### **Wavelet-based Image Compression**

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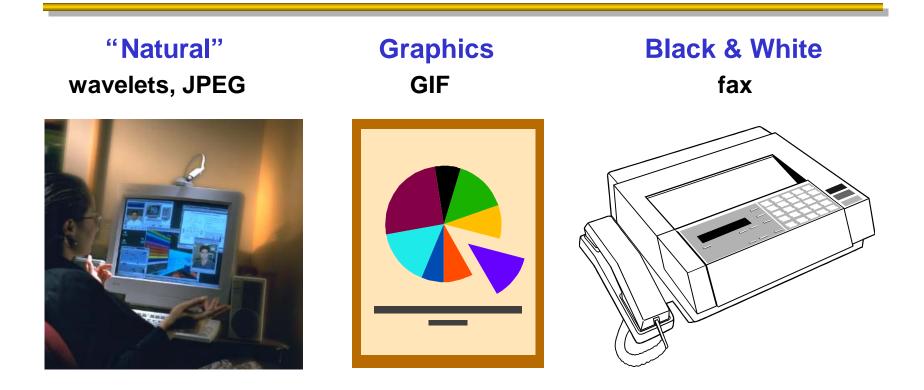
## **Overview**

- Image compression features
- Principles of image compression
- Transform coding
- Wavelet image transforms
- Properties of image wavelet coefficients
- Efficient coding wavelet coefficients
- Zerotrees and set partitioning
- Application issues
- Conclusions

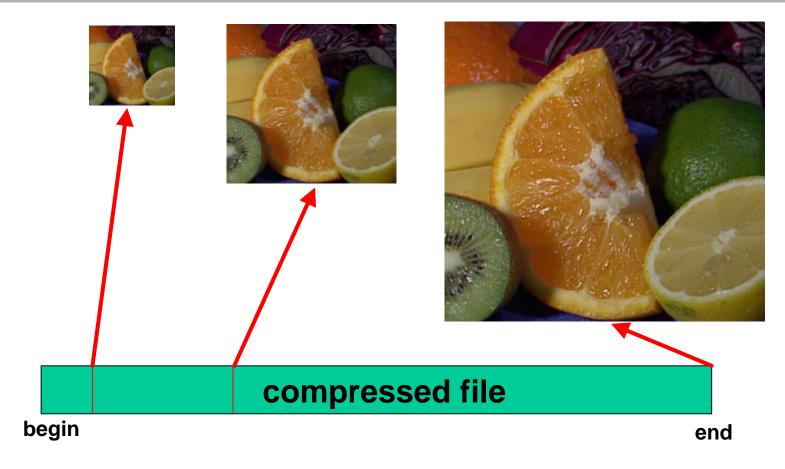
# **Image Compression Standards**

- Good old times: JPEG
  - Choose quality number
  - Compress image
  - Other features proposed, but most not widely supported
- New standard: JPEG 2000
  - Based on HP Labs proposal
  - Wavelet-based compression
  - MANY new features
  - Complex file structure, coding, decoding, etc.

# **Image Types**

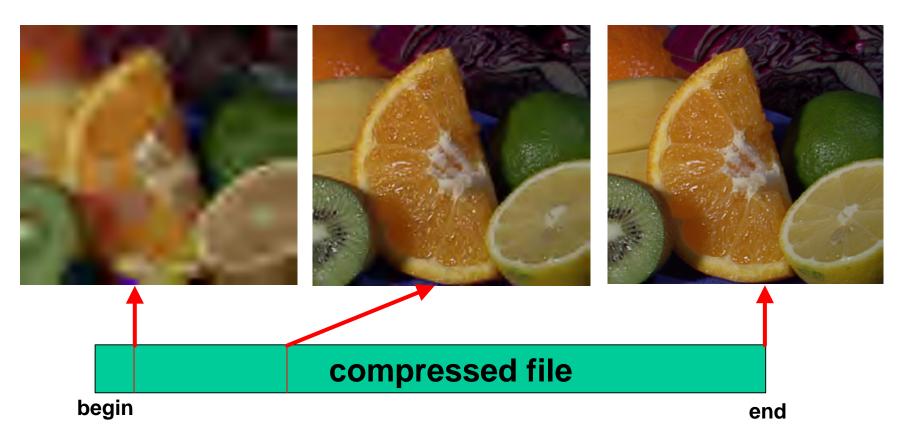


## **Progressive Resolution**

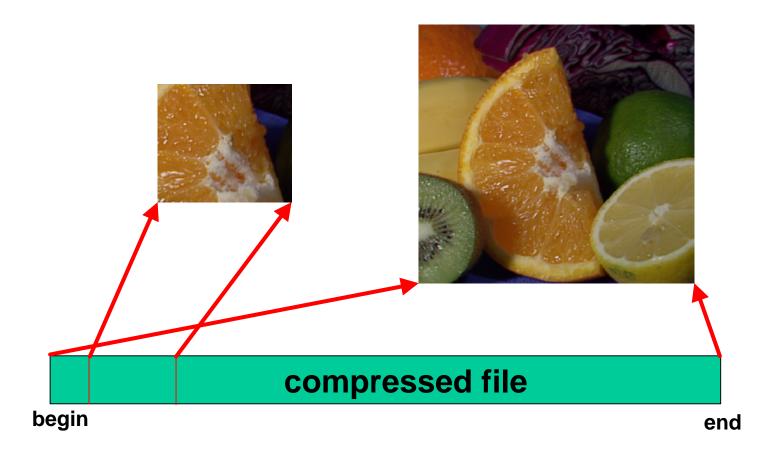




# **Progressive Quality**



### **Random Access**





# **Desirable Compression Features**

- Scalability
  - same algorithm for wide range of quality, compression ratios
- Flexibility/adaptability
  - efficient compression on wide range of image characteristics
- Automatic rate and quality control
  - one-pass creation of compressed file with desired size or quality
- Same algorithm for lossy and lossless compression
- Support for Region-of-Interest (ROI) decoding
- Low complexity (speed, memory)
- Efficient compression
- Error resilience
- Good visual quality

# **Image Compression**

- Based on the elimination of data that is
  - 1. Redundant
  - 2. Irrelevant
- Redundancy is reduced by using more efficient representation
  - lossless process
  - entropy-coding
- Irrelevant data is discarded
  - lossy process
  - depends on image use
    - subjective visual quality
    - maximum error

# **Entropy Coding**

### • Standard coding techniques

- Huffman codes (good compression, fast)
- Arithmetic codes (better compression, slower)
- Lempel-Ziv (not so good)
- Techniques specialized for images
  - Exploit two-dimensional structure
    - Example: code large single-color square by identifying (origin, size, color)
  - Use properties that are present in normal images
  - Exploit structures on different scales

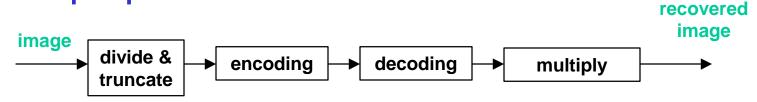
# Quantization

- Reduction of allowable images to a much smaller set
  - Example: set least significant bit in pixel values to zero
- The new set should contain most important cases
  - Difference should be the irrelevant data
- Quantization is tightly connected to entropy coding
  - Smaller number of possible outcomes means less bits

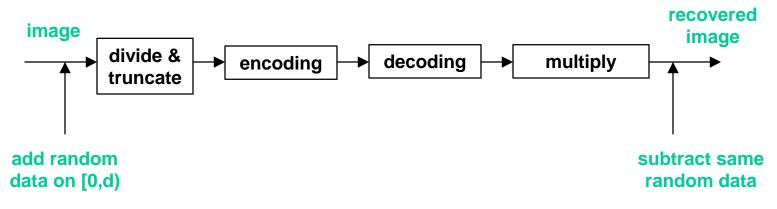
#### Where d is the quantization factor

# **Visual Properties**

### • Simple quantization



• Same + "error shaping"



# **Quantized Image**

Lena image after setting 4 least significant bits to zero (direct 2:1 compression)



# **Quantized Image**

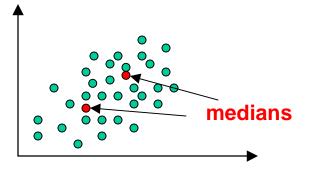
Lena image after removing 4 least significant bits (2:1) + dithered quantization



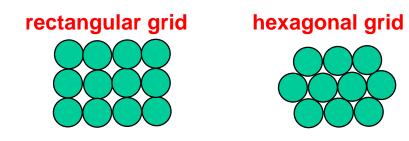
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## **Vector Quantization**

• Exploit clustered data



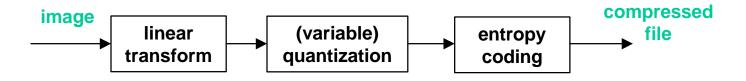
• More efficient "sphere packing"



• Real advantage for image compression unproved

# **Transform Coding**

• New block



• Example: 8 x 8 discrete cosine transform (DCT)

$$T_{m,n} = \frac{1}{2} \sum_{i=0}^{7} \sum_{j=0}^{7} p_{i,j} \cos[(2m+1)i\mathbf{p}/16] \cos[(2n+1)j\mathbf{p}/16]$$

# **Properties of Transform Coding**

DC

- Unitary transform: MSE conservation
- Energy compaction
  - Easier, more efficient entropy coding
- Good error shaping
  - Inverse transform greatly reduces quantization artifacts
- Clustering vector quantization less effective
- Small "sphere-packing" gains
- Block-based transform yields
  - Blocking artifacts
  - Potentially worse compression

# **Blocking Artifacts**



### **Haar Transform**

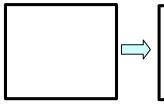
• Definition for one-dimensional array

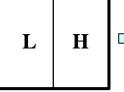
$$p_{i}^{k+1} = \frac{\sqrt{2}}{2} \left( p_{2i}^{k} + p_{2i+1}^{k} \right) \quad h_{i}^{k+1} = \frac{\sqrt{2}}{2} \left( p_{2i}^{k} - p_{2i+1}^{k} \right)$$

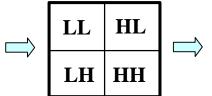
Recursive computation

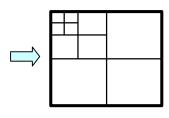
# **Multiresolution Transforms**

### Two-dimensional computation









rows transformed

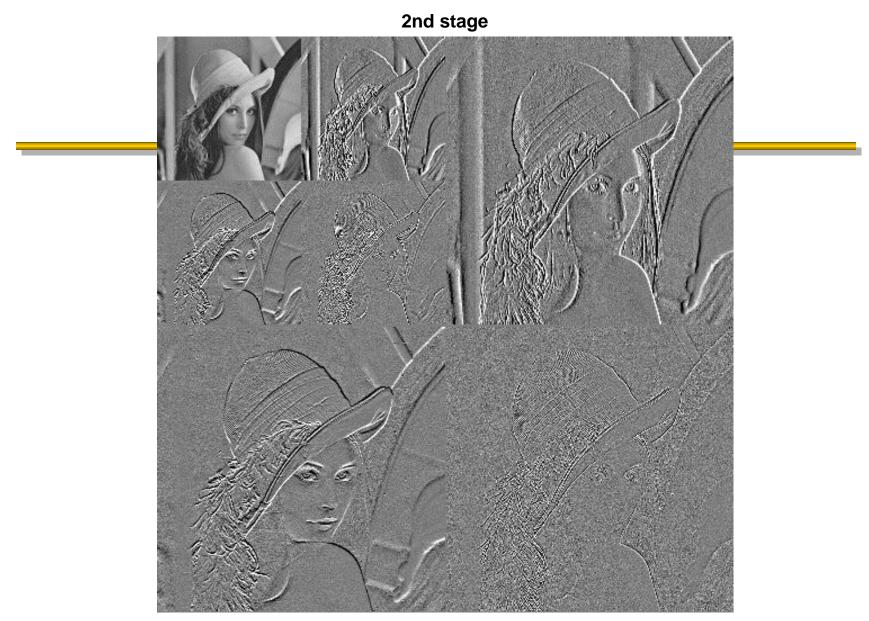
#### columns transformed

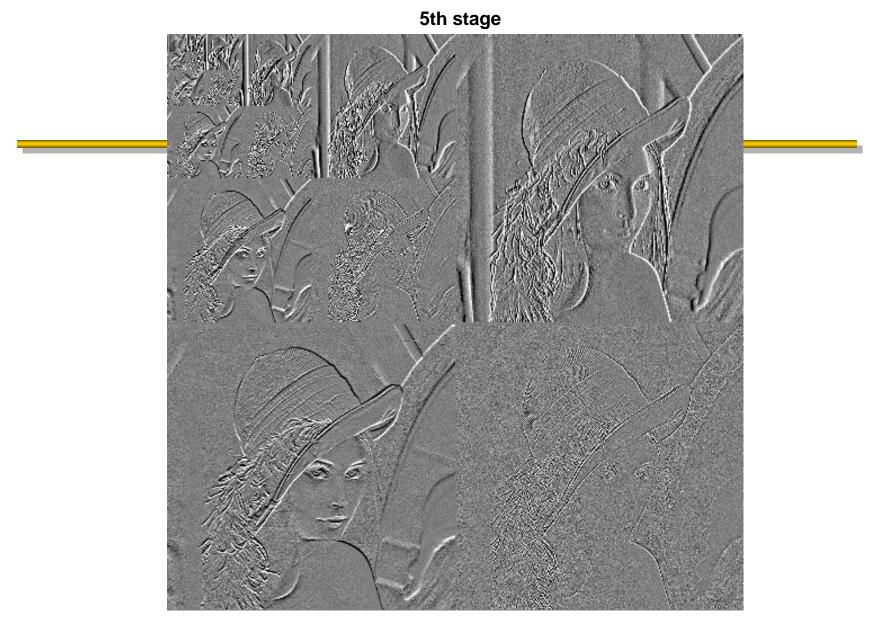
multiresolution pyramid

- Properties
  - Can exploit structures on several scales (large, small)
  - Hierarchical decomposition progressive transmission
  - Good energy compaction
  - Preliminary classification for entropy coding (subbands)
  - Haar transform produces blocking artifacts



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# **Overlapping Kernels**

• One formula for overlapping multiresolution transform

$$p_{i}^{k+1} = \frac{\sqrt{2}}{8} \left( -p_{2i-2}^{k} + 2p_{2i-1}^{k} + 6p_{2i}^{k} + 2p_{2i+1}^{k} - p_{2i+2}^{k} \right)$$
$$h_{i}^{k+1} = \frac{\sqrt{2}}{8} \left( -2p_{2i}^{k} + 4p_{2i+1}^{k} - 2p_{2i+2}^{k} \right)$$

• Inverse transform

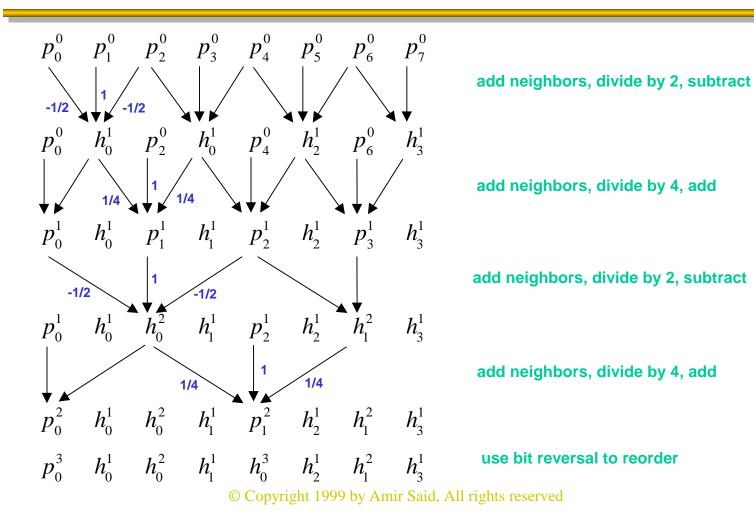
$$p_{2i}^{k} = \frac{\sqrt{2}}{8} \left( -2h_{i-1}^{k+1} + 4p_{i}^{k+1} - 2h_{i}^{k+1} \right)$$
$$p_{2i+1}^{k} = \frac{\sqrt{2}}{8} \left( -h_{i-1}^{k+1} + 2p_{i}^{k+1} + 6h_{i}^{k+1} + 2p_{i+1}^{k+1} - h_{i+1}^{k+1} \right)$$

### **Matrix Formulation**

• Example: 10 samples, cyclic convolution, 5/3 filters

$\begin{array}{cccc} 2 & 6 \\ 0 & -2 \\ 0 & -1 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{array}$	$\begin{array}{cccc} 2 & -1 \\ 4 & -2 \\ 2 & 6 \\ 0 & -2 \\ 0 & -1 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{array}$	$\begin{array}{cccc} 0 & 0 \\ 0 & 0 \\ 2 & -1 \\ 4 & -2 \\ 2 & 6 \\ 0 & -2 \\ 0 & -1 \\ 0 & 0 \end{array}$	$\begin{array}{cccc} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 2 & -1 \\ 4 & -2 \\ 2 & 6 \\ 0 & -2 \end{array}$	$ \begin{array}{c c} 0 & -2 \\ 0 & -1 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 2 & -1 \\ 4 & -2 \\ 2 & 6 \end{array} \times \begin{bmatrix} 6 \\ -2 \\ -1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ -1 \\ -2 \end{bmatrix} $	$\begin{array}{cccc} 4 & - & 2 \\ 2 & 6 \\ 0 & - & 2 \\ 0 & - & 1 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{array}$	$\begin{array}{cccc} 0 & 0 \\ 2 & -1 \\ 4 & -2 \\ 2 & 6 \\ 0 & -2 \\ 0 & -1 \\ 0 & 0 \end{array}$	$\begin{array}{cccc} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 2 & -1 \\ 4 & -2 \\ 2 & 6 \\ 0 & -2 \\ 0 & -1 \end{array}$	$\begin{array}{cccc} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 2 & -1 \\ 4 & -2 \\ 2 & 6 \end{array}$	$\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 2 \end{bmatrix} = 32\mathbf{I}$
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# The "Lifting" Technique



# **Properties of Wavelet Coefficients**

- Residual correlation too small for any practical use
- Different distribution on different parts (subbands)
- Stationary assumption quite unrealistic
- Most coefficient are zero after quantization
- Distribution somehow replicated on resolution hierarchy
- Variable quantization needs to be addressed (bit allocation)

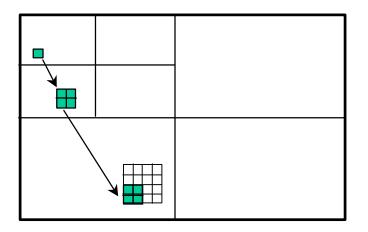
• What is the best coding method for wavelet coefficients?

# **Zerotrees and Set Partitioning**

- Some efficient methods for coding wavelet coefficients
  - A.S. Lewis & g. Knowles (1991) first to use, for efficient coding, trees defined on the multiresolution pyramid
  - J.M. Shapiro (1992) EZW (embedded zerotrees of wavelets) developed method of progressive refinement for fully embedded coding, used efficient entropy-coding
  - A. Said & W.A. Pearlman (1993) SPIHT (set partitioning in hierarchical trees) - more efficient coding, generalization of setpartitioning, equivalence to sorting, lossless compression, *public domain demos*

# **Significance Trees**

- Sets of insignificant coefficients
  - All magnitudes smaller than a threshold
  - "Zerotrees" when sets are defined as trees
- Spatial orientation trees

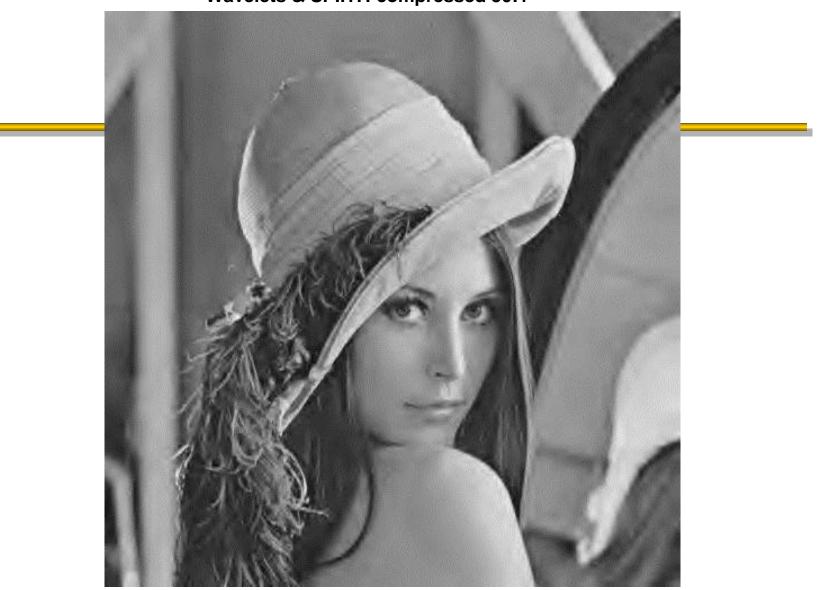


# **Basic Algorithm Ideas**

- Use one bit to indicate if all wavelet coefficients in a tree are zero
  - If all zero, nothing else to do
  - If not
    - Subdivide tree in several (4) parts
    - Apply same test to new parts
- Repeat until all nonzero coefficients found
  - Apply simple entropy-coding to nonzero coefficients

# **Set-partitioning Properties**

- Very simple entropy coding (mostly partitioning data)
- No explicit bit allocation
- Only simple scalar (uniform) quantization used
- Low encoding complexity
- Very efficient decoding
- Best compression when first published
- Efficient compression from high rates up to lossless recovery

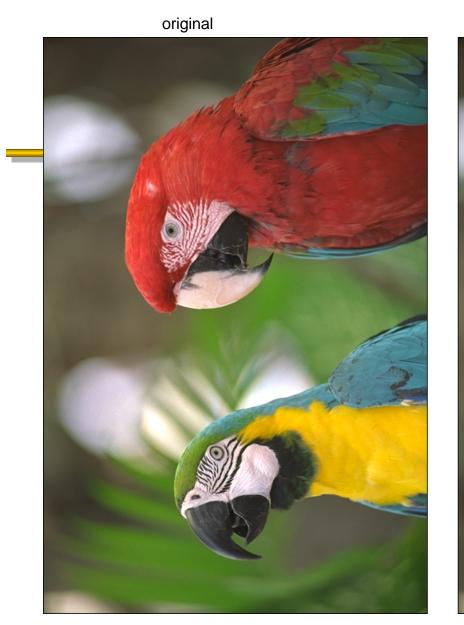


Wavelets & SPIHT: compressed 50:1





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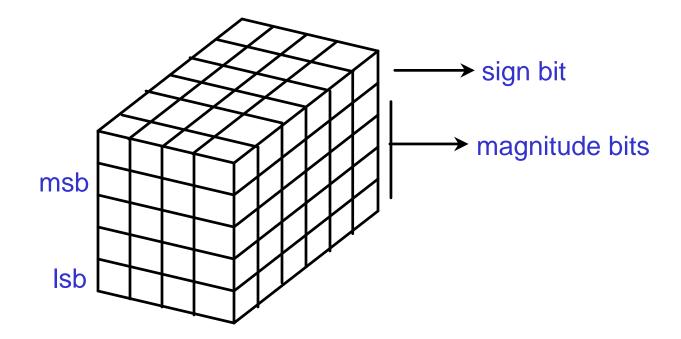




#### Wavelet & SPIHT: compressed 50:1

## **Bit-plane Coding**

• **Progressive coding of wavelet coefficients** 



## **Lessons Learned**

- Most important problem: efficient coding of the location of zero coefficients
- Vector quantization, optimal bit allocation hardly necessary
- Exploits spatial clustering of *magnitude* distribution
- Efficient entropy coding does not have to be complex
- Multiresolution properties can be effectively exploited

# **Application Issues - I**

### Complexity of the transform

- DCT
  - O(log(b)) operations per pixel, b = block size
  - Inverse transform frequently skipped or simplified
  - All block data on L1 cache
  - Efficient hardware implementations
- Wavelet
  - O(t) operations per pixel, t = average kernel size
  - Inverse transform = smoothing, cannot be skipped
  - Lifting reduces the number of operations
  - Bandwidth may be more important than number of operations

# **Application Issues - II**

### Memory usage

- DCT
  - Minimum b-b block
  - Commonly width-b
- Wavelet
  - Simplest implementation: full image
- "Rolling wavelet"
  - Minimum k-t (typical k = 8)
  - Commonly width-k-t
- Fully embedded coding
  - Must keep full image buffered *or* compressed image buffered

# **Application Issues - III**

- Quantization & entropy-coding complexity
  - Basically independent of the image transforms
- Compression efficiency & visual appearance
  - Wavelets do yield best results
  - Poor visual quality due to obsession with MSE
- Versatility
  - Wavelets naturally support progressive resolution
  - Easy combination of lossy and lossless compression
  - Efficient methods for embedded coding
  - Region-of-interest modes supported

# **Application Issues - IV**

### • Error resiliency

- Very complicated problem
  - Protocols
  - Error propagation
  - Error detection and error correction
- Hierarchical structure allows sorting data by importance, for unequal error protection
- Simple entropy-coding allows identification of bits that do not lead to catastrophic error propagation
- Overlapping kernels produce smooth error artifacts

# Conclusions

- Wavelet transform has several features required for effective image compression
  - Error shaping yield good visual quality
  - Efficient energy compaction
  - Can exploit image features in several scales
- Its structure allows
  - Easy implementation of progressive transmission and multiresolution
  - More efficient compression
  - Better error resiliency
- Not all application issues solved, but significant progress recently

## **Wavelet & Image Compression Links**

- http://www.cipr.rpi.edu/research/SPIHT/EE\_Forum.pdf
- http://www.cipr.rpi.edu/research/SPIHT/
- http://www.cipr.rpi.edu/research/SPIHT/spiht8.html
- http://www.wavelet.org/wavelet/index.html
- http://www.code.ucsd.edu/~jkrogers/Papers/
- http://cm.bell-labs.com/who/wim/papers/papers.html#iciam95
- http://cm.bell-labs.com/who/wim/papers/papers.html
- http://www.mat.sbg.ac.at/~uhl/wav.html
- http://www.jpeg.org
- http://www.cis.ohio-state.edu/hypertext/faq/usenet/compression-faq/top.html
- http://www.mathsoft.com/wavelets.html
- http://biron.usc.edu/~chrysafi/Publications.html