



Fundamentals of Multimedia

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6、 Lossless Compression Algorithms



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1、 Introduction and Basics of Information Theory



1.1 Background

- **More and more data into digital form**
 - Libraries, museums, governments
 - To be stored without any loss
- **For example -- To encode 120 million call numbers**
 - Each item need a 27-bit number, $2^{27} > 120\text{M}$
 - Compression to reduce the number of bits needed
- **Different data appear at different frequencies**
 - To assign **fewer bits** to present **more frequently** appeared data
 - VLC—Variable-Length Coding
- **Lossless coding**
 - Both the compression and decompression processes induce no information loss

1.2 Data Compression Scheme

- **Definition: Compression Ratio**
 - **Compression ratio = $B0 / B1$**
 - The number of bits before compression is $B0$
 - The number of bits after compression is $B1$
- **Compression ratio must be larger than 1.0;**
 - The higher the compression ratio, the better the lossless compression scheme

A general data compression scheme





1.3 Basics of Information Theory

- **The entropy of an information source**
 - With alphabet $S = \{s_1, s_2, \dots, s_n\}$
 - $\eta = H(S) = \sum_{i=1}^n p_i \log_2 \frac{1}{p_i} = -\sum_{i=1}^n p_i \log_2 p_i$
 - p_i is the probability that symbol s_i in S will occur

- $\log_2 \frac{1}{p_i}$ indicate the amount of information contained in characters (**Self-information**)



1.3 Basics of Information Theory

- **For example:** the probability of n in a manuscript is $1/32$, so
 - The amount of information is **5 bits**
 - A character string **nnn** require **15 bits** to code

- **What is entropy?**
 - A measure of the disorder of a system
 - The more entropy, the more disorder



1.3 Basics of Information Theory

□ Examples:

- Suppose a system has 4 states outcome, each outcome has probability 1/4:

$$4 \times (1/4) \times \log_2(1/(1/4)) = 2\text{bits}$$

- If one state had probability 1/2, the other three had probability 1/6:

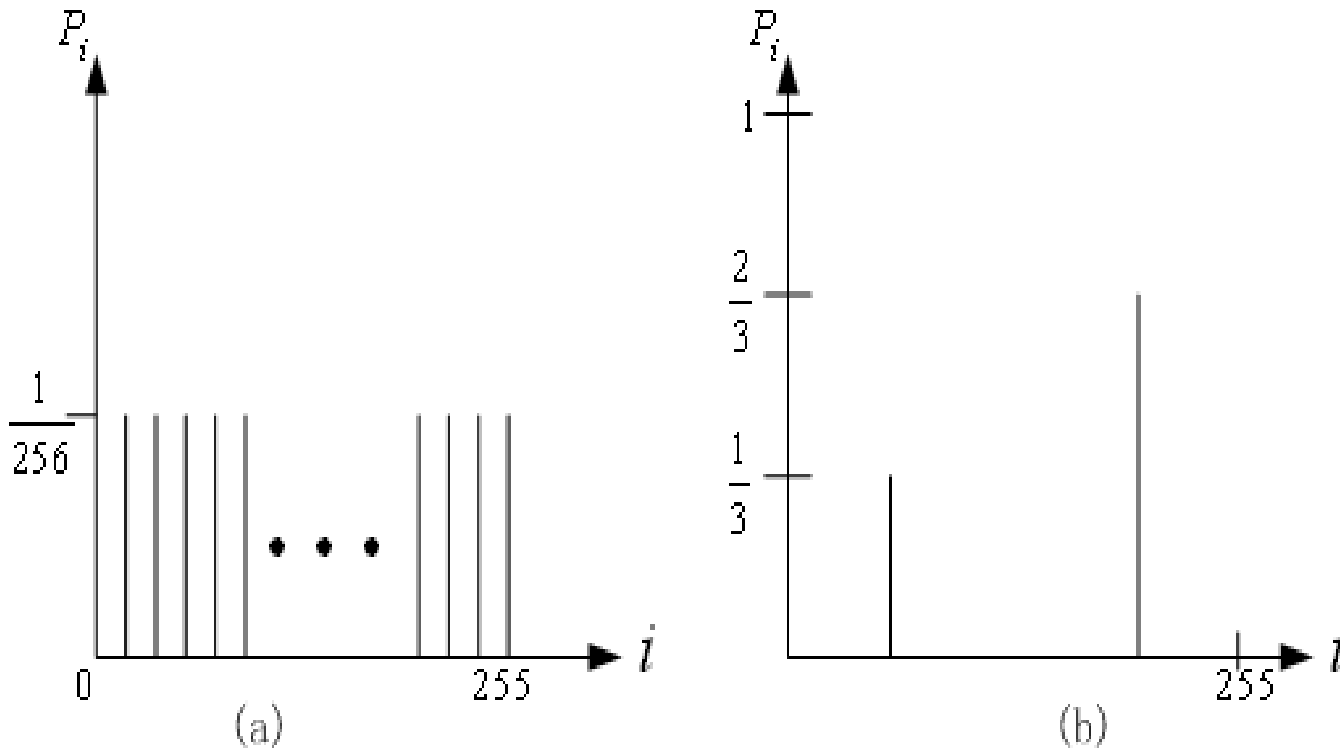
$$\frac{1}{2} \times \log_2 2 + 3 \times \frac{1}{6} \times \log_2 6 = 1.795 < 2\text{bits}$$

- The most-occurring one means fewer bits to send

□ The definition of entropy -- **identifying often-occurring symbols as short *codewords***

- Variable-Length Coding

1.3 Basics of Information Theory



Histograms for two gray-level images



1.3 Basics of Information Theory

□ The entropy of the two above images

■ The entropy of image a is:

$$\eta = \sum_{i=0}^{255} \frac{1}{256} \cdot \log_2 256 = 8$$

■ The entropy of image b is:

$$\begin{aligned} \eta &= \frac{1}{3} \cdot \log_2 3 + \frac{2}{3} \cdot \log_2 \frac{3}{2} \\ &= 0.33 \times 1.59 + 0.67 \times 0.59 = 0.92 \end{aligned}$$

□ The entropy is greater when the probability is flat and smaller when it is more peaked.



2、 Lossless Coding Algorithms



2.1 Run-Length Coding

- **RLC (RUN-LENGTH CODING)**
 - One of the simplest forms of data compression
- **Basic idea:**
 - If symbols of information source tend to form continuous groups, **Code one such symbol** and the **length of the group** instead of coding each symbol individually
- **Example: a bi-level image can be efficiently coded using RLC**
- **Two-Dimensional RLC is usually used to code bi-level image.**



2.2 Variable-Length Coding

- **Basic idea**
 - Entropy indicates the information content in an information source
- **VLC is one of the best-know entropy coding methods**
 - Shannon-Fano algorithm
 - Huffman coding
 - Adaptive Huffman coding



2.2 Variable-Length Coding

Shannon-Fano Algorithm

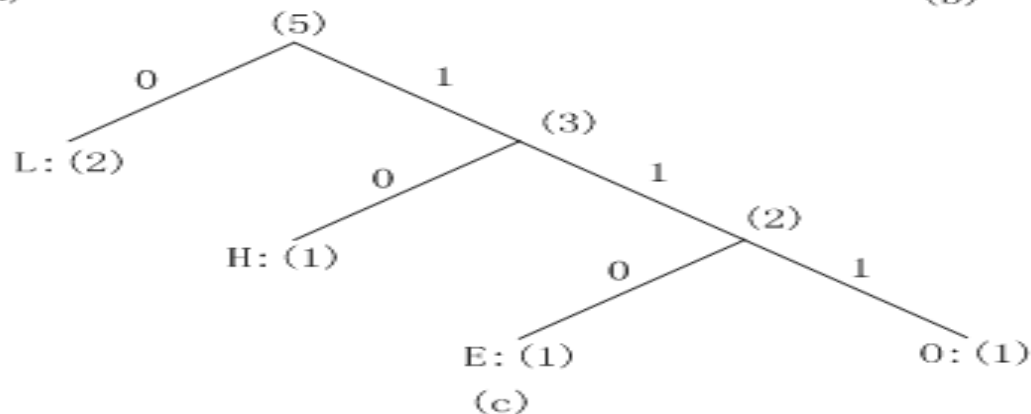
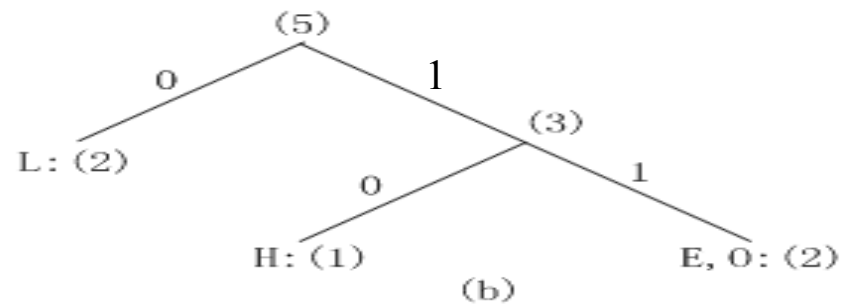
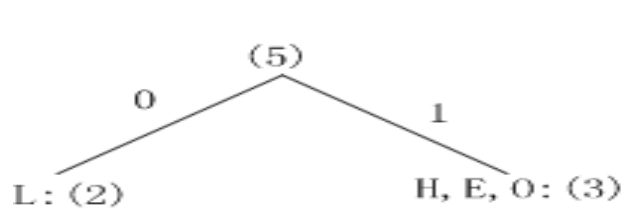
- ❑ Developed by Shannon at Bell Labs and Robert Fano at MIT
- ❑ The Top-Down manner
 - **Sort the symbols** according to the frequency count of their occurrences
 - **Recursively divide the symbols into two parts**, each with approximately the same number of counts, until all parts contain only one symbol
- ❑ A way of implementing the above procedure is to build a binary tree



2.2 Variable-Length Coding

Example: Hello

Symbol	H	E	L	O
Count	1	1	2	1





2.2 Variable-Length Coding

- The entropy of the example:

$$0.4 \times 1.32 + 0.2 \times 2.32 + 0.2 \times 2.32 + 0.2 \times 2.32 \\ = 1.92$$

- One result of performing the S-F algorithm on “Hello”: average bits $10/5=2$

symbol	Count	$\text{Log}_2 P_i^{-1}$	Code	Number of bits used
L	2	1.32	0	2
H	1	2.32	10	2
E	1	2.32	110	3
O	1	2.32	111	3
Total number of bits: 10				



2.2 Variable-Length Coding

Huffman Coding

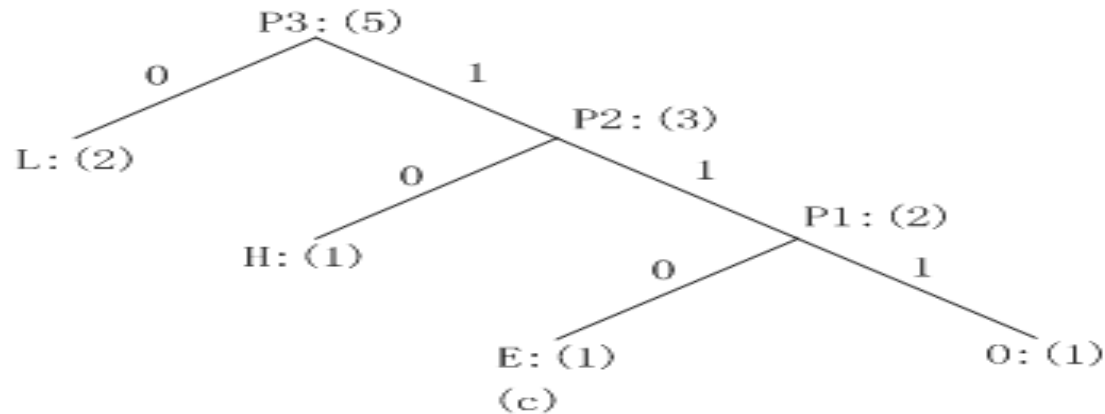
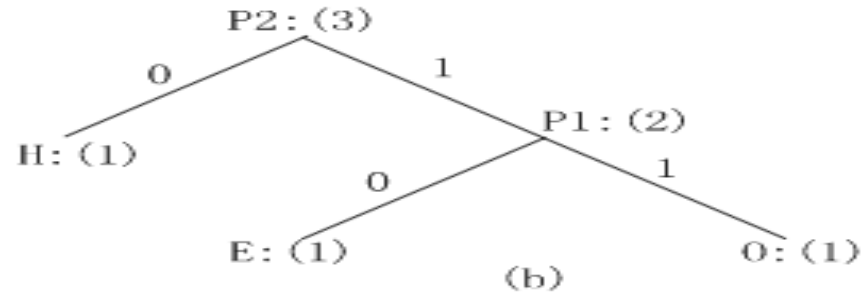
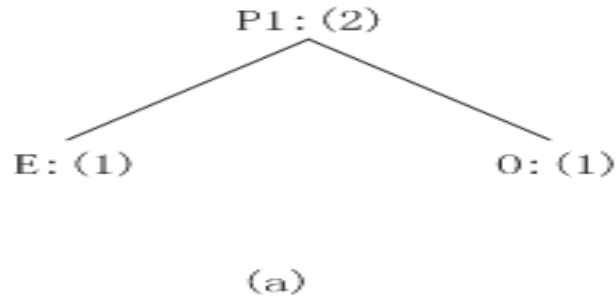
- First presented by David A. Huffman in 1952
- Adopted in applications, Such as fax、 JPEG、 MPEG
- **A bottom-up manner:**
 - Initialization: put all symbols on the list **sorted according to their frequency** counts
 - Repeat until the list has only one symbol left:
 - From the list, pick **two symbols with the lowest frequency** counts, form a Huffman sub-tree that has these two symbols as child nodes and **create a parent node for them**
 - Assign the sum of the children's frequency counts to the parent and insert it into the list, such that the order is maintained.
 - Delete the children from the list
 - Assign a codeword for each leaf based on the path from the root



2.2 Variable-Length Coding

Example: Huffman Coding “Hello”

Symbol	H	E	L	O
Count	1	1	2	1





2.2 Variable-Length Coding

- ❑ For above example, Huffman coding **generate the same coding result** as Shannon-Fano algorithm
- ❑ Another example
 - A:(15), B:(7), C:(6), D:(6) and E:(5)
 - Shannon-Fano needs 89bits;
 - Huffman needs 87 bits
- ❑ Conclusions
 - If correct probabilities are available, **Huffman coding produces good compression results.**
 - Important properties:
 - ❑ Unique prefix property
 - ❑ Optimality
- ❑ Extended Huffman coding



2.2 Variable-Length Coding

Adaptive Huffman Coding

- ❑ Huffman Coding requires **prior statistical knowledge** about the information source, which is often not available
- ❑ Even when the statistics are available, the **transmission of the symbol table** could represent heavy overhead
- ❑ Adaptive algorithm, **statistics are gathered and updated dynamically** as the data-stream arrives
- ❑ The probabilities are no longer based on prior knowledge but **on actual data received so far**

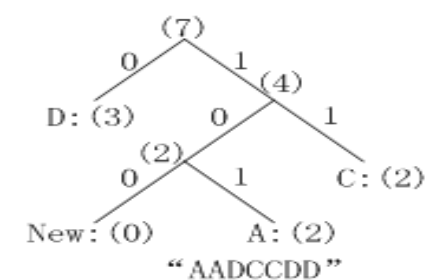
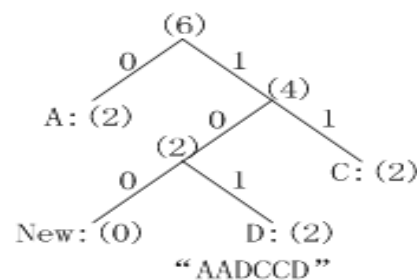
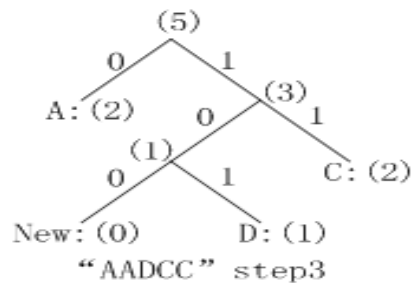
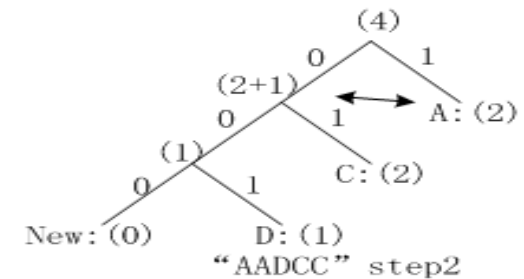
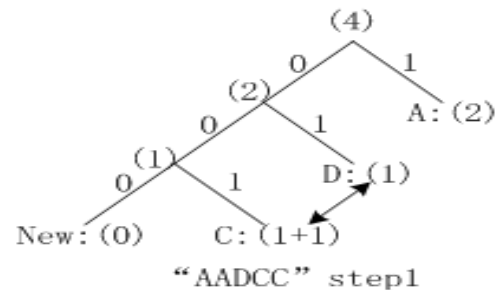
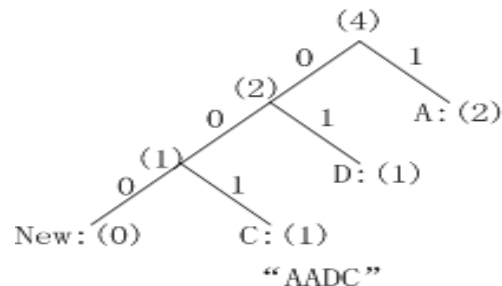
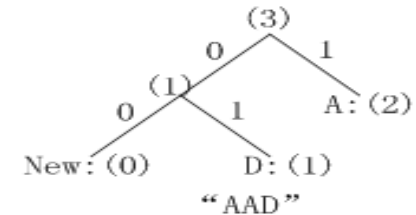
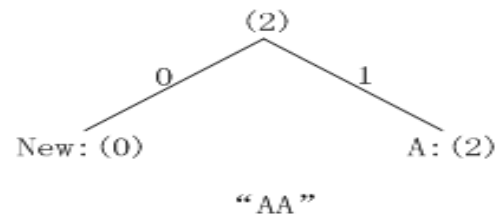
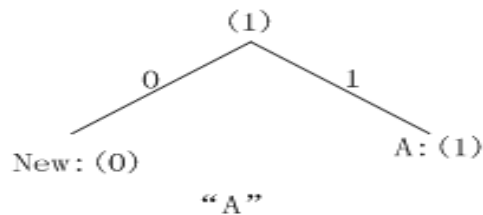


2.2 Variable-Length Coding

- **Basic idea of Adaptive Huffman Coding**
 - **Intial_code: assigns symbols with some initially agreed-upon codes;**
 - **Update_Tree: constructing an adaptive Huffman tree**
 - Increment the frequency counts for the symbols;
 - Update the configuration of the tree.
 - **The encoder and decoder must use exactly the same intial_code and Update_Tree routines.**

2.2 Variable-Length Coding

□ An example: “AADCCDD”





2.3 Dictionary-Based Coding

- ❑ First proposed by Ziv and Lempel in 1977 and 1978 respectively
- ❑ Terry Welch improved the technique in 1984
- ❑ Lempel-Ziv-Welch algorithm (called **LZW compression**)
- ❑ It is used in e.g., *UNIX compress*, GIF, V.42 bis for modems



2.3 Dictionary-Based Coding

□ LZW Compression Algorithm

```
w = NIL;
while ( read a character k ) {
  if wk exists in the dictionary
    w = wk;
  else
    add wk to the dictionary;
    output the code for w;
    w = k;
}
```

Suppose a dictionary contains 4,096 entries, with the first 256(0~255) entries being ASCII codes.



2.3 Dictionary-Based Coding

Example:

Input string:

"^WED^WE

^WEE^WEB

^WET".

<i>w</i>	<i>k</i>	<i>Output</i>	<i>Index</i>	<i>Symbol</i>
NIL	^			
^	W	^	256	^W
W	E	W	257	WE
E	D	E	258	ED
D	^	D	259	D^
^	W			
^W	E	256	260	^WE
E	^	E	261	E^
^	W			
^W	E			
^WE	E	260	262	^WEE
E	^			
E^	W	261	263	E^W
W	E			
WE	B	257	264	WEB
B	^	B	265	B^
^	W			
^W	E			
^WE	T	260	266	^WET
T	EOF	T		



2.3 Dictionary-Based Coding

■ LZW Decompression

w = NIL;

while (read a character **k) { /* k could be a character or a code. */**

entry = dictionary entry for **k;**

output entry;

if(s!=NIL)

add w + entry[0] to dictionary with a new code;

w = entry;

}



2.3 Dictionary-Based Coding

Example (continued):

Input string:

**"^WED<256>E<260>
<261><257>B<260>T".**

<i>w</i>	<i>k</i>	<i>Output</i>	<i>Index</i>	<i>Symbol</i>
	^	^		
^	W	W	256	^W
W	E	E	257	WE
E	D	D	258	ED
D	<256>	^W	259	D^
<256>	E	E	260	^WE
E	<260>	^WE	261	E^
<260>	<261>	E^	262	^WEE
<261>	<257>	WE	263	E^W
<257>	B	B	264	WEB
B	<260>	^WE	265	B^
<260>	T	T	266	^WET



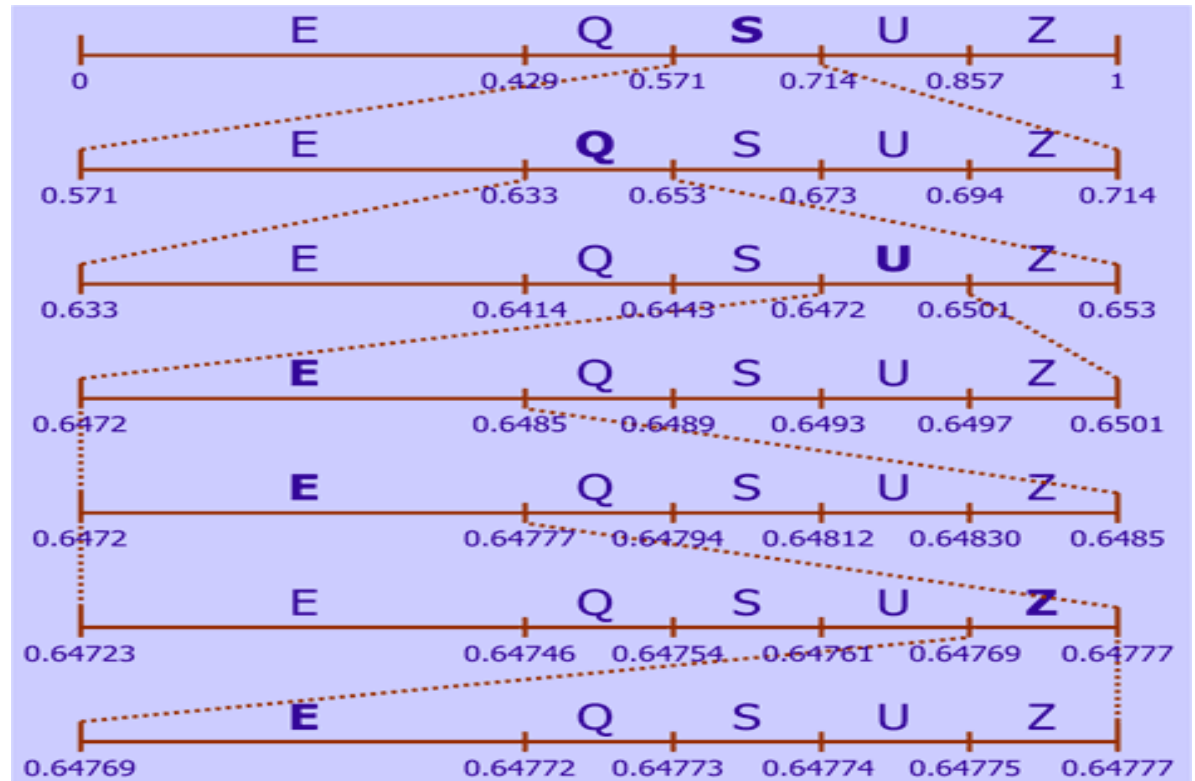
2.4 Arithmetic Coding

- **Basic idea**
 - **Instead of present each character** as a codeword, Arithmetic Coding **represent the whole message** by a half-open interval $[a,b)$ contained in $[0,1]$.
 - The length of the **interval $[a,b)$ equals the probability of the message**. Choose a decimal in $[a,b)$ and transform it into binary form as coding output.
 - **Each character can shorten the interval**, so the more characters ,the more shorter the interval will be.
 - As the interval become **shorter, more bits** are needed to present the interval

- **Average bits used for each character can be decimal**

2.4 Arithmetic Coding

□ Example: “SQUEEZE”





3、 Lossless Image Compression



3.1 Lossless Image Compression

- **Differential coding**
 - One of the most commonly used compression techniques in multimedia data compression

- **The basic of data reduction in differential coding**
 - Existing **redundancy in consecutive symbols** in a data-stream



3.2 Differential Coding of Images

Given an original image $I(x, y)$, defining a difference image $d(x, y)$

- Using a simple difference operator
 - $d(x, y) = I(x, y) - I(x-1, y)$
- Discrete 2D Laplacian operator
 - $d(x, y) = 4I(x, y) - I(x, y-1) - I(x, y+1) - I(x+1, y) - I(x-1, y)$
- **Image I has larger entropy than image d**
 - VLC -- shorter bit-length for the difference image
 - Compression works better on a difference image

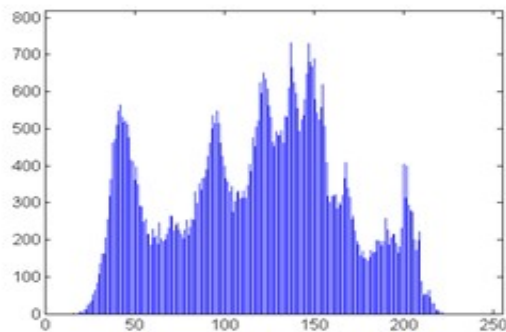
3.2 Differential Coding of Images



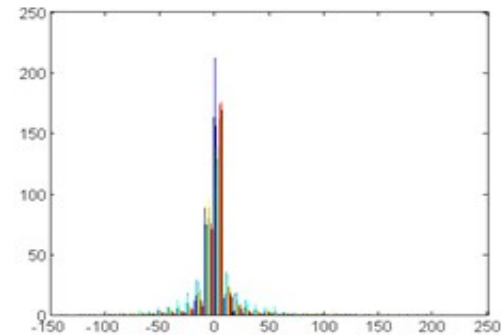
(a)



(b)



(c)



(d)



3.3 Lossless JPEG

- **Lossless JPEG**
 - Special case of JPEG image compression which has no lossy steps
- **Involves two steps: forming a differential prediction and encoding**
 - **Predictor:** combines the values of up to three neighboring pixels as the predicted value for the current pixel
 - **Encoder:** Compares the prediction with the actual pixel and encodes the difference using lossless compression algorithm
 - Lossless JPEG usually yields a relatively low compression ratio, which renders it impractical for most multimedia applications

3.3 Lossless JPEG

□ Lossless JPEG Predictors

		C	B	
		A	X	

Predictor	Prediction
P1	A
P2	B
P3	C
P4	$A+B-C$
P5	$A+(B-C)/2$
P6	$B+(A-C)/2$
P7	$(A+B)/2$

3.3 Lossless JPEG

- **Comparison of Lossless JPEG with other lossless compression programs**

Compression program	Compression ratio			
	Lena	Football	F-18	Flower
Lossless JPEG	1.45	1.54	2.29	1.26
Optimal lossless JPEG	1.49	1.67	2.71	1.33
Compress(LZW)	0.86	1.24	2.21	0.87
gzip(LZ77)	1.08	1.36	3.10	1.05
gzip-9(optimal LZ77)	1.08	1.36	3.13	1.05
pack (Huffman coding)	1.02	1.12	1.19	1.00



The End!

Thanks !