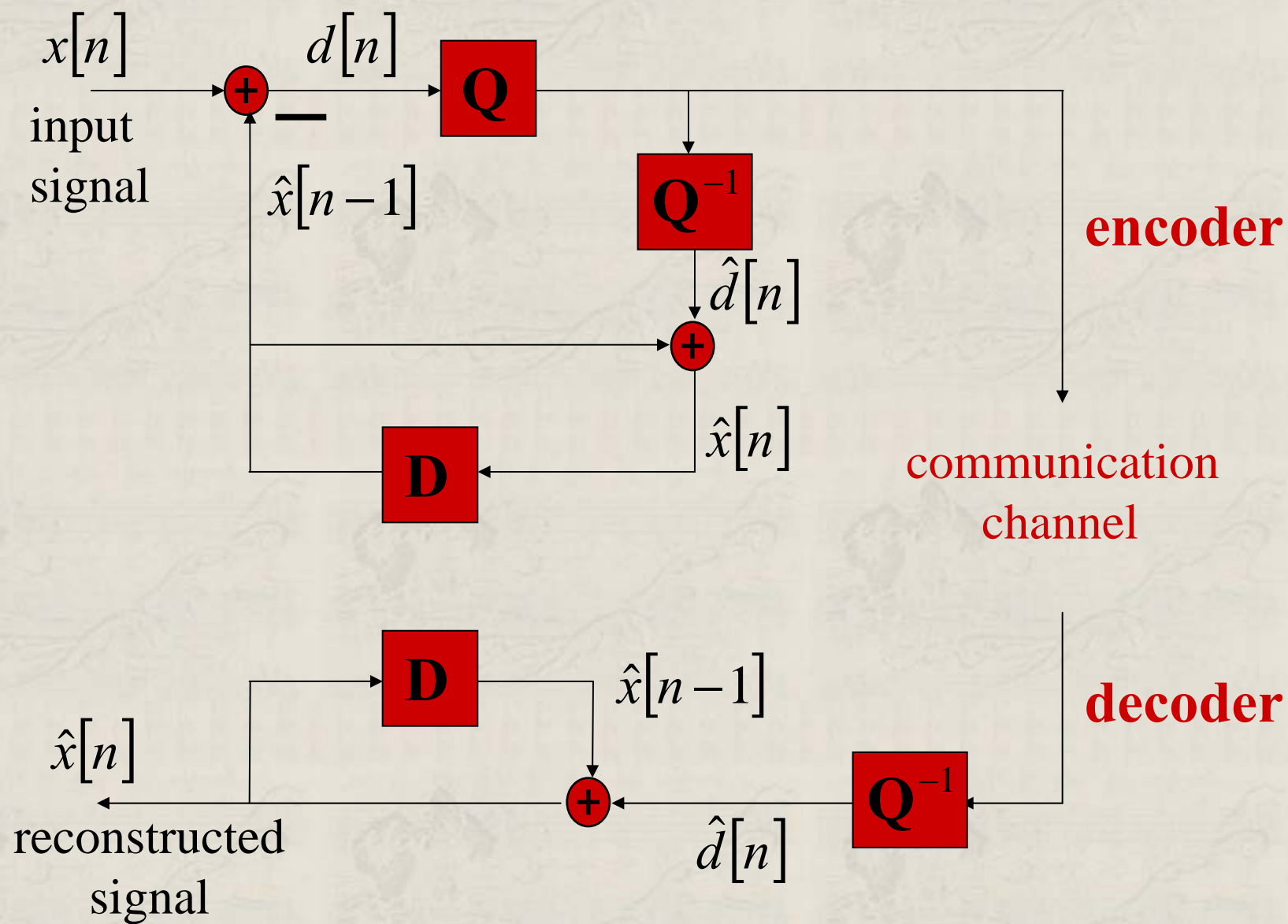
$$\hat{d}[1] = d[1] + q[1]$$

$$\begin{aligned}\hat{x}[1] &= \hat{d}[1] + \hat{x}[0] = d[1] + q[1] + x[0] + q[0] \\ &= x[1] - \hat{x}[0] + q[1] + x[0] + q[0] \\ &= x[1] + q[1]\end{aligned}$$

$$\hat{x}[n] = x[n] + q[n]$$

No error accumulation!

Closed-Loop DPCM

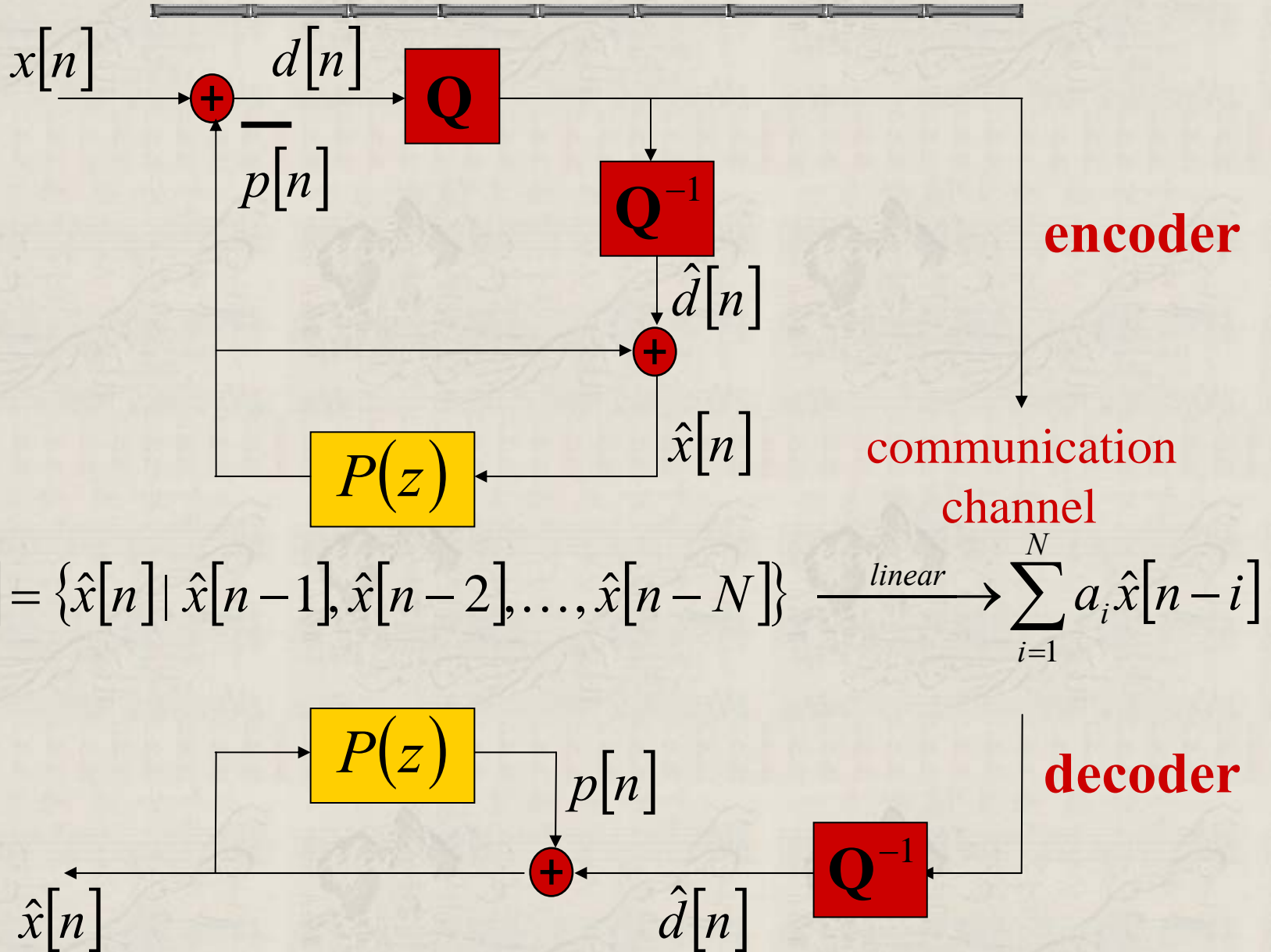




Closed-Loop DPCM: Observations

- ◆ Quantization error does not accumulate
- ◆ Minor modification in prediction scheme leads to major encoder modification
 - Encoder now has decoder embedded inside
- ◆ Closed-loop & open-loop DPCM has the same decoder
- ◆ DPCM predicts current sample from last reconstructed one
- ◆ Generalization?
 - Replace the simple delay operator by more complicated & more sophisticated predictor $P(z)$

Linear Prediction



Optimal Linear Prediction

- ◆ Problem

Find $\{a_i\}$ s.t. $D = \sigma_d^2 = E \left[\left(x[n] - \sum_{i=1}^N a_i \hat{x}[n-i] \right)^2 \right]$ is minimized

- ◆ Assumptions

- Signal is WSS $R_{xx}(k) = E[x[n]x[n+k]]$
- High bit rates, i.e., fine quantization

$$p[n] = \sum_{i=1}^N a_i \hat{x}[n-i] \approx \sum_{i=1}^N a_i x[n-i]$$

- ◆ Approach

$$\frac{\delta}{\delta a_i} D = 0$$

Optimal Linear Prediction

$$\frac{\delta}{\delta a_i} D = \frac{\delta}{\delta a_i} E \left[\left(x[n] - \sum_{i=1}^N a_i \hat{x}[n-i] \right)^2 \right] = 0$$

$$\frac{\delta}{\delta a_1} D = -2E \left[\left(x[n] - \sum_{i=1}^N a_i \hat{x}[n-i] \right) x[n-1] \right] = 0$$

$$\frac{\delta}{\delta a_2} D = -2E \left[\left(x[n] - \sum_{i=1}^N a_i \hat{x}[n-i] \right) x[n-2] \right] = 0$$

⋮

$$\frac{\delta}{\delta a_N} D = -2E \left[\left(x[n] - \sum_{i=1}^N a_i \hat{x}[n-i] \right) x[n-N] \right] = 0$$

Optimal Linear Prediction

$$\begin{aligned} E[x[n]x[n-1]] &= \sum_{i=1}^N a_i E[x[n-i]x[n-1]] \Rightarrow R_{xx}(1) = \sum_{i=1}^N a_i R_{xx}(i-1) \\ E[x[n]x[n-2]] &= \sum_{i=1}^N a_i E[x[n-i]x[n-2]] \Rightarrow R_{xx}(2) = \sum_{i=1}^N a_i R_{xx}(i-2) \\ &\vdots \\ E[x[n]x[n-N]] &= \sum_{i=1}^N a_i E[x[n-i]x[n-N]] \Rightarrow R_{xx}(N) = \sum_{i=1}^N a_i R_{xx}(i-N) \end{aligned}$$

Optimal Linear Prediction

$$\mathbf{R}_{xx} \mathbf{a} = \mathbf{p} \quad \Rightarrow \quad \mathbf{a} = \mathbf{R}_{xx}^{-1} \mathbf{p}$$

approximated from time averaging

Linear Signal Representation

input
signal

transform
coefficient

basis
function

Synthesis

$$\mathbf{x} = \sum_{i=0}^{N-1} y_i \hat{\Phi}_i$$

Analysis

$$y_i = \langle \mathbf{x}, \Phi_i \rangle = \Phi_i^T \mathbf{x}$$

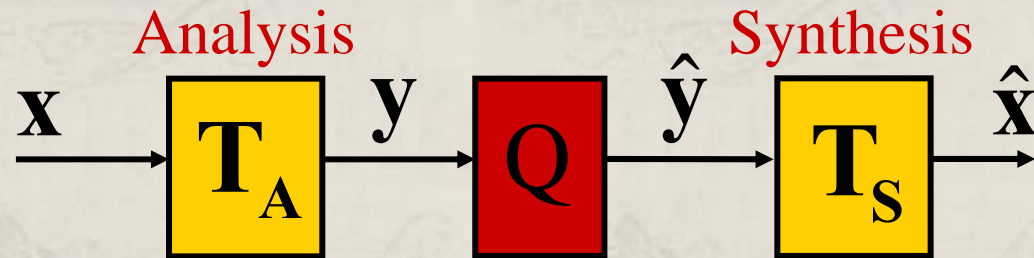
Approximation

$$\hat{\mathbf{x}} = \sum_{i=0}^{N-1} \hat{y}_i \hat{\Phi}_i$$

using as few
coefficients
as possible



Transform Fundamentals



- ◆ 1D Analysis Transform

$$\mathbf{y} = \mathbf{T}_A \mathbf{x}$$

$\{\Phi_i\}$ Analysis

basis functions

$$\begin{bmatrix} y_0 \\ y_1 \\ \vdots \\ y_{N-1} \end{bmatrix} = \underbrace{\begin{bmatrix} \text{---} \Phi_0^T \text{---} \\ \text{---} \Phi_1^T \text{---} \\ \vdots \\ \text{---} \Phi_{N-1}^T \text{---} \end{bmatrix}}_{\mathbf{T}_A} \begin{bmatrix} x_0 \\ x_1 \\ \vdots \\ x_{N-1} \end{bmatrix}$$

$y_i = \langle \Phi_i, \mathbf{x} \rangle = \Phi_i^T \mathbf{x}$

- ◆ 1D Synthesis Transform

$$\hat{\mathbf{x}} = \mathbf{T}_S \hat{\mathbf{y}}$$

$\{\hat{\Phi}_i\}$ Synthesis

basis functions

$$\begin{bmatrix} \hat{x}_0 \\ \hat{x}_1 \\ \vdots \\ \hat{x}_{N-1} \end{bmatrix} = \underbrace{\begin{bmatrix} | & | & \dots & | \\ \hat{\Phi}_0 & \hat{\Phi}_1 & \dots & \hat{\Phi}_{N-1} \\ | & | & \dots & | \end{bmatrix}}_{\mathbf{T}_S} \begin{bmatrix} \hat{y}_0 \\ \hat{y}_1 \\ \vdots \\ \hat{y}_{N-1} \end{bmatrix}$$

Invertibility & Unitary

- ◆ Invertibility

- perfect reconstruction, bi-orthogonal, reversible

$$\mathbf{T}_S = \mathbf{T}_A^{-1} \Rightarrow \mathbf{T}_S \mathbf{T}_A = \mathbf{T}_A \mathbf{T}_S = \mathbf{I}$$
$$\langle \Phi_i, \hat{\Phi}_j \rangle = \delta[i - j]$$

- ◆ Unitary

- orthogonal, orthonormal

$$\mathbf{T}_S = \mathbf{T}_A^{-1} = \mathbf{T}_A^T \Rightarrow \mathbf{T}_A^T \mathbf{T}_A = \mathbf{T}_A \mathbf{T}_A^T = \mathbf{I}$$
$$\langle \Phi_i, \Phi_j \rangle = \delta[i - j]$$

same analysis & synthesis basis functions

Norm Preservation

- ◆ Norm preservation property of orthonormal transform

$$\|\mathbf{y} - \hat{\mathbf{y}}\|_2 = \|\mathbf{x} - \hat{\mathbf{x}}\|_2 ?$$

- ◆ From a coding perspective
 - Q error in the transform domain equals Q error in the spatial domain!
 - Concentrate on the quantization of the transform coefficients

2D Separable Transformation

- ◆ 2D Analysis

$$\underset{N \times N}{\mathbf{y}} = \underset{N \times N}{\mathbf{T}_A} \underset{N \times N}{\mathbf{x}} \underset{N \times N}{\mathbf{T}_A^T}$$

transforming rows
↔
transforming columns

- ◆ 2D Synthesis

$$\underset{N \times N}{\mathbf{x}} = \underset{N \times N}{\mathbf{T}_S} \underset{N \times N}{\mathbf{y}} \underset{N \times N}{\mathbf{T}_S^T} = \underset{N \times N}{\mathbf{T}_S} \underset{N \times N}{\mathbf{T}_A} \underset{N \times N}{\mathbf{x}} \underset{N \times N}{\mathbf{T}_A^T} \underset{N \times N}{\mathbf{T}_S^T}$$

- ◆ 2D Orthogonal Synthesis

$$\underset{N \times N}{\mathbf{x}} = \underset{N \times N}{\mathbf{T}_A^T} \underset{N \times N}{\mathbf{y}} \underset{N \times N}{\mathbf{T}_A} = \underset{N \times N}{\mathbf{T}_A^T} \underset{N \times N}{\mathbf{T}_A} \underset{N \times N}{\mathbf{x}} \underset{N \times N}{\mathbf{T}_A^T} \underset{N \times N}{\mathbf{T}_A}$$

Example

- ◆ Discrete Fourier Transform (DFT)

$$F[k] = \sum_{n=0}^{N-1} f[n] W_N^{nk}$$

$$f[n] = \frac{1}{N} \sum_{k=0}^{N-1} F[k] W_N^{-nk}$$

$$n, k \in \{0, 1, \dots, N-1\} \quad W_N \equiv e^{-j\frac{2\pi}{N}}$$

$$\mathbf{T}_A = \left\{ W_N^{nk} \right\}$$

$$N = 4$$

$$\mathbf{T}_A = \begin{matrix} & \xrightarrow{n} \\ \begin{matrix} \downarrow k \\ \left[\begin{array}{cccc} 1 & 1 & 1 & 1 \\ 1 & -j & -1 & j \\ 1 & -1 & 1 & -1 \\ 1 & j & -1 & -j \end{array} \right] \end{matrix} \end{matrix}$$

$$\mathbf{T}_S = \frac{1}{N} \mathbf{T}_A^H$$

KLT: Optimal Linear Transform

- ◆ Karhunen-Loeve Transform (KLT)
 - Hotelling transform, principle component analysis (PCA)
- ◆ Question:
 - Amongst the linear transforms, which one is the best decorrelator, offering the best “compression”?
- ◆ Problem:

Given an N - point signal \mathbf{x} . Find the set of orthonormal basis functions $\{\Phi_i\}, i \in \{0, 1, \dots, N - 1\}$, such that the MSE between the L - point truncated representation $\hat{\mathbf{x}} = \sum_{i=0}^{L-1} y_i \Phi_i$ ($L < N$) and the original signal \mathbf{x} is minimized.
- ◆ Assumptions: \mathbf{x} is zero-mean WSS RP.

KLT

- ◆ Reminder:
 - Orthonormal constraint: $\langle \Phi_i, \Phi_j \rangle = \Phi_i^T \Phi_j = \delta[i - j]$
 - Autocorrelation matrix

$$\mathbf{R}_{xx} = E[\mathbf{xx}^T] = \begin{bmatrix} R_{xx}(0) & R_{xx}(1) & \cdots & R_{xx}(N-1) \\ R_{xx}(1) & R_{xx}(0) & & R_{xx}(N-2) \\ \vdots & \vdots & \ddots & \vdots \\ R_{xx}(N-1) & R_{xx}(N-2) & \cdots & R_{xx}(0) \end{bmatrix}$$

$$\begin{aligned} MSE &\equiv E[\|\mathbf{x} - \hat{\mathbf{x}}\|^2] = E\left[\left\|\sum_{i=0}^{N-1} y_i \Phi_i - \sum_{i=0}^{L-1} y_i \Phi_i\right\|^2\right] = E\left[\left\|\sum_{i=L}^{N-1} y_i \Phi_i\right\|^2\right] \\ &= E\left[\left\langle \sum_{i=L}^{N-1} y_i \Phi_i, \sum_{j=L}^{N-1} y_j \Phi_j \right\rangle\right] = E\left[\left(\sum_{i=L}^{N-1} y_i \Phi_i^T\right) \left(\sum_{j=L}^{N-1} y_j \Phi_j\right)\right] \\ &= E\left[\sum_{i=L}^{N-1} |y_i|^2\right] = E\left[\sum_{i=L}^{N-1} \Phi_i^T \mathbf{xx}^T \Phi_i\right] = \sum_{i=L}^{N-1} \Phi_i^T E[\mathbf{xx}^T] \Phi_i \end{aligned}$$

KLT

- Reminder: $\mathbf{R}_{xx} \mathbf{e} = \lambda \mathbf{e}$
- eigenvalue $\frac{\delta}{\delta \mathbf{v}} [\mathbf{u}^T \mathbf{v}] = \mathbf{u}$
- eigenvector $\frac{\delta}{\delta \mathbf{v}} [\mathbf{v}^T \mathbf{A} \mathbf{v}] = 2 \mathbf{A} \mathbf{v}$

$$\text{Minimize } MSE = \sum_{i=L}^{N-1} \Phi_i^T E[\mathbf{x} \mathbf{x}^T] \Phi_i = \sum_{i=L}^{N-1} \Phi_i^T \mathbf{R}_{xx} \Phi_i$$

$$\text{wrt } \langle \Phi_i, \Phi_j \rangle = \delta[i - j]$$

- ◆ Lagrange Multiplier

$$\frac{\delta}{\delta \Phi_i} \left[\sum_{i=L}^{N-1} \Phi_i^T \mathbf{R}_{xx} \Phi_i - \lambda_i (\langle \Phi_i, \Phi_j \rangle - 1) \right] = 0$$

$$\frac{\delta}{\delta \Phi_i} \left[\Phi_i^T \mathbf{R}_{xx} \Phi_i - \lambda_i (\langle \Phi_i, \Phi_i \rangle - 1) \right] = 0$$

$$2\mathbf{R}_{xx} \Phi_i - 2\lambda_i \Phi_i = 0 \Rightarrow \mathbf{R}_{xx} \Phi_i = \lambda_i \Phi_i \Rightarrow MSE = \sum_{i=L}^{N-1} \lambda_i$$

- ◆ Optimal coding scheme: send the larger eigenvalues first!

KLT Problems

- ◆ KLT problems
 - Signal dependent
 - Computationally expensive
 - statistics need to be computed
 - no structure, no symmetry, no guarantee of stability
 - Real signals are really stationary
 - Encoder/Decoder communication
- ◆ Practical solutions
 - Assume a reasonable signal model
 - Blocking the signals to ensure stationary assumption holds
 - Making the transform matrix sparse & symmetric
 - Good KLT approximation for smooth signals: DCT!

KLT: Summary

$$\mathbf{R}_{\mathbf{xx}} \Phi_i = \lambda_i \Phi_i$$

eigenvectors

$$E[\mathbf{xx}^T] \quad KLT = \begin{bmatrix} \Phi_0 & \Phi_1 & \dots & \Phi_{N-1} \end{bmatrix}$$

- ◆ Signal dependent
- ◆ Require stationary signals
- ◆ How do we communicate bases to the decoder?
- ◆ How do we design “good” signal-independent transform?

Best Basis Revisited

- ◆ Fundamental question: what is the best basis?
 - energy compaction: minimize a pre-defined error measure, say MSE, given L coefficients
 - maximize perceptual reconstruction quality
 - low complexity: fast-computable decomposition and reconstruction
 - intuitive interpretation
- ◆ How to construct such a basis? Different viewpoints!
- ◆ Applications
 - compression, coding
 - signal analysis
 - de-noising, enhancement
 - communications

Discrete Cosine Transforms

- ◆ Type I

$$[C^I] = \sqrt{\frac{2}{M}} \left[K_m K_n \cos\left(\frac{mn\pi}{M}\right) \right], \quad m, n \in \{0, 1, \dots, M\}$$
$$K_i = \begin{cases} 1/\sqrt{2}, & i = 0, M \\ 1, & \text{otherwise} \end{cases}$$

- ◆ Type II

$$[C^{II}] = \sqrt{\frac{2}{M}} \left[K_m \cos\left(\frac{m(n+1/2)\pi}{M}\right) \right], \quad m, n \in \{0, 1, \dots, M-1\}$$

- ◆ Type III

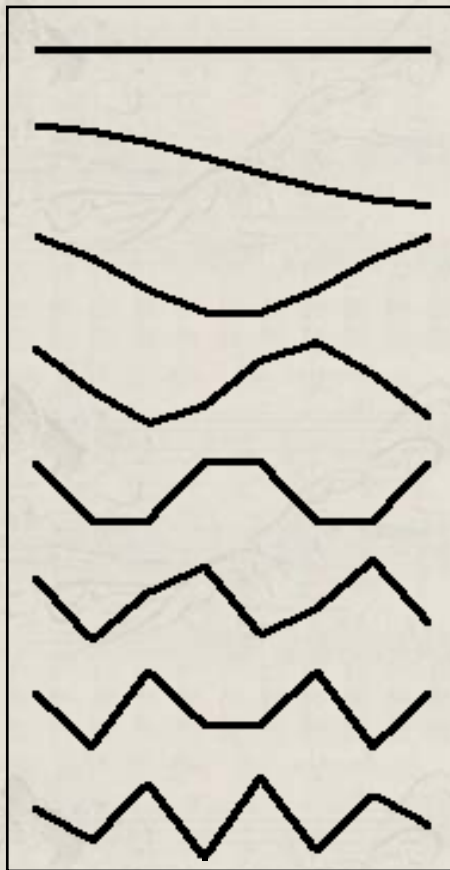
$$[C^{III}] = \sqrt{\frac{2}{M}} \left[K_n \cos\left(\frac{(m+1/2)n\pi}{M}\right) \right], \quad m, n \in \{0, 1, \dots, M-1\}$$

- ◆ Type IV

$$[C^{IV}] = \sqrt{\frac{2}{M}} \left[\cos\left(\frac{(m+1/2)(n+1/2)\pi}{M}\right) \right], \quad m, n \in \{0, 1, \dots, M-1\}$$

DCT Type-II

DCT basis



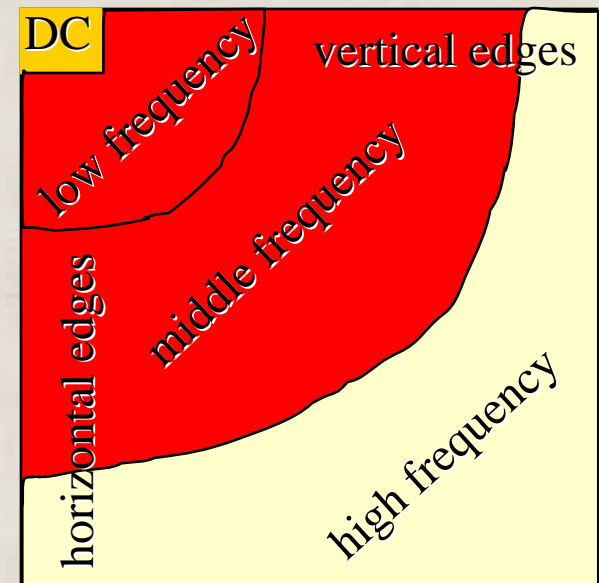
$$\begin{cases} X[m] = \sqrt{\frac{2}{M}} K_m \sum_{n=0}^{M-1} x[n] \cos \left[\frac{(2n+1)m\pi}{2M} \right] \\ x[n] = \sqrt{\frac{2}{M}} K_n \sum_{m=0}^{M-1} X[m] \cos \left[\frac{(2m+1)n\pi}{2M} \right] \end{cases}$$

$$m, n = 0, 1, \dots, M-1$$

$$K_i = \begin{cases} \frac{1}{\sqrt{2}}, & i = 0 \\ 1, & i \neq 0 \end{cases}$$

- orthogonal
- real coefficients
- symmetry
- near-optimal
- fast algorithms

8 x 8 block



DCT Symmetry

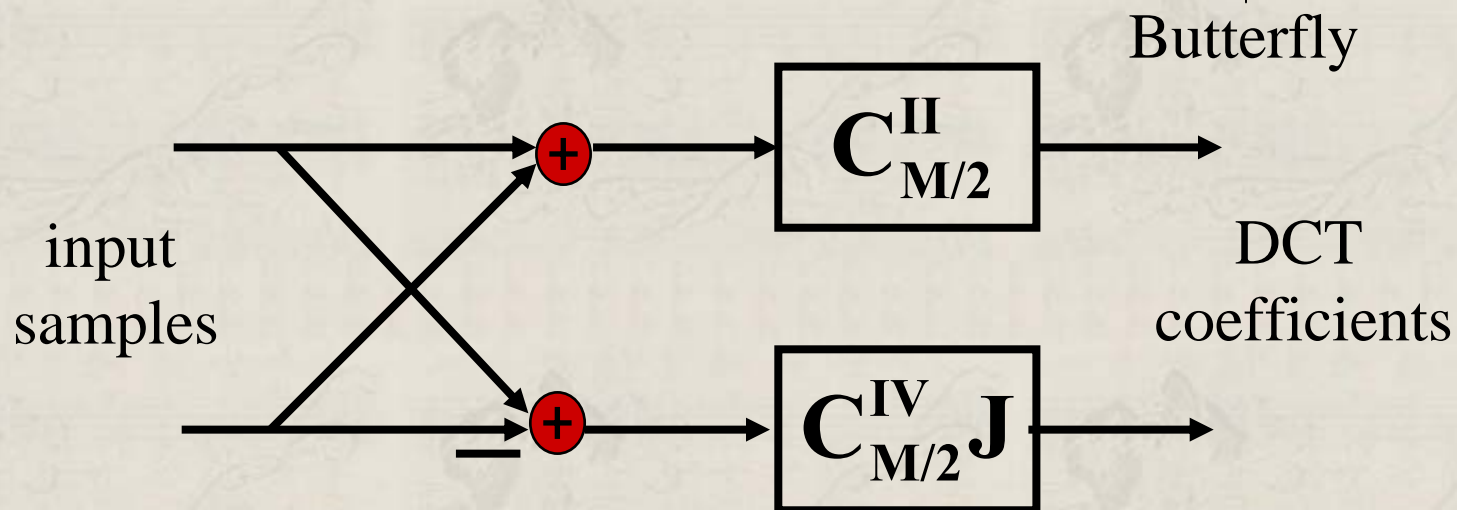
$$\begin{aligned} & \cos\left(\frac{m(2(M-1-n)+1)\pi}{2M}\right) \\ &= \cos\left(\frac{(2M-2-2n+1)m\pi}{2M}\right) \\ &= \cos\left[\frac{2Mm\pi}{2M} - \frac{(2n+1)m\pi}{2M}\right] \\ &= \pm \cos\left[\frac{(2n+1)m\pi}{2M}\right] \end{aligned}$$

DCT basis functions
are either symmetric
or anti-symmetric

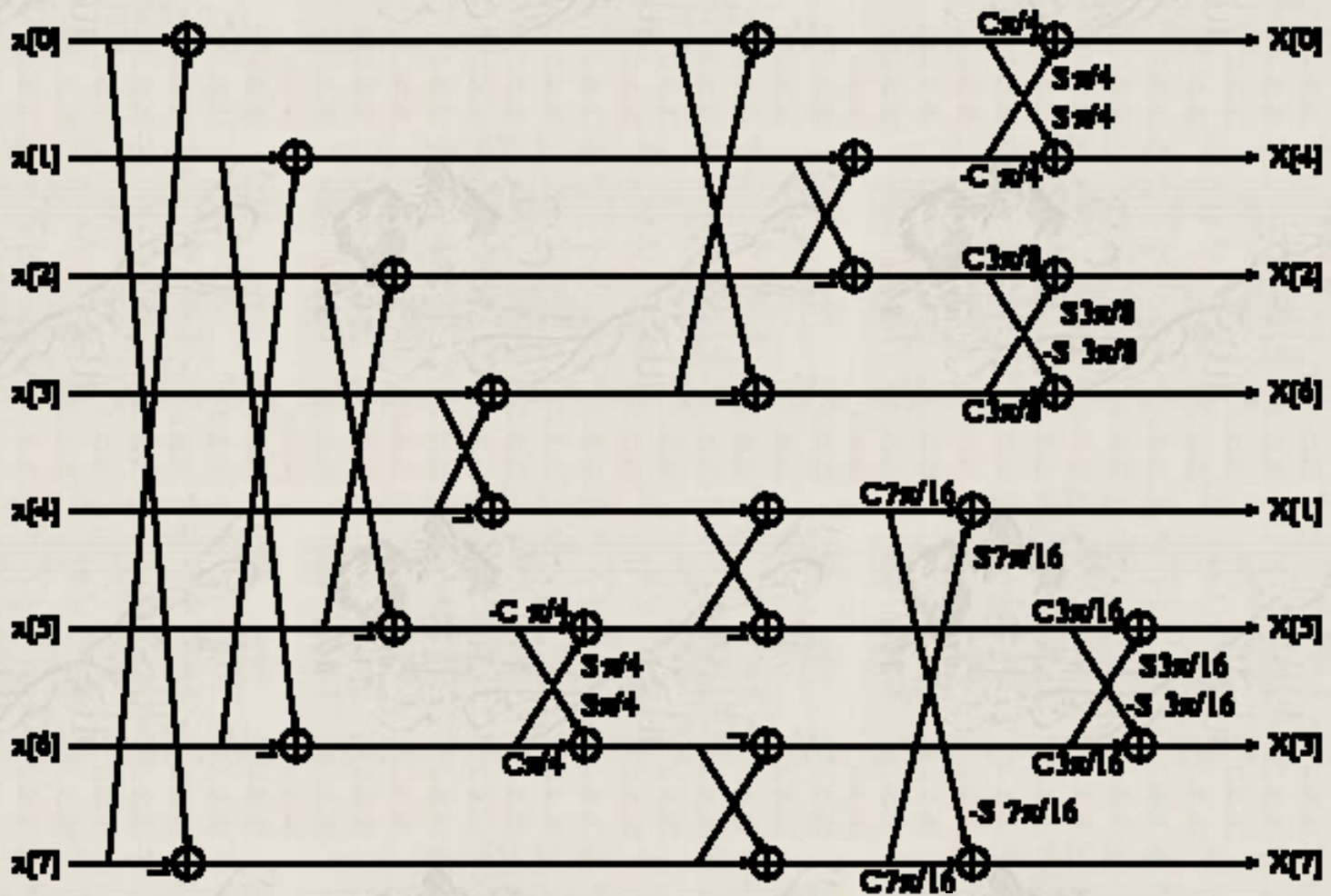
DCT: Recursive Property

- ◆ An M-point DCT-II can be implemented via an M/2-point DCT-II and an M/2-point DCT-IV

$$[C_M^{II}] = \frac{1}{\sqrt{2}} \begin{bmatrix} C_{M/2}^{II} & \mathbf{0} \\ \mathbf{0} & C_{M/2}^{IV} J \end{bmatrix} \begin{bmatrix} \mathbf{I} & \mathbf{J} \\ \mathbf{J} & -\mathbf{I} \end{bmatrix}$$



Fast DCT Implementation



13 multiplications and 29 additions per 8 input samples

Block DCT

$$\begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_N \end{bmatrix} = \begin{bmatrix} C_M^{\text{II}} & 0 & & \\ 0 & C_M^{\text{II}} & 0 & \\ & 0 & C_M^{\text{II}} & 0 \\ & & 0 & C_M^{\text{II}} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{bmatrix}$$

output blocks
of DCT coefficients,
each of size M

input blocks,
each of size M

JPEG Still Image Coding Standard



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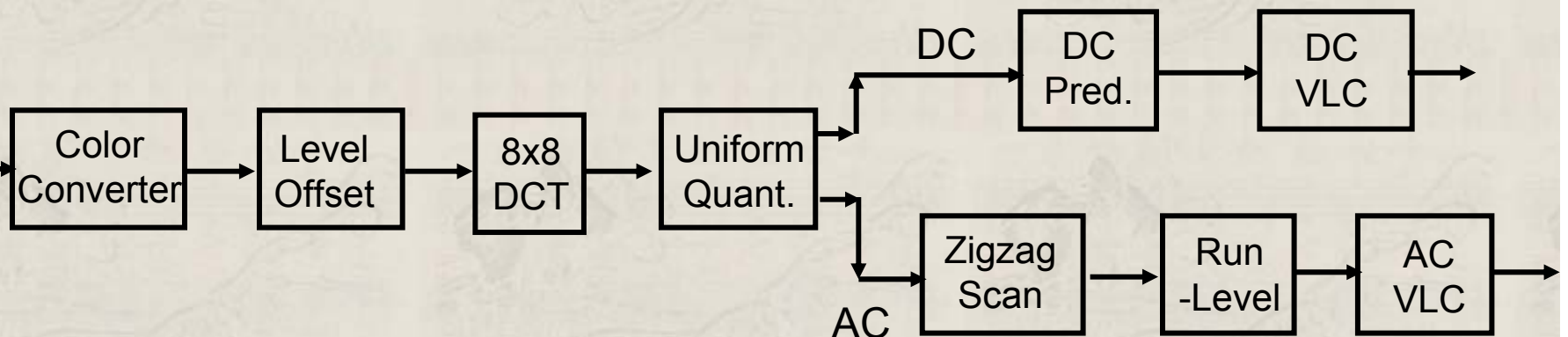
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Overall Structure of JPEG



- ◆ Color converter
 - RGB to YUV
- ◆ Level offset
 - subtract $2^{(N-1)}$. N: bits / pixel.
- ◆ Quantization
 - Different step size for different coefficients
- ◆ DC
 - Predict from DC of previous block
- ◆ AC:
 - Zigzag scan to get 1-D data
 - Run-level: joint coding of non-zero coeffs and number of zeros before it.

JPEG Quantization

- ◆ Uniform mid-tread quantizer
- ◆ Larger step sizes for chroma components
- ◆ Different coefficients have different step sizes
 - Smaller steps for low frequency coefficients (more bits)
 - Larger steps for high frequency coefficients (less bits)
 - Human visual system is not sensitive to error in high frequency

◆ Luma Quantization Table

16	11	10	16	24	40	51	51
12	12	14	19	26	58	60	55
14	13	16	24	40	57	69	56
14	17	22	29	51	87	80	62
18	22	37	56	68	109	103	77
24	35	55	64	81	104	113	92
49	64	78	87	103	121	120	101
72	92	95	98	112	100	103	99

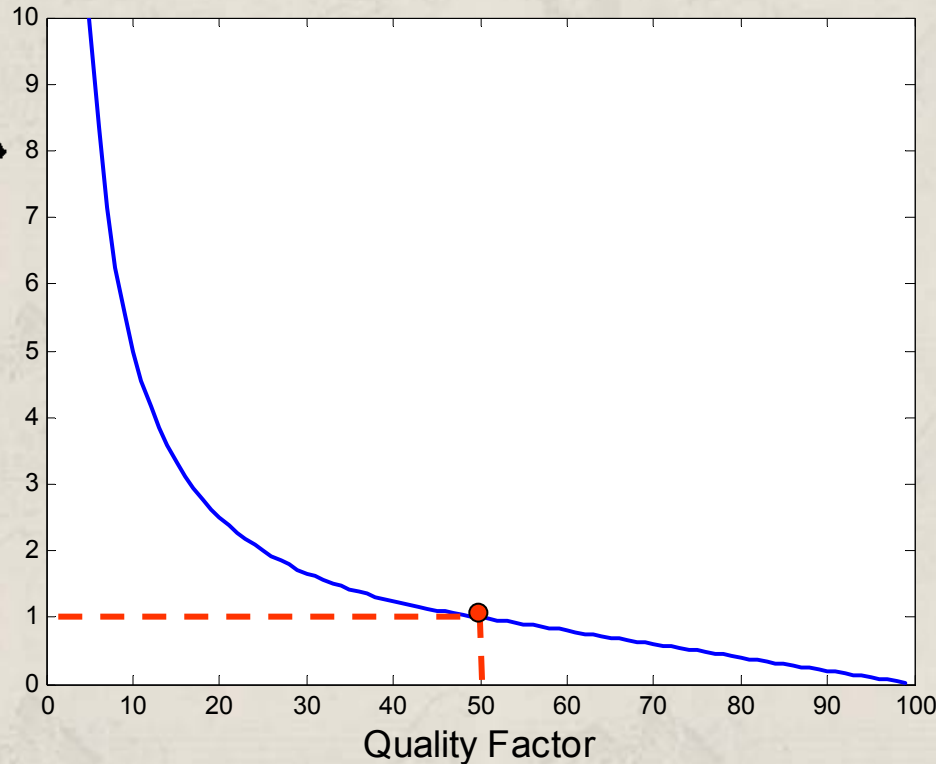
◆ Chroma Quantization Table

17	18	24	47	99	99	99	99
18	21	26	66	99	99	99	99
24	26	56	99	99	99	99	99
47	66	99	99	99	99	99	99
99	99	99	99	99	99	99	99
99	99	99	99	99	99	99	99
99	99	99	99	99	99	99	99
99	99	99	99	99	99	99	99

- ◆ Actual step size: Scale the basic table by a quality factor

Scaling of Quantization Table

- ◆ Actual Q table = scaling x Basic Q table:
 - quality factor ≤ 50 : scaling = $50/\text{quality}$
 - quality factor > 50 : scaling = $2 - \text{quality}/50$

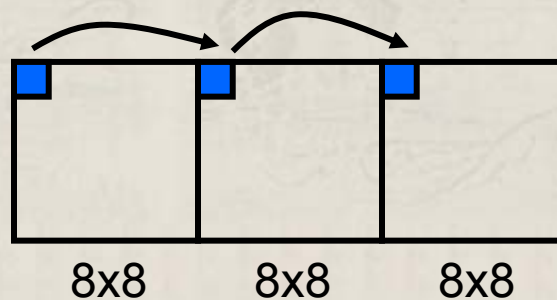


16	11	10	16	24	40	51	51
12	12	14	19	26	58	60	55
14	13	16	24	40	57	69	56
14	17	22	29	51	87	80	62
18	22	37	56	68	109	103	77
24	35	55	64	81	104	113	92
49	64	78	87	103	121	120	101
72	92	95	98	112	100	103	99

Quality Factor	Scaling
10	5.0
20	2.5
50	1.0
75	0.5

DC Prediction

- ◆ DC Coefficients: average of a block
- ◆ DC of neighboring blocks are still similar to each others: redundancy
- ◆ The redundancy can be removed by differential coding:
 - $e(n) = DC(n) - DC(n-1)$
- ◆ Only encode the prediction error $e(n)$



DC coeffs
of Lena

Coefficient Category

- ◆ Divide coefficients into categories of **exponentially increased sizes**
- ◆ Use Huffman code to encode category ID
- ◆ Use **fixed length code within each category**
- ◆ Similar to Exponential Golomb code

Ranges	Range Size	DC Cat. ID	AC Cat. ID
0	1	0	N/A
-1, 1	2	1	1
-3, -2, 2, 3	4	2	2
-7, -6, -5, -4, 4, 5, 6, 7	8	3	3
-15, ..., -8, 8, ..., 15	16	4	4
-31, ..., -16, 16, ..., 31	32	5	5
-63, ..., -32, 32, ..., 63	64	6	6
...
[-32767, -16384], [16384, 32767]	32768	15	15

Coding of DC Coefficients

- ◆ Encode $e(n) = DC(n) - DC(n-1)$

DC Cat.	Prediction Errors	Base Codeword
0	0	010
1	-1, 1	011
2	-3, -2, 2, 3	100
3	-7, -6, -5, -4, 4, 5, 6, 7	00
4	-15, ..., -8, 8, ..., 15	101
5	-31, ..., -16, 16, ..., 31	110
6	-63, ..., -32, 32, ..., 63	1110
...

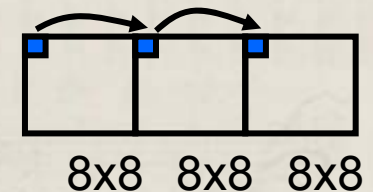
Our example:

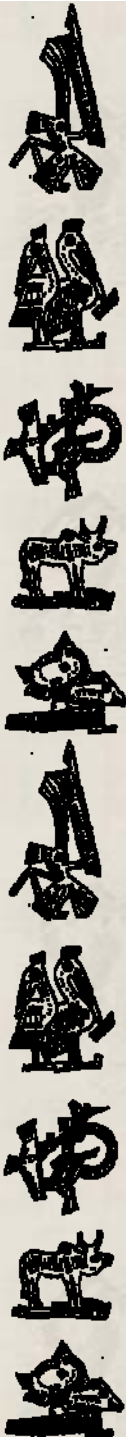
DC: 8. Assume last DC: 5

Cat.: 2, index 3

→ $e = 8 - 5 = 3.$

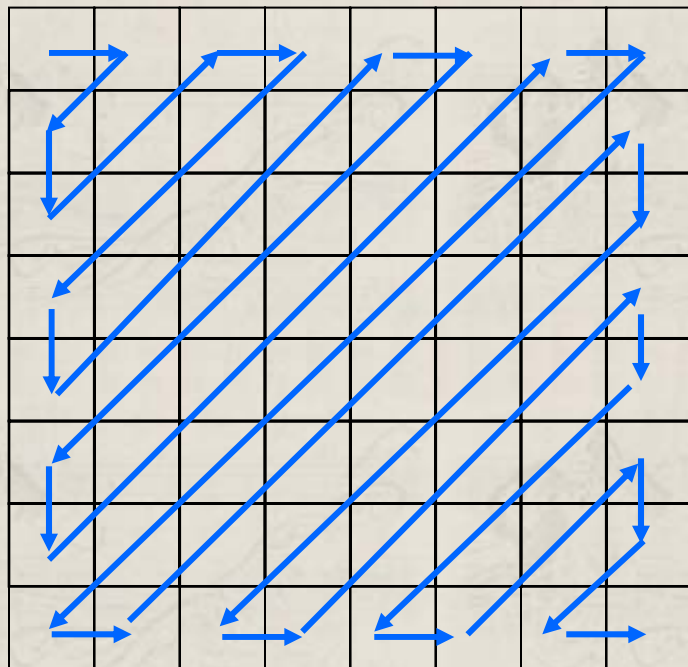
→ Bitstream: 10011





Coding of AC Coefficients

- ◆ Most non-zero coefficients are in the upper-left corner
- ◆ Zigzag scanning



◆ Example

8	24	-2	0	0	0	0	0
-31	-4	6	-1	0	0	0	0
0	-12	-1	2	0	0	0	0
0	0	-2	-1	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0

- ◆ Zigzag scanning result (DC is coded separately):

24 -31 0 -4 -2 0 6 -12 0 0 0 -1 -1 0 0 0 2 -2 0 0 0 0 -1 EOB

EOB: End of block symbol. The remaining coeffs are all 0.

Coding of AC Coefficients

- ◆ Many AC coefficients are zeros:
 - Huffman coding is not efficient for symbol with prob. $> 1/2$
- ◆ **Run-level coding**: Jointly encode a non-zero coefficient and the number of zeros **before** it (**run of zeros**): (**run, level**) event
- ◆ **Disadvantage**: Symbol set is enlarged: #Run x #Level
- ◆ **Tradeoff**:
 - Run: encode up to 15 zeros. Apply **escape coding** for greater values.
 - Level: Divide level into 16 categories, as in DC.
 - Apply Huffman coding to the joint **Run / Category** event:
 - Max symbol set size: $16 \times 16 = 256$.
 - Followed by fixed length code to signal the level index within each category
- ◆ **Example**: zigzag scanning result
24 -31 0 -4 -2 0 6 -12 0 0 0 -1 -1 0 0 0 2 -2 0 0 0 0 0 -1 EOB
- ◆ (Run, level) representation:
- ◆ (0, 24), (0, -31), (1, -4), (0, -2), (1, 6), (0, -12), (3, -1), (0, -1), (3, 2), (0, -2), (5, -1), EOB

Coding of AC Coefficients

Run / Cat.	Base codeword	Run / Cat.	Base Codeword	...	Run / Cat.	Base codeword
EOB	1010	-	-	...	ZRL	1111 1111 001
0/1	00	1/1	1100	...	15/1	1111 1111 1111 0101
0/2	01	1/2	11011	...	15/2	1111 1111 1111 0110
0/3	100	1/3	1111001	...	15/3	1111 1111 1111 0111
0/4	1011	1/4	111110110	...	15/4	1111 1111 1111 1000
0/5	11010	1/5	11111110110	...	15/5	1111 1111 1111 1001
...

- ◆ ZRL: represent 16 zeros when number of zeros exceeds 15.
 - Example: 20 zeros followed by -1: (ZRL), (4, -1).
 - ◆ (Run, Level) sequence: (0, 24), (0, -31), (1, -4),
 - ◆ Run/Cat. Sequence: 0/5, 0/5, 1/3, ...
- 24 is the 24-th entry in Category 5 → (0, 24): **11010** 11000
- 4 is the 3-th entry in Category 3 → (1, -4): **1111001** 011

A Complete Example

◆ Original data:

124	125	122	120	122	119	117	118
121	121	120	119	119	120	120	118
126	124	123	122	121	121	120	120
124	124	125	125	126	125	124	124
127	127	128	129	130	128	127	125
143	142	143	142	140	139	139	139
150	148	152	152	152	152	150	151
156	159	158	155	158	158	157	156

2-D DCT

39.8	6.5	-2.2	1.2	-0.3	-1.0	0.7	1.1
-102.4	4.5	2.2	1.1	0.3	-0.6	-1.0	-0.4
37.7	1.3	1.7	0.2	-1.5	-2.2	-0.1	0.2
-5.6	2.2	-1.3	-0.8	1.4	0.2	-0.1	0.1
-3.3	-0.7	-1.7	0.7	-0.6	-2.6	-1.3	0.7
5.9	-0.1	-0.4	-0.7	1.9	-0.2	1.4	0.0
3.9	5.5	2.3	-0.5	-0.1	-0.8	-0.5	-0.1
-3.4	0.5	-1.0	0.8	0.9	0.0	0.3	0.0

◆ Quantized by basic table

2	1	0	0	0	0	0	0
-9	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0

Q table:

16	11	...
12	...	
14	...	

$\text{floor}(39.8/16 + 0.5) = 2$
 $\text{floor}(6.5/11 + 0.5) = 1$
 $-\text{floor}(102.4/12 + 0.5) = -9$
 $\text{floor}(37.7/14 + 0.5) = 3$

◆ Zigzag scanning

2 1 -9 3 EOB

A Complete Example

- ◆ Zigzag scanning

2 1 -9 3 EOB

- ◆ Inverse Quantization

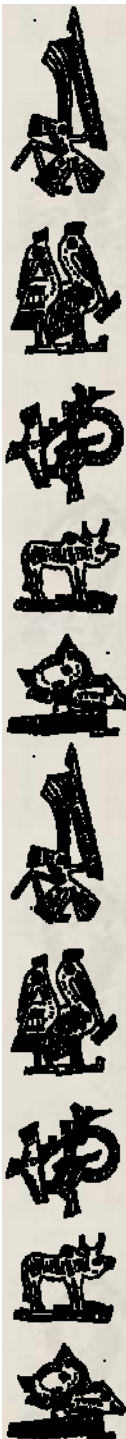
32	11	0	0	0	0	0	0	122	122	121	121	120	119	119	118
-108	0	0	0	0	0	0	0	121	121	120	119	119	118	117	117
42	0	0	0	0	0	0	0	120	120	120	119	118	117	117	117
0	0	0	0	0	0	0	0	123	123	122	122	121	120	120	120
0	0	0	0	0	0	0	0	131	130	130	129	128	128	127	127
0	0	0	0	0	0	0	0	142	141	141	140	139	139	138	138
0	0	0	0	0	0	0	0	153	152	152	151	150	150	149	149
0	0	0	0	0	0	0	0	159	159	159	158	157	157	156	156

- ◆ Reconstructed block

- ◆ MSE: 5.67

Progressive JPEG

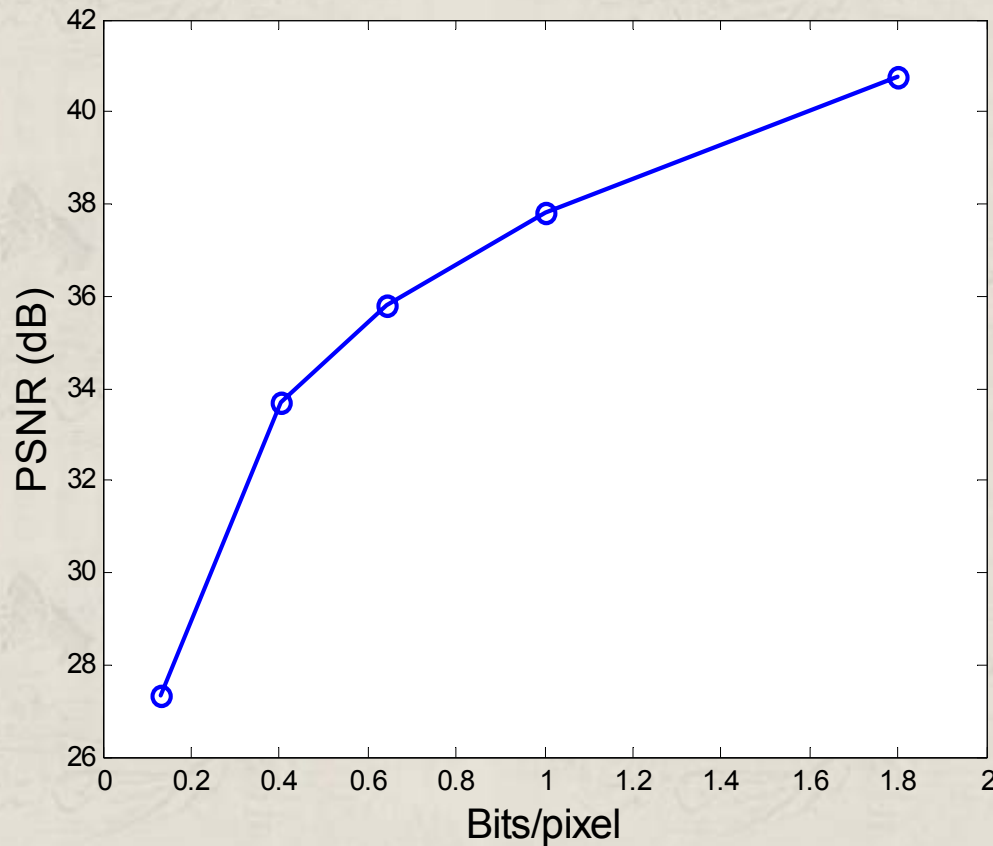
- ◆ Baseline JPEG encodes the image block by block:
 - Decoder has to wait till the end to decode and display the entire image
- ◆ Progressive: Coding DCT coefficients in multiple scans
 - The first scan generates a low-quality version of the entire image
 - Subsequent scans refine the entire image gradually.
- ◆ Two procedures defined in JPEG:
 - Spectral selection:
 - Divide all DCT coefficients into several bands (low, middle, high frequency subbands...)
 - Bands are coded into separate scans
 - Successive approximation:
 - Send MSB of all coefficients first
 - Send lower significant bits in subsequent scans



JPEG Coding Result for Lena



Lena



Quality factor:

5 25 50 75 90

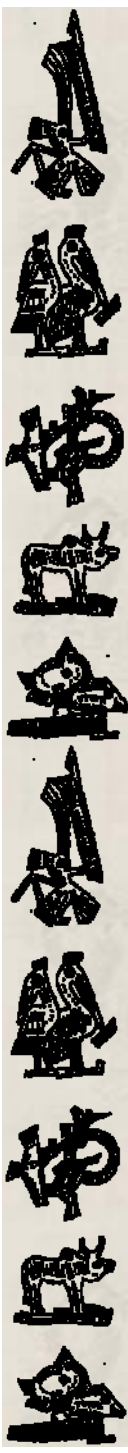
QF
25



QF
5



Blocking artifact →



Scalable Coding & JPEG2000



Trac D. Tran

ECE Department

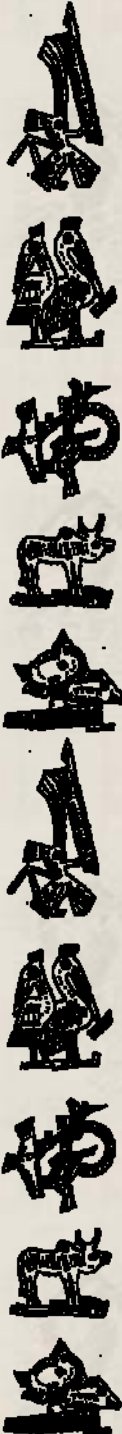


The Johns Hopkins University

Baltimore MD 21218

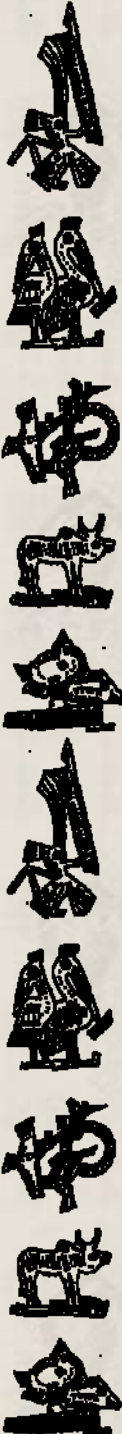
Goals and Approaches

- ◆ **Simulcast coding**
 - Encode the same signal several times, each with a different quality setting
 - Each of the generated bit-stream is non-scalable
 - Advantage: simple, efficient for each particular setting
 - Disadvantage: inefficient overall
- ◆ **Design goal in scalable coding**
 - Realizing requirement for scalability
 - Minimizing the reduction in coding efficiency
- ◆ **Approach**
 - Coarse-granularity scalability: only have a few layers, usually two to three only
 - Fine-granularity scalability: many layers, offer more decoding options and precise bit-rate control

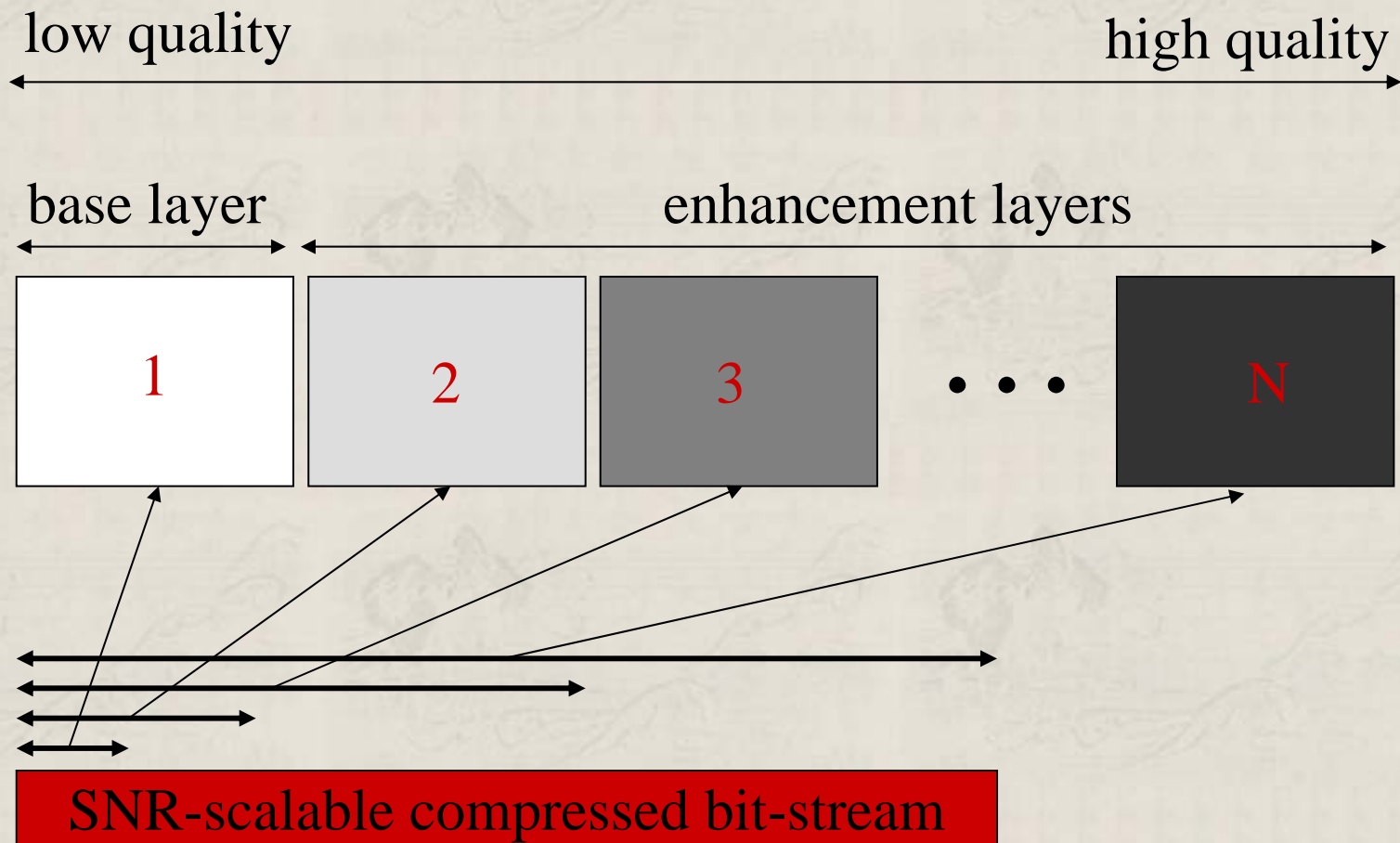


Scalable Applications

- ◆ Quality/SNR scalability
 - Digital broadcast TV or HDTV with different quality layers
 - Multi-quality video-on-demand services
 - Error-resilient video over ATM and other networks
- ◆ Spatial scalability
 - Inter-working between two different video standards
 - Layered digital TV broadcast
 - Video on LAN and computer networks
 - Error-resilient video over lossy channels
- ◆ Temporal scalability
 - Migration from low to high temporal resolution
 - Networked video. Error resilience
 - Multi-quality video-on-demand services based on decoder capability as well as communication bit-rate
- ◆ Frequency scalability
 - Error resilience

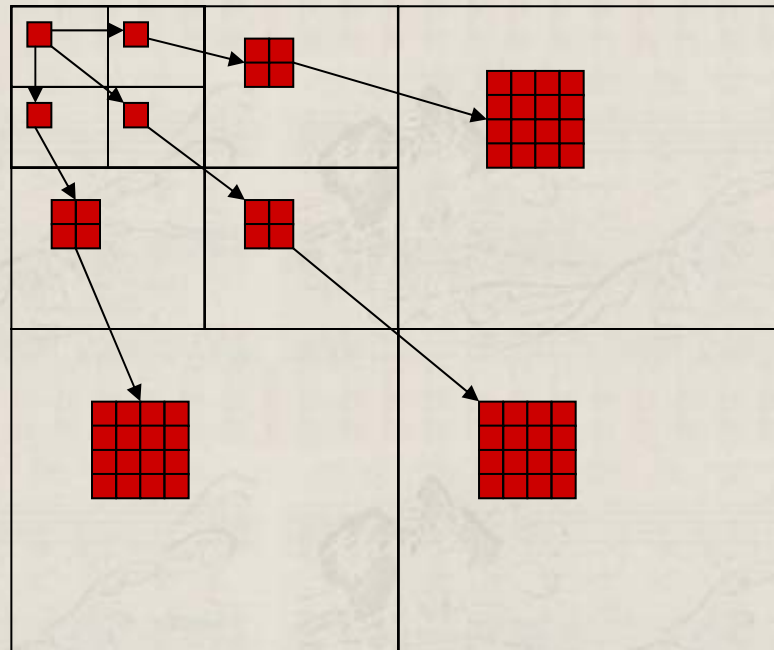


Quality/SNR Scalability



- ◆ N layers of quality/SNR scalability

Wavelet Zero-Tree



- ◆ Main observation: there is self-similarity between wavelet coefficients across different scales
- ◆ If a parent is insignificant with respect to a threshold T , i.e. $|C| < T$, then so are its children

parent: $c_{i,j}$

children: $\{c_{2i,2j}, c_{2i+1,2j}, c_{2i,2j+1}, c_{2i+1,2j+1}\}$

EZW Coding

- ◆ Embedded zero-tree wavelet coding [Shapiro 1993]
 - Wavelet transform for image de-correlation
 - Exploitation of self-similarity of wavelet coefficients across different scales to predict the location of significant information
 - Further compression with adaptive arithmetic coding
- ◆ Main features
 - Bit-plane coding
 - One sorting pass and one refinement pass per bit plane with a pre-defined scan pattern
 - Use four symbols to classify wavelet coefficients
 - POS: positive significant
 - NEG: negative significant
 - ZTR: zero-tree root; parent and all children are insignificant
 - IZ: isolated insignificant; parent is insignificant but at least one of the children is significant



Toy Example

wavelet coefficients

18	3	2	2
6	-5	1	-2
8	13	-6	4
-7	1	3	-2

- ◆ Rank coefficients by magnitude
- ◆ Transmit coefficients bit plane by bit plane: 0 010 10011100
- ◆ Problem: how do we transmit the rank order to the decoder?

Sign	+	+	+	+	+	-	-	+	+	+	+	+	-	-	+	+
MSB	1															
	0	1	1													
	0	1	0	1	1	1	1	1								
	1	0	0	1	1	1	0	0	1	1	1	1	1	1		
LSB	0	1	0	1	0	0	1	0	1	1	0	0	0	0	1	1
	18	13	8	7	6	-6	-5	4	3	3	2	2	-2	-2	1	1

Recall: Embedded Quantization

1
0
1
1
0

Original
coefficient
 $C = 22$

1
X
X
X
X

Truncate
4 bit planes
Range=[16, 32)

$$Cr = 24$$

1
0
X
X
X

Receive 1
refinement bit
Range=[16, 24)

$$Cr = 20 \\ = 24 - 4$$

1
0
1
X
X

Receive 2
refinement bits
Range=[20, 24)

$$Cr = 22 \\ = 20 + 2$$

- ◆ N -bit-plane truncation = scalar quantization with

$$\Delta = 2^N$$

EZW Basic Algorithm

- ◆ Set initial threshold: $T = 2^{\lfloor \log_2 |\max| \rfloor}$
- ◆ Sorting Pass – Dominant Pass
 - scan coefficients from top left corner
 - parent nodes are always scanned before children
 - For each coefficient, output a symbol among {POS, NEG, ZTR, IZ} depending on the threshold T
- ◆ Refinement Pass – Subordinate Pass
 - refine the accuracy of each significant coefficient by sending one additional bit of its binary representation
- ◆ Reduce the threshold by a factor of 2: $T = \frac{1}{2}T$ and repeat Step 2

EZW Example: First Bit Plane

18	3	2	2
6	-5	1	-2
8	13	-6	4
-7	1	3	-2

POS =11
 NEG =10
 IZ =01
 ZTR =00

- ◆ T=16
- ◆ Dominant Pass 1
 - POS ZTR ZTR ZTR
 - Subordinate list = {18}
- ◆ Subordinate Pass 1
 - No symbols because subordinate step i works on significant coefficients from dominant step $i-1$ and earlier

Compressed bit-stream

11 00 00 00 – 8 bits

Reconstruction = {24 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0}



EZW Example: 2nd Bit Plane

*	3	2	2
6	-5	1	-2
8	13	-6	4
-7	1	3	-2

POS =11
 NEG =10
 IZ =01
 ZTR =00

◆ T=8

◆ Dominant Pass 2

- ZTR IZ ZTR POS POS IZ IZ
- Subordinate list = {18 8 13}

Compressed bit-stream

00 01 00 11 11 01 01 – 14 bits

◆ Subordinate Pass 2

- Send the bit plane of coefficients involved in Dominant Pass 1

0 – 1 bit

Reconstruction = {20 12 12 0 0 0 0 0 0 0 0 0 0 0 0}

Bit budget = 23 bits



EZW Example: 3rd Bit Plane

*	3	2	2
6	-5	1	-2
*	*	-6	4
-7	1	3	-2

POS = 11
 NEG = 10
 IZ = 01
 ZTR = 00

◆ T=4

◆ Dominant Pass 3

- ZTR POS NEG NEG IZ NEG POS IZ IZ
- Subordinate list = {18,8,13,6,-5,-7,-6,4}

Compressed bit-stream

◆ Subordinate Pass 3

00 11 10 10 01 10 11 01 01 – 18 bits

- Send the bit plane of coefficients involved in Dominant Pass 2

001 – 3 bits

Reconstruction = {18 10 14 6 -6 -6 -6 6 0 0 0 0 0 0 0}

Bit budget = 44 bits



EZW Decoding

- ◆ The decoder needs
 - Initial threshold T (or the max absolute value of all coefficients)
 - Original image size
 - Number of wavelet decomposition levels
 - Encoded bit-stream
- ◆ Decoding process
 - Decode the arithmetic-encoded bit-stream into a stream of symbols
 - Based on the side information, create data structures of appropriate sizes
 - Traverse the encoding algorithm

Other Approaches

- ◆ Idea can be generalized to other different data structures
- ◆ For example, quad-tree
- ◆ **Sorting Pass 1**
 - 1 0 0 0 1 0 0 0
- ◆ **Refinement Pass 1:** nothing
- ◆ **Sorting Pass 2**
 - 0 0 1 0 1 1 0 0
- ◆ **Refinement Pass 2**
 - Like EZW, 1 bit for 18
- ◆ **Sorting Pass 3**
 - 1 0 1 1 0 1 1 1 0 1 1 0 0
- ◆ **Refinement Pass 3**
 - Like EZW, 3 bits for 18 8 13

18	3	2	2
6	-5	1	-2
8	13	-6	4
-7	1	3	-2

0	3	2	2
6	-5	1	-2
8	13	-6	4
-7	1	3	-2

0	3	2	2
6	-5	1	-2
0	0	-6	4
-7	1	3	-2



JPEG2000 Image Coding

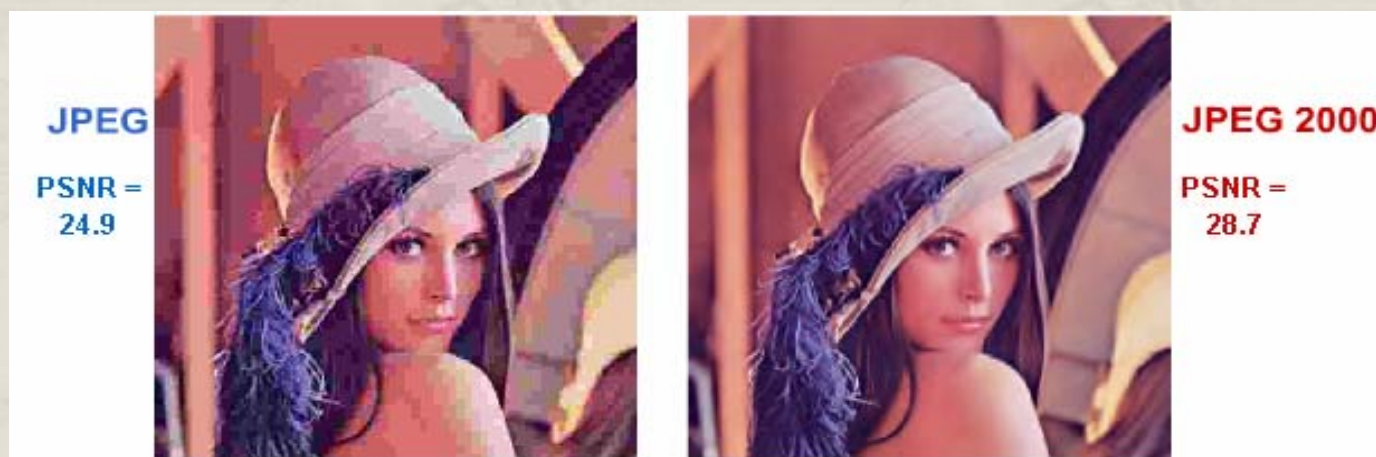
- ◆ About JPEG2000 (ISO/IEC15444)
- ◆ Objectives of JPEG2000
 - ◆ To provide new functionalities and features that current standards fail to support
 - ◆ To support advanced applications in the new millennium
 - ◆ To extend the applicability of image coding in more applications
 - ◆ To allow imaging applications to be interactive and adaptive

JPEG2000 vs. JPEG

◆ Key Advantages

- ◆ Wavelet based – better rate-distortion performance
- ◆ Scalable by resolution, quality, color channel, location in image
- ◆ Lossless encoding, including lossy to lossless scalability
- ◆ Error resilience
- ◆ Region-of-Interest coding and progressive decoding

Compression ratio: 100:1



http://www.aware.com/products/compression/demos/lena_compare.html

JPEG2000 Flexible Decoding

Encoder choices:
tiling,
lossy/lossless
+ other choices



Bit stream



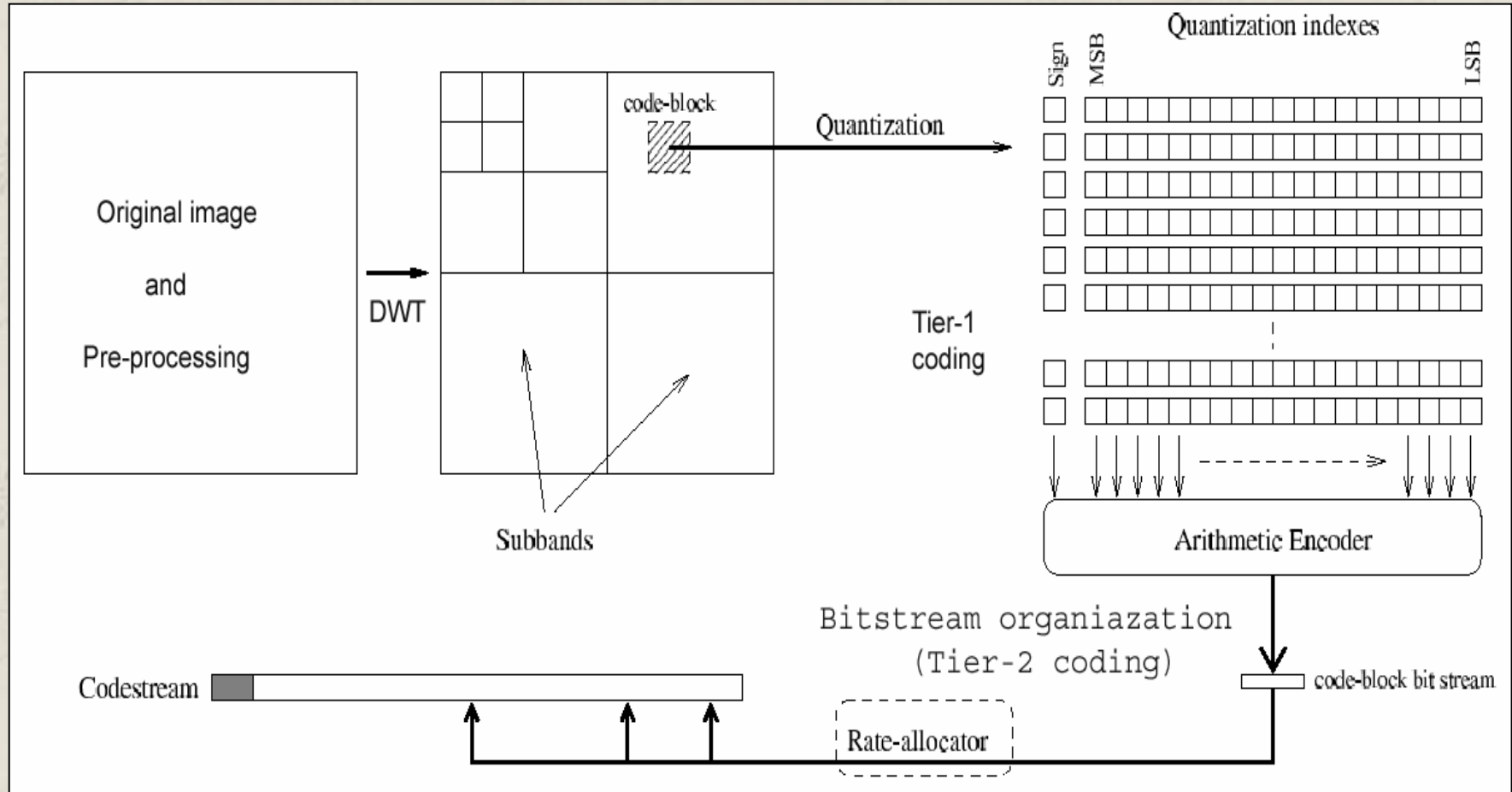
Decoder choices:

image resolution,
image fidelity,
region-of-interest,
fixed-rate,
components

JPEG 2000 offers flexible decoding



JPEG2000 Compression Scheme



R. Grosbois, *et al.*, "New approach to JPEG2000 compliant Region-of-Interest coding", Proc. of the SPIE 46th Annual Meeting, San Diego, CA, 2001

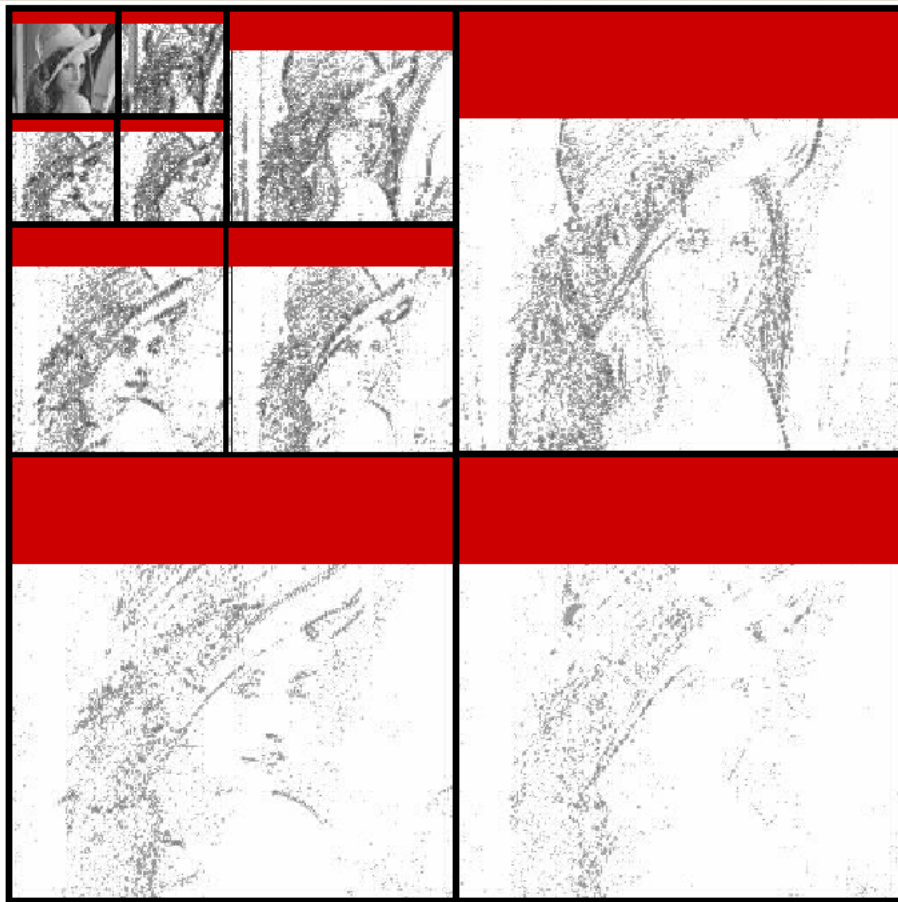


Part 1: Discrete Wavelet Transform

- ◆ Inherent to normal DWT:
 - Multi-resolution image representation
 - Eliminate blocking artifacts at high compression ratio
 - Each subband can be quantized differently
- ◆ Special techniques:
 - Provide integer filter (e.g. (5,3) filter) to support lossless and lossy compression within a single compressed bit-stream;
 - Line-based DWT and lifting implementations to reduce the memory requirement and computational complexity.

Except for a few special case, e.g., the (5,3) integer filter, the DWT is generally more computationally complexity (~2 to 3) than the block-based DCT; and DWT also requires more memory than DCT.

Line-based DWT Implementation



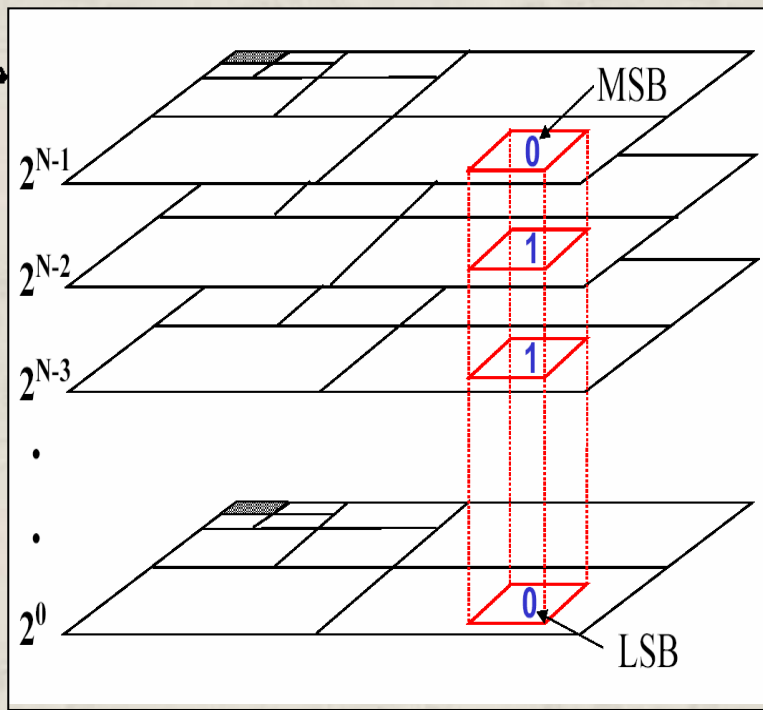
- ◆ There is no need to buffer an entire image in order to perform wavelet transform
- ◆ Depending on filter lengths and decomposition levels, a line of wavelet coefficients can be made available only after processing a few lines of the input image

Part 2: Quantization

◆ Embedded Quantization

Quantization index is encoded bit by bit, starting from Most Significant Bit (MSB) to Least Significant Bit (LSB)

◆ Example



Wavelet coefficient = 209

Quantizer step size $\Delta_b = 2$

Quantization index = $\lfloor 209/2 \rfloor = 104$
= 01101000;

Dequantized value based on fully decoded index:
 $(104+0.5)*2 = 209$;

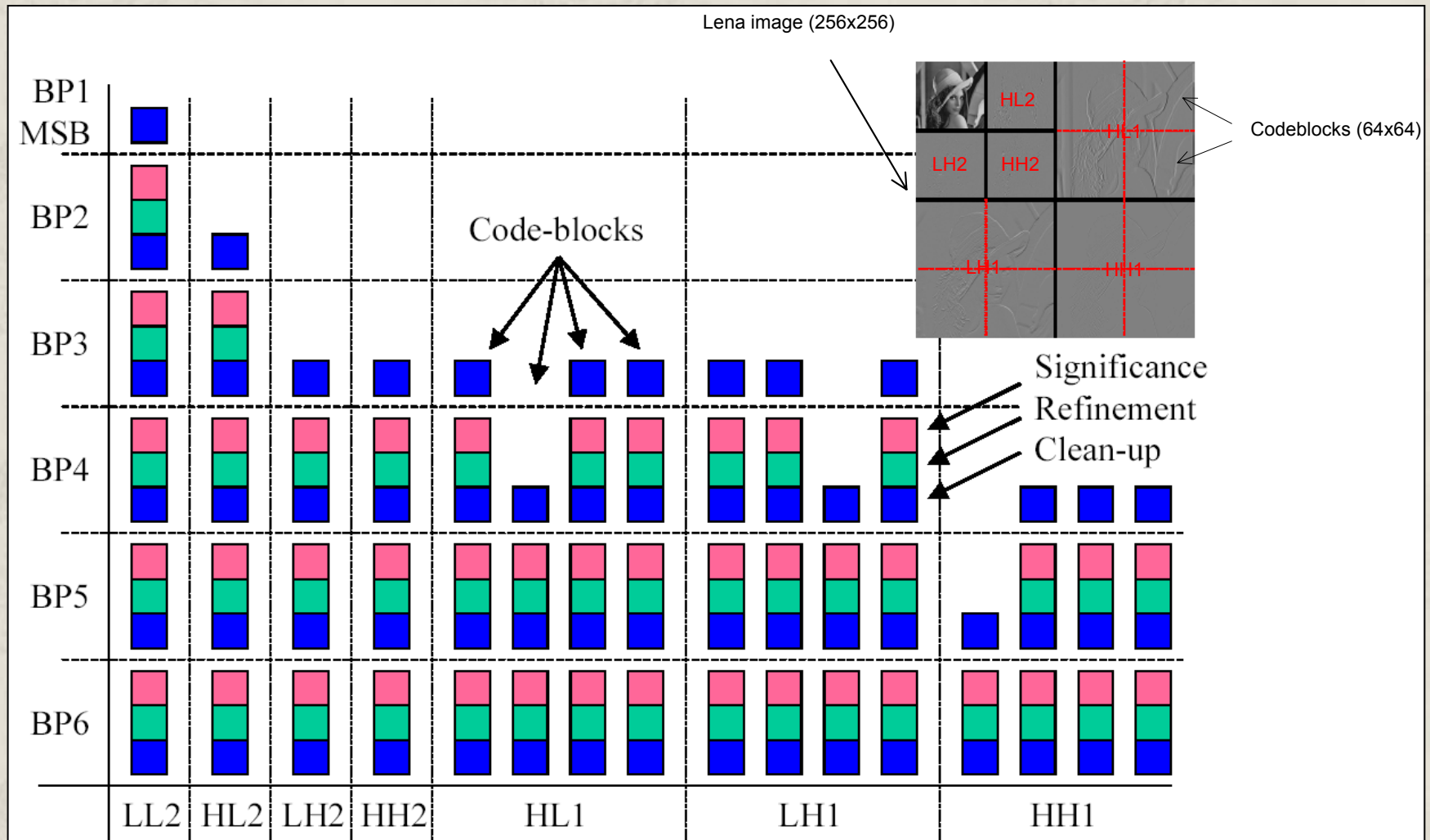
Decoding value after decoding 3 bit planes:

- Decoded index = 011 = 3;
- Step size = $2*32=64$
- Dequantized value = $(3+0.5)*64 = 224$

Part 3: Entropy Coding (Tier-1)

- ◆ Tier-1 Entropy coding
 - Each bit-plane is individually coded by the context-based adaptive binary arithmetic coding (JBIG2 MQ-coder)
 - Each bit plane is partitioned into blocks, named *code-blocks*, which are encoded independently
 - Each bit plane of each block is encoded in three *sub-bit-plane passes*
 - Significance propagation pass
 - Magnitude refinement pass
 - Clean-up pass

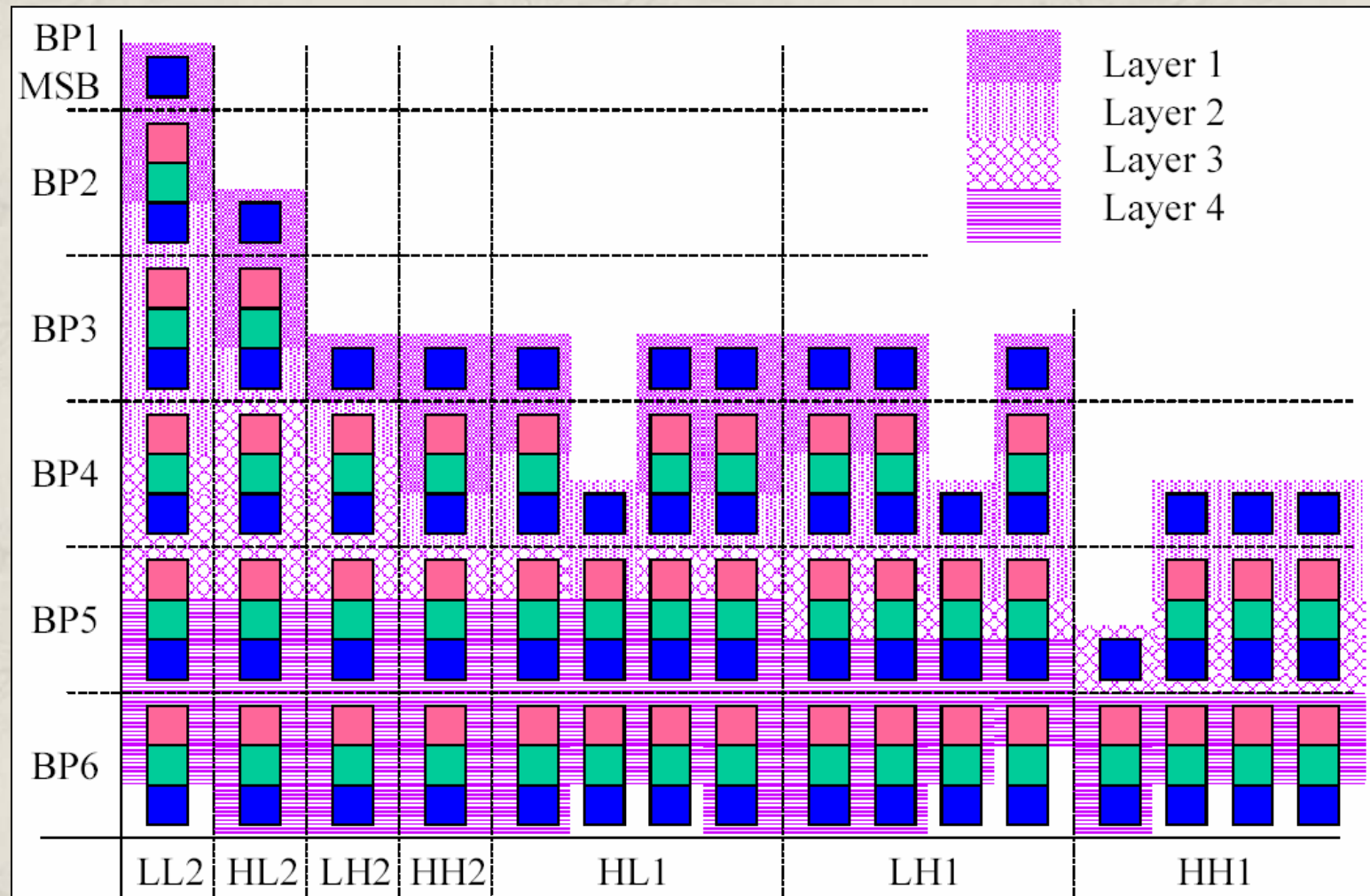
Example of Bit-plane Coding



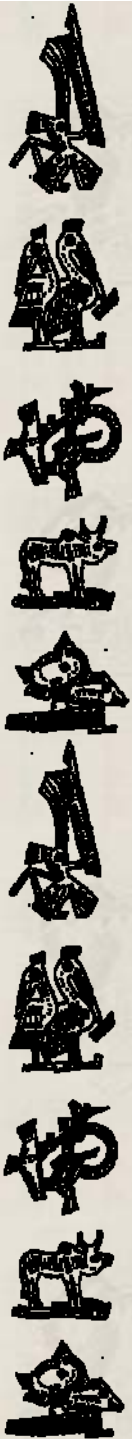
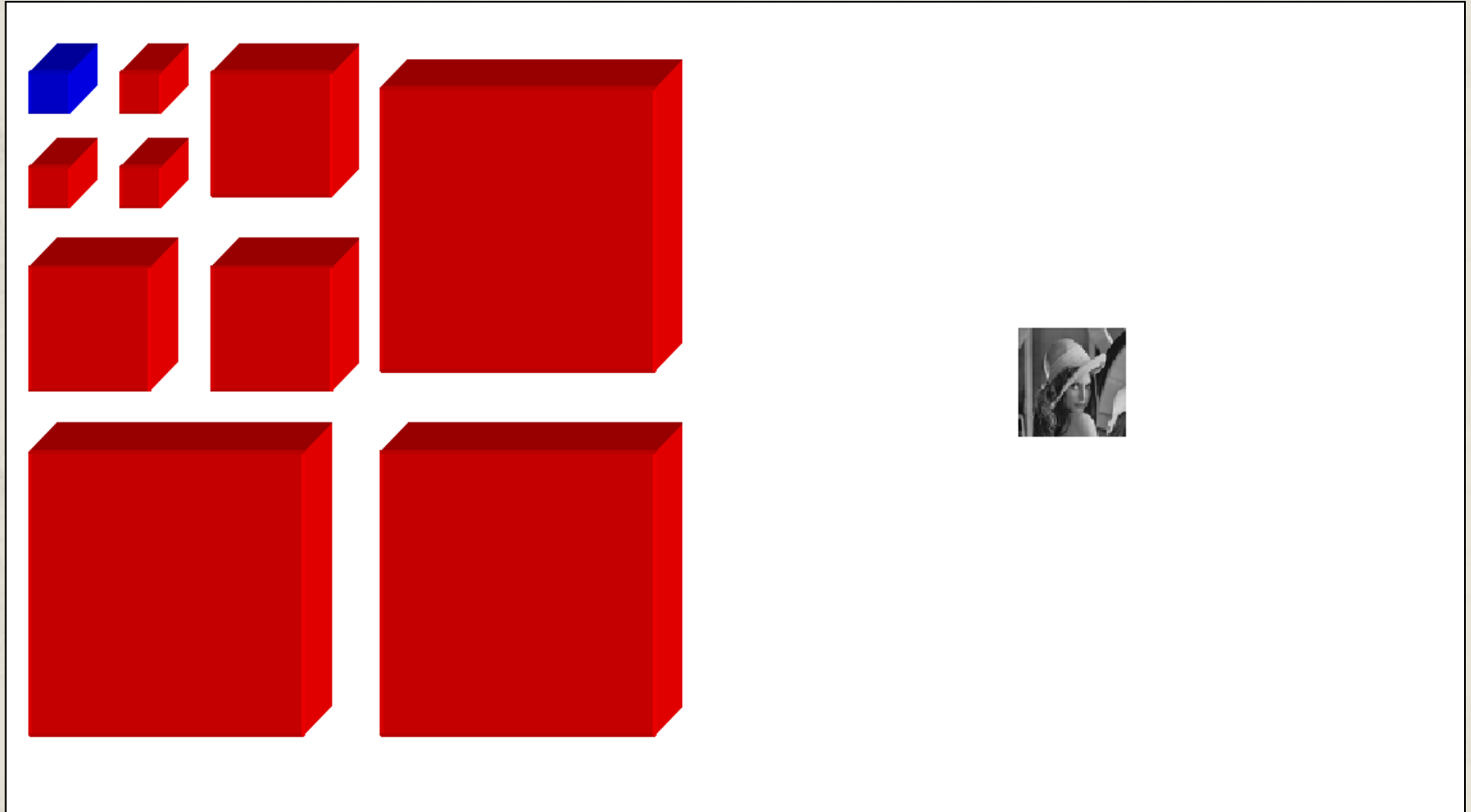
Part 4: Bit stream Organization (Tier 2)

- ◆ Tier-1 generates a collection of bitstreams
 - One independent bitstream from each code block
 - Each bitstream is embedded
- ◆ Tier-2 multiplexes the bitstreams for inclusion in the codestream and signals the ordering of the resulting coded bitplane passes in an efficient manner.
- ◆ Tier-2 coded data can be rather easily parsed
- ◆ Tier-2 enables SNR, resolution, spatial, ROI and arbitrary progression and scalability

Example: Bit-stream Organization



Example: Progressive Resolution



JPEG2000 Summary

- ◆ JPEG2000 offers the state-of-the-art features
 - Superior low bit rate performance and coding efficiency (up to 30% compared with DCT)
 - Lossless and lossy compression
 - Progressive transmission by pixel accuracy and resolution
 - Region-of-Interest coding
 - Random codestream access and processing
 - Error resilience
 - Open architecture
 - Content-based description
 - Side channel spatial information (transparency)
 - Protective image security
 - Continuous-tone and bi-level compression

Summary

- ◆ Prediction
 - DPCM, generalized to linear prediction
- ◆ Transformation
 - Transform fundamentals
 - Karhunen-Loeve Transform (KLT): optimal linear transform
 - Discrete Cosine Transform (DCT): properties
 - Discrete Wavelet Transform (DWT): multi-resolution representation
- ◆ JPEG: first international compression standard for still images
 - DCT – Quantization – Run-length – Huffman
- ◆ JPEG2000: latest technology, wavelet-based
 - Scalable, progressive coding with flexible intelligent functionalities

