



INTRODUCTION TO EECS II DIGITAL COMMUNICATION SYSTEMS

6.02 Fall 2010
Lecture #23: Adaptive Source Coding
December 1, 2010

- Information & entropy
- Adaptive codes: LZW algorithm
- Lossy compression (JPEG overview)

LZW: An Adaptive Variable-length Source Code

- Algorithm first developed by Ziv and Lempel, later improved by Welch. Now commonly referred to as the "LZW algorithm"
- As message is processed a "string table" is built which maps symbol sequences to a fixed-length code
 - Table size = $2^{**}(\text{size of fixed-length code})$
- Note: String table can be reconstructed by the decoder based on information in the encoded stream – the table, while central to the encoding and decoding process, is never transmitted!
- This idea is a crucial one – build a table (mapping between codes and strings) but DON'T transmit it!

LZW Encoding (Compression)

```
for i in xrange(256): table.append(chr(i)) # code for each 8-bit character is its ASCII value
f = open(sys.argv[1], 'r')
data = f.read()
compressed = [] # final output compressed list of codes (each code is some string)

string = data[0]
for symbol in data[1:]:
    if (string + symbol) in table: # "+" is concatenation, of course!
        string = string + symbol
    else:
        code = table.index(string) # code for "string", from table
        compressed.append(code)
        table.append(string+symbol)
        string = symbol
    compressed.append(table.index(string)) # don't forget last code!
return compressed
```

lzw('abcabcabcabcabcabcabcabcabcabc')

← indicates current value of STRING

```
<-> READ a
<-> READ b, ab not in table
XMIT 0 ADD 0: ab
<-> READ c, bc not in table
XMIT 1 ADD 1: bc
<-> READ d, cd not in table
XMIT 2 ADD 2: cd
<-> READ e, abc not in table
XMIT 3 ADD 3: abc
<-> READ f, abcd not in table
XMIT 4 ADD 4: abcd
<-> READ g, abcabc not in table
XMIT 5 ADD 5: abcabc
<-> READ h, abcabcabc not in table
XMIT 6 ADD 6: abcabcabc
<-> READ i, abcabcabcabc not in table
XMIT 7 ADD 7: abcabcabcabc
<-> READ j, abcabcabcabcabc not in table
XMIT 8 ADD 8: abcabcabcabcabc
<-> READ k, abcabcabcabcabcabc not in table
XMIT 9 ADD 9: abcabcabcabcabcabc
<-> READ l, abcabcabcabcabcabcabc not in table
XMIT 10 ADD 10: abcabcabcabcabcabcabc
<-> READ m, abcabcabcabcabcabcabcabc not in table
XMIT 11 ADD 11: abcabcabcabcabcabcabcabc
<-> READ n, abcabcabcabcabcabcabcabcabc not in table
XMIT 12 ADD 12: abcabcabcabcabcabcabcabcabc
<-> READ end--
XMIT 13
```

LZW Decoding - Simple (but Incorrect!)

```
dtable = []
for i in xrange(256): dtable.append(chr(i)) # same init table as compressor
code = compressed[0] # compressed is a list of codes input to decoding function
decompressed = dtable[code]
string = decompressed

for code in compressed[1:]:
    entry = dtable[code]

    dtable.append(string + entry[0])
    string = entry
    decompressed = decompressed + entry

return decompressed
```

LZW Decoding (Decompression) - Correct Version

```
dtable = []
for i in xrange(256): dtable.append(chr(i)) # same init table as compressor
code = compressed[0] # compressed is a list of codes input to decoding function
decompressed = dtable[code]
string = decompressed

for code in compressed[1:]:
    if code < len(dtable): # i.e., code is in dtable
        entry = dtable[code]
    else: # this part is subtle -- why wouldn't code be in table?
        entry = string + string[0]

    dtable.append(string + entry[0])
    string = entry
    decompressed = decompressed + entry

return decompressed
```

wzl(['a', 'b', 'c', 0, 2, 1, 3, 6, 5, 8, 4, 10, 7, 'c'])

```

READ 'a' RCV 'a'
READ 'b' RCV 'b' ADD 0: ab
READ 'c' RCV 'c' ADD 1: bc
READ [0] RCV 'ab' ADD 2: ca
READ [2] RCV 'ca' ADD 3: abc
READ [1] RCV 'bc' ADD 4: cab
READ [3] RCV 'abc' ADD 5: bca
READ [6] RCV 'abca' ADD 6: abca
READ [5] RCV 'bca' ADD 7: abcab
READ [8] RCV 'bcab' ADD 8: bcabc
READ [4] RCV 'cab' ADD 9: bcabc
READ [10] RCV 'cabc' ADD 10: cabc
READ [7] RCV 'abcab' ADD 11: cabca
READ 'c' RCV 'c' ADD 12: abcabc

```

String table reconstructed from received codes

Lossless vs. Lossy Compression



- Huffman and LZW encodings are **lossless**, i.e., we can reconstruct the original bit stream exactly: $\text{bits}_{\text{OUT}} = \text{bits}_{\text{IN}}$.
 - What we want for “naturally digital” bit streams (documents, messages, datasets, ...)
- Any use for **lossy** encodings: $\text{bits}_{\text{OUT}} \approx \text{bits}_{\text{IN}}$?
 - “Essential” information preserved
 - Appropriate for sampled bit streams (audio, video) intended for human consumption via imperfect sensors (ears, eyes).

Perceptual Coding

- Start by evaluating input response of bitstream consumer (eg. human ears or eyes), i.e., how consumer will perceive the input.
 - Frequency range, amplitude sensitivity, color response, ...
 - Masking effects
- Identify information that can be removed from bit stream without perceived effect, e.g.,
 - Sounds outside frequency range, or masked sounds
 - Visual detail below resolution limit (color, spatial detail)
 - Info beyond maximum allowed output bit rate
- Encode remaining information efficiently
 - Use DCT-based transformations (real instead of complex)
 - Quantize DCT coefficients
 - Entropy code (eg. Huffman encoding) results

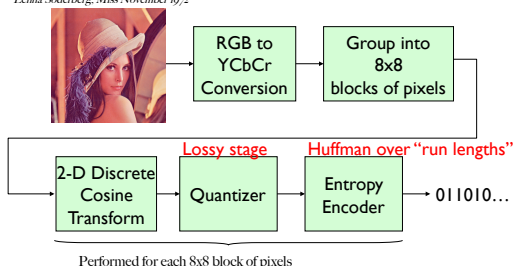
Perceptual Coding Example: Images

- Characteristics of our visual system
 - opportunities to remove information from the bit stream
 - More sensitive to changes in luminance than color
 - spend more bits on luminance than color (encode separately)
 - More sensitive to large changes in intensity (edges) than small changes
 - quantize intensity values
 - Less sensitive to changes in intensity at higher spatial frequencies
 - use larger quanta at higher spatial frequencies
- So to perceptually encode image, we would need:
 - Intensity at different spatial frequencies
 - Luminance (grey scale intensity) separate from color intensity

JPEG Image Compression

JPEG = Joint Photographic Experts Group

Lenna Söderberg, Miss November 1972



Summary

- Source coding: recode message stream to remove redundant information, aka **compression**.
- Our goal: match data rate to actual information content.
- Information content from choice, $= \log_2(1/p_i)$ bits
- Shannon's Entropy: average information content on learning a choice $= \sum p_i \log_2(1/p_i)$.
- Huffman's encoding algorithm builds optimal variable-length codes when symbols encoded individually.
- LZW: adaptive lossless compression – efficient on text, used in GIF, etc.
- JPEG: lossy compression; *perceptual coding*