

Introduction to Image Compression

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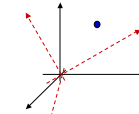
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M. Wu: ENEE631 Digital Image Processing (Fall'01)

Review of Last Time



- 1-D transform of a vector
 - Represent an N-sample sequence as a vector in N-dimension vector space
 - Transform
 - ♦ Different representation of this vector in the space via different basis
 - ♦ e.g., 1-D DFT from time domain to frequency domain
 - Forward transform
 - ♦ In the form of inner product
 - ♦ Project a vector onto a new set of basis to obtain N "coefficients"
 - Inverse transform
 - ♦ Use linear combination of basis vectors weighted by transform coeff. to represent the original signal
- 2-D transform of a matrix
 - Rewrite the matrix into a vector and apply 1-D transform
 - Separable transform allows applying transform to rows then columns



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Lec7 – Image Compression 9/20/01 [2]

Review of Last Time (cont'd)

- Representation with orthonormal basis \Leftrightarrow Unitary transform
 - Preserve energy, decorrelation, etc.
- Common unitary transforms
 - DFT, DCT, KLT
- Which transform to choose?
 - Depend on need in particular task/application
 - DFT ~ reflect physical meaning of frequency or spatial frequency
 - KLT ~ optimal in energy compaction
 - DCT ~ real-to-real, and close to KLT's energy compactability
 - Today's addition: Haar Transform



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Lec7 – Image Compression 9/20/01 [3]

Construction of Haar functions

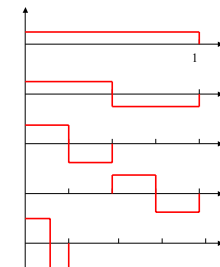
$$k = \overbrace{2^p}^{\text{power of 2}} + \underbrace{q-1}_{\text{"remainder"}}$$

- Unique decomposition of integer $k \Leftrightarrow (p, q)$
 - $k = 0, \dots, N-1$ with $N = 2^n$, $0 \leq p \leq n-1$
 - $q = 0, 1$ (for $p=0$); $1 \leq q \leq 2^p$ (for $p>0$)
 - e.g., $k=0 \Leftrightarrow (0,0)$, $k=1 \Leftrightarrow (0,1)$; $k=2 \Leftrightarrow (1,1)$, $k=3 \Leftrightarrow (1,2)$

- $h_k(x) = h_{p,q}(x)$ for $x \in [0,1]$

$$h_0(x) = h_{0,0}(x) = \frac{1}{\sqrt{N}} \quad \text{for } x \in [0,1]$$

$$h_k(x) = h_{p,q}(x) = \begin{cases} \frac{1}{\sqrt{N}} 2^{p/2} & \text{for } \frac{q-1}{2^p} \leq x < \frac{q}{2^p} \\ \frac{1}{\sqrt{N}} 2^{p/2} & \text{for } \frac{q-1}{2^p} \leq x < \frac{q}{2^p} \\ 0 & \text{for other } x \in [0,1] \end{cases}$$



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Lec7 – Image Compression 9/20/01 [4]

Haar Transform

- Haar transform H

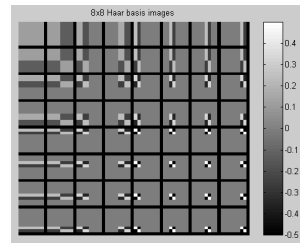
- Sample $h_k(x)$ at $\{m/N\}$
 - ♦ $m = 0, \dots, N-1$

- Real and orthogonal
- Transition at each scale p is localized according to q

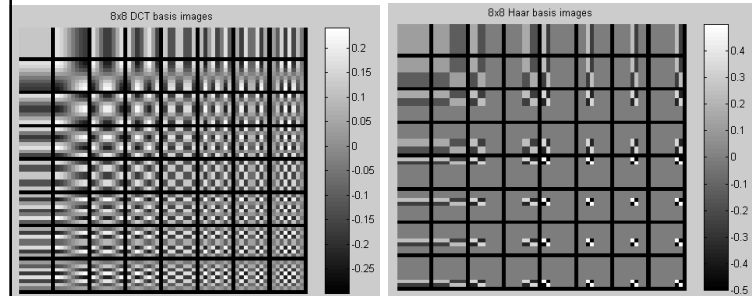
- Basis images of 2-D (separable) Haar transform

- One example of wavelets and multiresolution concepts

$$\frac{1}{\sqrt{8}} \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & -1 & -1 & -1 & -1 \\ \sqrt{2} & \sqrt{2} & -\sqrt{2} & -\sqrt{2} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \sqrt{2} & \sqrt{2} & -\sqrt{2} & -\sqrt{2} \\ 2 & -2 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 2 & -2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 2 & -2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 2 & -2 \end{bmatrix}$$



Compare Basis Images of DCT and Haar



- NxN DCT basis images reflect transitions throughout the NxN image
 - Ordered by frequency
- Haar basis images can reflect local transitions
 - Ordered both by frequency and by spatial location index



Image Compression

Part-1. Basics



Why Need Compression?

- Savings in storage and transmission
 - multimedia data (esp. image and video) have large data volume
 - difficult to send real-time uncompressed video over current network
- Accommodate relatively slow storage devices
 - they do not allow playing back uncompressed multimedia data in real time
 - ♦ 1x CD-ROM transfer rate ~ 150 kB/s
 - ♦ 320 x 240 x 24.fps color video bit rate ~ 5.5MB/s
 - => 36 seconds needed to transfer 1-sec uncompressed video from CD



Example: Storing An Encyclopedia

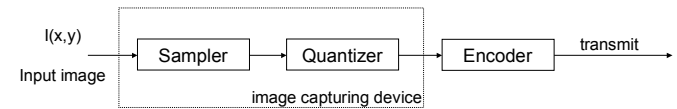
- 500,000 pages of text (2kB/page) ~ 1GB => **2:1 compress**
- 3,000 color pictures (640×480×24bits) ~ 3GB => **15:1**
- 500 maps (640×480×16bits=0.6MB/map) ~ 0.3GB => **10:1**
- 60 minutes of stereo sound (176kB/s) ~ 0.6GB => **6:1**
- 30 animations with average 2 minutes long
(640×320×16bits×16frames/s=6.5MB/s) ~ 23.4GB => **50:1**
- 50 digitized movies with average 1 minute long
(640×480×24bits×30frames/s = 27.6MB/s) ~ 82.8GB => **50:1**

- ➔ Require a total of 111.1GB storage capacity if without compression
- ➔ Reduce to 2.96GB if with compression



PCM coding

- **How to encode a digital image into bits?**
 - Sampling and perform uniform quantization
 - ♦ “Pulse Coded Modulation” (PCM)
 - ♦ 8 bits per pixel ~ good for grayscale image/video
 - ♦ 10-12 bpp ~ needed for medical images
- **Reduce # of bpp for reasonable quality via quantization**
 - Quantization reduces # of possible levels to encode
 - Visual quantization: companding, contrast quantization, dithering, etc.
 - ♦ Halftone use 1bpp but usually upsampling ~ saving less than 2:1



Discussion on Improving PCM

- **Quantized PCM values may not be equally likely**
 - Can we do better than encode each value using same # bits?
- **Example**
 - $P("0") = 0.5$, $P("1") = 0.25$, $P("2") = 0.125$, $P("3") = 0.125$
 - If use same # bits for all values
 - ♦ Need 2 bits to represent the four possibilities if treat
 - If use less bits for likely values “0” ~ Variable Length Codes (VLC)
 - ♦ “0” => [0], “1” => [10], “2” => [110], “3” => [111]
 - ♦ Use 1.75 bits on average ~ saves 0.25 bpp!
- **Bring probability into the picture**
 - Previously use prob. distr. to reduce MSE of quantization
 - Now use prob. distr. to reduce average # bits per quantized sample



Entropy coding

- **Idea: use less bits for commonly seen values**
- **How many # bits needed?**
 - Limit of compression => “Entropy”
 - ♦ Measures the uncertainty or amount of avg. information of a source
 - ♦ Definition: $H = \sum_i p_i \log_2 (1/p_i)$ bits
 - e.g., entropy of previous example is 1.75
 - ♦ Can't represent a source perfectly with less than avg. H bits per sample
 - ♦ Can represent a source perfectly with avg. $H + \epsilon$ bits per sample (Shannon Lossless Coding Theorem)
 - “Compressability” depends on the sources
- **Important to decode coded stream efficiently without ambiguity**
- **See info. theory course for more theoretical details**

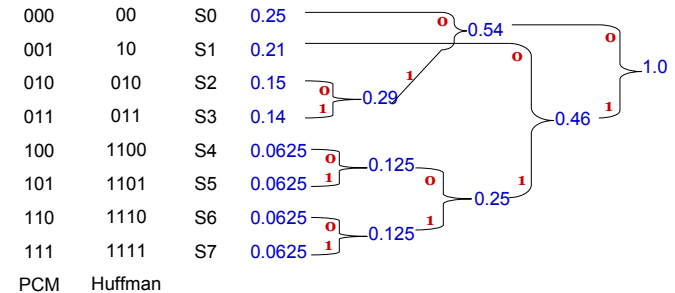


E.g. of Entropy Coding: Huffman Coding

- **Variable length code**
 - assigning about $\log_2 (1 / p_i)$ bits for the i^{th} value
 - ♦ *has to be integer# of bits per symbol*
- **Step-1**
 - Arrange p_i in decreasing order and consider them as tree leaves
- **Step-2**
 - Merge two nodes with smallest prob. to a new node and sum up prob.
 - Arbitrarily assign 1 and 0 to each pair of merging branch
- **Step-3**
 - Repeat until no more than one node left.
 - Read out codeword sequentially from root to leaf



Huffman Coding (cont'd)



Huffman Coding: Pros & Cons

- **Pro**
 - Simplicity in implementation (table lookup)
 - For a given block size Huffman coding gives the best coding efficiency
- **Con**
 - Need to obtain source statistics
- **Improvement**
 - Code a group of symbols as a whole to allow fractional # bit per symbol
 - Arithmetic coding
 - Lempel-Ziv coding or LZW algorithm
 - ♦ “universal”, no need to estimate source statistics



Discussion: Coding a Binary Image

- **How to efficiently encode it?**
 - “000011000101000000111...”
- **Run-length coding (RLC)**
 - Code length of runs of “0” between successive “1”
 - ♦ *run-length of “0” ~ # of “0” between “1”*
 - ♦ *good if often getting frequent large runs of “0” and sparse “1”*
 - E.g., => (4) (0) (3) (1) (6) (0) (0) ...
 - Assign fixed-length codeword to run-length
 - Or use variable-length code like Huffman to further improve
- **RLC Also applicable to general binary data sequence with sparse “1” (or “0”)**



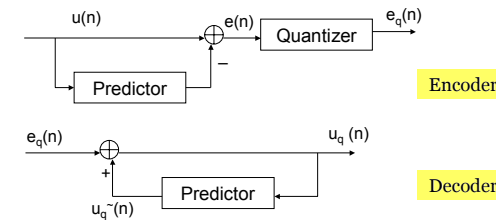
Probability Model of Run-Length Coding

- Assume successive "0" occur independently w.p. p
- Prob. of getting an L runs of "0" ($L=0, 1, \dots, M$)
 - $P(L) = p^L (1-p)$ for $0 \leq L \leq M-1$ (geometric distribution)
 - $P(L) = p^M$ for $L=M$
- Avg. # binary symbols per run
 - $S_{avg} = \sum_{L=0}^M (L+1) p^L (1-p) + M p^M = (1-p^M) / (1-p)$
 - Compression ratio $C = S_{avg} / \log_2(M+1) = (1-p^M) / [(1-p) \log_2(M+1)]$
- Example
 - $P = 0.9, M=15 \rightarrow S_{avg} = 7.94, C = 1.985, H = 0.469$ bpp
 - Avg. run-length coding rate $B_{avg} = 4 \text{ bit} / 7.94 \sim 0.516$ bpp
 - Coding efficiency $= H / B_{avg} \sim 91\%$



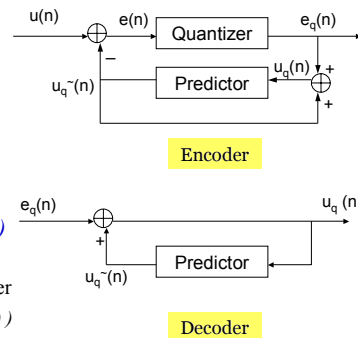
How to Encode Correlated Sequence?

- Consider: high correlation between successive samples
- Predictive coding
 - Basic principle: Remove redundancy between successive pixels and only encode residual between actual and predicted
 - Residue usually has much smaller dynamic range
 - Allow fewer quantization levels for the same MSE \Rightarrow get compression
 - Compression efficiency depends on intersample redundancy
- First try



Predictive Coding (cont'd)

- Problem with 1st try
 - Input to predictor are different at encoder and decoder
 - decoder doesn't know $u(n)$!
 - Mismatch error could propagate to future reconstructed samples
- Solution: Differential PCM (DPCM)
 - Use quantized sequence $u_q(n)$ for prediction at both encoder and decoder
 - $u_q^-(n) = f(u_q(n-1), u_q(n-2), \dots, u_q(n-m))$
 - Prediction error $e(n)$
 - Quantized prediction error $e_q(n)$
 - Distortion $d(n) = e(n) - e_q(n)$



Summary

- Finish image transform
- Begin basics on image coding/compression
 - PCM coding
 - Entropy coding
 - Huffman
 - Run-length
 - Predictive coding
- Next time: transform coding



Assignment

- Readings
 - Jain's 11.1-11.3
- Reference
 - Bovik's Handbook Sec.5.1
- "Food for thoughts"
 - What predictors to use for image predictive coding?
 - ♦ *pros and cons*
- Announcement
 - 1st in-class exam will be given after "Image Compression"



ENE631 Course Project: Introduction



Topic: Video Coding and Processing

- Team project
 - 2 students per team
 - A few 3-person teams are allowed by instructor's permission
- What to turn in finally?
 - A video codec (encoder-decoder)
 - Self-proposed part on video processing/analysis



Step-by-Step Approach

- [9-10/01] 3 Building Blocks (BB) ~ similar to "assignment"
 - individual work
 - should keep a big picture of the project in mind
- [11/2001] Team-up and submit project proposal
- [12/2001] Project demo, presentation, and report
 - peer review
- Details will be announced soon
- First BB on image transform will be posted this weekend

