# **Image Compression**

Instructor LE Thanh Sach, Ph.D. Ltsach@cse.hcmut.edu.vn http://www.cse.hcmut.edu.vn/~ltsach/

## Outline

Introduction

- Lossless Compression
- Lossy Compression

## Introduction

- The goal of image compression is to reduce the amount of data required to represent a digital image.
- Important for reducing storage



## **Approaches**

#### Lossless

- >>> Information preserving
- **Low compression ratios**
- 🖎 e.g., Huffman

#### Lossy

- > Does not preserve information
- >>> High compression ratios
- 🖎 e.g., JPEG

#### ✤<u>Tradeoff</u>: image quality vs compression ratio

## Data vs Information

Data and information <u>are not</u> synonymous terms!

Data is the means by which information is conveyed.

Data compression aims to reduce the amount of data required to represent a given quantity of information while preserving as much information as possible.

## Data Redundancy

## Data redundancy is a mathematically quantifiable entity!



## Data Redundancy (cont'd)

**Compression ratio:** 
$$C_R = \frac{n_1}{n_2}$$

Relative data redundancy: 
$$R_D = 1 - \frac{1}{C_R}$$
  
Example:

If  $C_R = \frac{10}{1}$ , then  $R_D = 1 - \frac{1}{10} = 0.9$ (90% of the data in dataset 1 is redundant) if  $n_2 = n_1$ , then  $C_R = 1$ ,  $R_D = 0$ (90% of the data in dataset 1 is redundant) if  $n_2 \ll n_1$ , then  $C_R \to \infty$ ,  $R_D \to 1$ if  $n_2 \gg n_1$ , then  $C_R \to 0$ ,  $R_D \to -\infty$ 

## **Types of Data Redundancy**

(1) Coding(2) Interpixel(3) Psychovisual

The role of compression is to reduce one or more of these redundancy types.

## **Coding Redundancy**

# Data compression can be achieved using an appropriate <u>encoding scheme</u>.

Example: binary encoding

0:000	4:100
1:001	5: 101
2:010	6: 110
3:011	7:111

## **Encoding Schemes**

Elements of an encoding scheme:

- <u>Code:</u> a list of symbols (letters, numbers, bits etc.)
- Code word: a sequence of symbols used to represent a piece of information or an event (e.g., gray levels)
- Code word length: number of symbols in each code word

Example: (binary code, symbols: 0,1, length: 3)

0:000	4:100
1:001	5:101
2:010	6: 110
3:011	7:111

## **Definitions**

N x M image  $r_k$ : k-th gray level  $P(r_k)$ : probability of  $r_k$  Expected value:

$$E(X) = \sum_{x} x P(X = x)$$

 $l(r_k)$ : # of bits for  $r_k$ 

Average # of bits:  $L_{avg} = E(l(r_k)) = \sum_{k=0}^{L-1} l(r_k)P(r_k)$ 

Total # of bits: NML<sub>avg</sub>

## **Constant Length Coding**

$l(\mathbf{r}_k) = \mathbf{c}$	which	n implie	es that L	avg=c
	r <sub>k</sub>	$p_r(r_k)$	Code 1	$l_1(r_k)$
	$r_0 = 0$	0.19	000	3
	$r_1 = 1/7$	0.25	001	3
	$r_2 = 2/7$	0.21	010	3
	$r_3 = 3/7$	0.16	011	3
Example:	$r_4 = 4/7$	0.08	100	3
PPP	$r_{5} = 5/7$	0.06	101	3
	$r_6 = 6/7$	0.03	110	3
	$r_7 = 1$	0.02	111	3

Assume an image with L = 8

Assume 
$$l(r_k) = 3$$
,  $L_{avg} = \sum_{k=0}^{7} 3P(r_k) = 3 \sum_{k=0}^{7} P(r_k) = 3$  bits

Total number of bits: 3NM

## Avoiding Coding Redundancy

To avoid coding redundancy, codes should be selected according to the probabilities of the events.

Variable Length Coding
 Assign fewer symbols (bits) to the more probable events (e.g., gray levels for images)

## Variable Length Coding

#### Consider the probability of the gray levels:



### Interpixel redundancy

Interpixel redundancy implies that any pixel value can be reasonably predicted by its neighbors (i.e., correlated).



*correlation*: 
$$f(x) \circ g(x) = \int_{-\infty}^{\infty} f^*(a)g(x+a)da$$

*autocorrelation*: g(x) = f(x)



Figure 6.2 Two images and their gray-level histograms and normalized autocorrelation

## Interpixel redundancy (cont'd)

- To reduce interpixel redundnacy, the data must be transformed in another format (i.e., through a transformation)
  - e.g., thresholding, or differences between adjacent pixels, or DFT
    Gray level (profile line 100)





Run-length encoding:

(1,63) (0,87) (1,37) (0,5) (1,4) (0,556) (1,62) (0,210)Using 11 bits/pair: (1+10)

88 bits are required (compared to 1024 !!)



SILLE. I

## **Psychovisual redundancy**

- Takes into advantage the peculiarities of the human visual system.
- The eye <u>does not</u> respond with equal sensitivity to all visual information.
- Humans search for important features (e.g., edges, texture, etc.) and do not perform quantitative analysis of every pixel in the image.

## Psychovisual redundancy (cont'd) Example: Quantization



i.e., add to each pixel a pseudo-random number prior to quantization

## How do we measure information?

What is the information content of a message/image?

What is the minimum amount of data that is sufficient to describe completely an image without loss of information?

### Modeling the Information Generation Process

Assume that information generation process is a <u>probabilistic process</u>.

A random event *E* which occurs with probability P(E) contains:  $I(E) = log(\frac{1}{P(E)}) = -log(P(E))$  units of information

[note that when P(E) = 1, then I(E) = 0: no information !

# How much information does a pixel contain?

Suppose that the gray level value of pixels is generated by a random variable, then r<sub>k</sub> contains

 $I(r_k) = -log(P(r_k))$  units of information

#### Average information of an image

\* Entropy: the average information content of an image  $H = \sum_{k=0}^{L-1} I(r_k) \Pr(r_k)$ 

using 
$$I(r_k) = -\log(P(r_k))$$

e have: 
$$H = -\sum_{k=0}^{L-1} P(r_k) log(P(r_k))$$
 units/pixel

**Assumption:** statistically independent random events

Advanced Image/Video Processing: Image Compression

W

#### Modeling the Information Generation Process (cont'd)

$$\bigstar \underline{\mathbf{Redundancy}} \quad R = L_{avg} - H$$

where: 
$$L_{avg} = E(l(r_k)) = \sum_{k=0}^{L-1} l(r_k)P(r_k)$$

note that if  $L_{avg} = H$ , then R = 0 - no redundancy

## **Entropy Estimation**

#### \*Not easy!

ımage
-------

٠

21	21	21	95	169	243	243	243
21	21	21	95	169	243	243	243
21	21	21	95	169	243	243	243
21	21	21	95	169	243	243	243

Gray Level	Count	Probability
21	12	3/8
95	4	1/8
169	4	1/8
243	12	3/8

Advanced Image/Video Processing: Image Compression

## **Entropy Estimation**

#### **First order estimate of H:**

$$H = -\sum_{k=0}^{3} P(r_k) log(P(r_k)) = 1.81 \text{ bits/pixel}$$
  
Total bits: 4 x 8 x 1.81 = 58 bits

Advanced Image/Video Processing: Image Compression

## Estimating Entropy (cont'd)

# Second order estimate of H:

**Solution States and S** 

			1	mage	e		
21	21	21	95	169	243	243	243
21	21	21	95	169	243	243	243
21	21	21	95	169	243	243	243
21	21	21	95	169	243	243	243

Gray Level Pair	Count	Probability
(21, 21)	8	1/4
(21, 95)	4	1/8
(95, 169)	4	1/8
(169, 243)	4	1/8
(243, 243)	8	1/4
(243, 21)	4	1/8

H = 2.5/2 = 1.25 bits/pixel

## Estimating Entropy (cont'd)

- Comments on first and second order entropy estimates:
  - The first-order estimate gives only a <u>lower-bound</u> on the compression that can be achieved.
  - Differences between higher-order estimates of entropy and the first-order estimate indicate the presence of <u>interpixel redundancies</u>.

## Question

# How do we deal with interpixel redundancy?

#### Apply a transformation!

Advanced Image/Video Processing: Image Compression

## Estimating Entropy (cont'd)

#### ✤E.g., consider <u>difference</u> image:



Gray Level or Difference	Count	Probability
0	12	1/2
21	4	1/8
74	12	3/8

Advanced Image/Video Processing: Image Compression

## Estimating Entropy (cont'd)

Entropy of <u>difference</u> image:

$$H = -\sum_{k=0}^{2} P(r_k) log(P(r_k)) = 1.41$$
 bits/pixel

• Better than before (i.e., H=1.81 for original image), however, a better transformation could be found:

1.41 bits/pixel > 1.25 bits/pixel (from 2nd order estimate of H)



# Image Compression Model (cont'd)



Mapper: transforms the input data into a format that facilitates reduction of interpixel redundancies.

# Image Compression Model (cont'd)



Quantizer: reduces the accuracy of the mapper's output in accordance with some pre-established fidelity criteria.

# Image Compression Model (cont'd)



#### Symbol encoder: assigns the shortest code to the most frequently occurring output values.

# Image Compression Models (cont'd)



✤ The inverse operations are performed.

◆ But ... quantization is irreversible in general.
# **Fidelity Criteria**



How close is f(x, y) to  $\hat{f}(x, y)$  ?

Criteria
Subjective: based on human observers
Objective: mathematically defined criteria

Advanced Image/Video Processing: Image Compression

# Subjective Fidelity Criteria

Value	Rating	Description
1	Excellent	An image of extremely high quality, as good as you could desire.
2	Fine	An image of high quality, providing enjoyable viewing. Interference is not objectionable.
3	Passable	An image of acceptable quality. Interference is not objectionable.
4	Marginal	An image of poor quality; you wish you could improve it. Interference is somewhat objectionable.
5	Inferior	A very poor image, but you could watch it. Objectionable interference is definitely present.
6	Unusable	An image so bad that you could not watch it.

### **Objective Fidelity Criteria**

#### Root mean square error (RMS)

$$e_{rms} = \sqrt{\frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (\hat{f}(x, y) - f(x, y))^2}$$

Mean-square signal-to-noise ratio (SNR)

$$SNR_{ms} = \frac{\sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (\hat{f}(x, y))^2}{\sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (\hat{f}(x, y) - f(x, y))^2}$$

## Example



## **Lossless Compression**



$$e(x, y) = \hat{f}(x, y) - f(x, y) = 0$$

- Huffman, Golomb, Arithmetic  $\rightarrow$  coding redundancy
- LZW, Run-length, Symbol-based, Bit-plane  $\rightarrow$  interpixel redundancy

# Huffman Coding (i.e., removes coding redundancy)



- It is a variable-length coding technique.
- It creates the *optimal code* for a set of source symbols.
- Assumption: symbols are encoded one at a time!

# Optimal code: minimizes the number of code symbols per source symbol.

• Forward Pass

- 1. Sort probabilities per symbol
- 2. Combine the lowest two probabilities
- 3. Repeat *Step2* until only two

probabilities remain.



#### Backward Pass

#### **Assign code symbols going backwards**



# $L_{avg}$ using Huffman coding:

$$L_{avg} = E(l(a_k)) = \sum_{k=1}^{6} l(a_k)P(a_k) =$$

 $3x0.1 + 1x0.4 + 5x0.06 + 4x0.1 + 5x0.04 + 2x0.3 = 2.2 \ bits/symbol$ 

#### L<sub>avg</sub> assuming binary codes: 6 symbols, we need a 3-bit code

 $(a_1: 000, a_2: 001, a_3: 010, a_4: 011, a_5: 100, a_6: 101)$ 

$$L_{avg} = \sum_{k=1}^{6} l(a_k)P(a_k) = \sum_{k=1}^{6} 3P(a_k) = 3\sum_{k=1}^{6} P(a_k) = 3 \text{ bits/symbol}$$

#### \*Comments

#### After the code has been created, coding/decoding can be implemented using a look-up table.

#### Decoding can be done in an unambiguous way !!

Sym.	Prob.	Code
0	0.4	1
a2	0.3	00
a.	0.1	011
a.	0.1	0100
a.	0.06	01010
a.	0.04	01011

# Arithmetic (or Range) Coding (i.e., removes coding redundancy)

- No assumption on encoding symbols one at a time.
   No one-to-one correspondence between source and code words.
- Slower than Huffman coding but typically achieves better compression.
- A sequence of source symbols is assigned a single arithmetic code word which corresponds to a sub-interval in [0,1]

- As the number of symbols in the message increases, the interval used to represent it becomes smaller.
  - **Each symbol reduces the size of the interval according to its probability.**
- Smaller intervals require more information units (i.e., bits) to be represented.

Encode message: a<sub>1</sub> a<sub>2</sub> a<sub>3</sub> a<sub>3</sub> a<sub>4</sub>

1) Assume message occupies [0, 1)

Source Symbol	Probability
$a_1$	0.2
$a_2$	0.2
$a_3$	0.4
$a_4$	0.2

0	1	Initial Subinterval
2) Subdivide [	$(0, 1)$ based on the probabilities of $\alpha_i$	$[0.0, 0.2) \\ [0.2, 0.4) \\ [0.4, 0.8) \\ [0.8, 1.0)$

3) Update interval by processing source symbols

# Example

Source Symbol	Probability	Initial Subinterval
$a_1$	0.2	[0.0, 0.2)
$a_2$	0.2	[0.2, 0.4)
<i>a</i> <sub>3</sub>	0.4	[0.4, 0.8)
$a_4$	0.2	[0.8, 1.0]



Advanced Image/Video Processing: Image Compression

Slide: 50

# Example

- The message  $a_1 a_2 a_3 a_3 a_4$  is encoded using 3 decimal digits or 0.6 decimal digits per source symbol.
- The entropy of this message is:
- $-(3 \times 0.2\log_{10}(0.2)+0.4\log_{10}(0.4))=0.5786$  digits/symbol

<u>Note:</u> Finite precision arithmetic might cause problems due to truncations!



#### \* Encode

- **≥ Low = 0**
- >>> High = 1

#### $\simeq$ Loop. For all the symbols.

- $\checkmark$  Range = high low
- High = low + range \* high\_range of the symbol being coded

Low = low + range \* low\_range of the symbol being coded

- **\*** Where:
  - Range, keeps track of where the next range should be.
  - >>> High and low, specify the output number.

Symbol	Range	Low value	High value			
		0	1	Symbol	Probability	Range
b	1	0.5	0.75	a	2	[0.0 , 0.5)
a	0.25	0.5	0.625	b	1	[0.5 , 0.75)
с	0.125	0.59375	0.625	с	1	[0.75 , 1.0)
a	0.03125	0.59375	0.609375			

#### \*Decode

#### **Loop.** For all the symbols.

- Range = high\_range of the symbol low\_range of the symbol
- ✓ Number = number low\_range of the symbol

✓Number = number / range

Symbol	Range	Number			
	0.05	0.500.75	Symbol	Probability	Range
b	0.25	0.59375	а	2	[0 0 0 5)
a	0.5	0.375		-	
c	0.25	0.75	b	1	[0.5 , 0.75)
	0.20		с	1	[0.75, 1.0)
a	0.5	0			

# LZW Coding (i.e., removes inter-pixel redundancy)

- Requires <u>no priori knowledge</u> of probability distribution of pixels
- Assigns fixed length code words to variable length sequences
- Patented Algorithm US 4,558,302
- Included in GIF and TIFF and PDF file formats

# LZW Coding

A codebook or a dictionary has to be constructed.
 Single pixel values and blocks of pixel values

- For an 8-bit image, the first 256 entries are assigned to the gray levels 0,1,2,...,255.
- As the encoder examines image pixels, gray level sequences (i.e., pixel combinations) that are not in the dictionary are assigned to a new entry.

## Example

#### Consider the following 4 x 4 8 bit image

- 39 39 126 126
- 39 39 126 126
- 39 39 126 126
- 39 39 126 126

Dictionary Location	Entry
0	0
1	1
255	255
256	
511	

**Initial Dictionary** 

## Example

- 39 39 126 126
- 39 39 126 126
- 39 39 126 126
- 39 39 126 126

Dictionary Location	Entry	
0	0	
1	1	
255	255	
256	39-39	
511		

- Is 39 in the dictionary......Yes
- What about 39-39.....No
- Then add 39-39 in entry 256



	Examp	le
concatenated sequence	(CS)	

39	39	126	126
39	39	126	126
39	39	126	126
39	39	126	126

If CS is found: (1) No Output (2) CR=CS

If CS not found: (1) Output D(CR) (2) Add CS to D (3) CR=P

Currently Recognized Sequence	Pixel Being Processed	Encoded Output	Dictionary Location (Code Word)	Dictionary Entry
	39			
39	39	39	256	39-39
39	126	39	257	39-126
126	126	126	258	126-126
126	39	126	259	126-39
39	39			
39-39	126	256	260	39-39-126
126	126			
126-126	39	258	261	126-126-39
39	39			
39-39	126			
39-39-126	126	260	262	39-39-126-126
126	39			
126-39	39	259	263	126-39-39
39	126			
39-126	126	257	264	39-126-126
126		126		

# Decoding LZW

• The dictionary which was used for encoding need not be sent with the image.

• A separate dictionary is built by the decoder, on the "fly", as it reads the received code words.

## Run-length coding (RLC) (i.e., removes interpixel redunancy)

Used to reduce the size of a repeating string of characters (i.e., runs)

a a a b b b b b c c  $\rightarrow$  (a,3) (b, 6) (c, 2)

- Encodes a run of symbols into two bytes , a count and a symbol.
- Can compress any type of data but cannot achieve high compression ratios compared to other compression methods.

# Run-length coding (i.e., removes interpixel redunancy)

Code each contiguous group of 0's and 1's, encountered in a left to right scan of a row, by its <u>length</u>.

 $1\ 1\ 1\ 1\ 1\ 0\ 0\ 0\ 0\ 0\ 1 \rightarrow (1,5)\ (0,6)$ (1,1)

## Bit-plane coding (i.e., removes interpixel redundancy)

- An effective technique to reduce inter pixel redundancy is to process each bit plane individually
- ✤ The image is decomposed into a series of binary images.
- Each binary image is compressed using one of well known binary compression techniques.
  - ➣ e.g., Huffman, Run-length, etc.

Combining Huffman Coding with Run-length Coding

Once a message has been encoded using Huffman coding, additional compression can be achieved by encoding the lengths of the runs using variable-length coding!

0 1 0 1 0 0 1 1 1 1 0 0

e.g., (0,1)(1,1)(0,1)(1,1)(0,2)(1,4)(0,2)

## **Lossy Compression**

- Transform the image into a domain where compression can be performed more efficiently.
- Note that the transformation itself does not compress the image!



Advanced Image/Video Processing: Image Compression

## Lossy Compression (cont'd)

# Example: Fourier Transform $f(x, y) = \frac{1}{N} \sum_{u=0}^{N-1} \sum_{v=0}^{N-1} F(u, v) e^{\frac{j2\pi(ux+vy)}{N}}, \quad x, y=0,1,...,N-1$ The magnitude of the FT decreases, as *u*, *v* increase! **K** << **N** $\hat{f}(x,y) = \frac{1}{N} \sum_{u=0}^{K-1} \sum_{v=0}^{K-1} F(u,v)e^{\frac{j2\pi(ux+vy)}{N}}, x,y=0,1,...,N-1$ $\sum (\hat{f}(x, y) - f(x, y))^2$ is very small !! x, y

Advanced Image/Video Processing: Image Compression

## **Transform Selection**

$$f(x, y) = \sum_{u=0}^{N-1} \sum_{v=0}^{N-1} T(u, v) h(x, y, u, v)$$

T(u,v) can be computed using various transformations, for example:
 DFT
 DCT (Discrete Cosine Transform)
 KLT (Karhunen-Loeve Transformation)

## DCT

#### forward

$$C(u, v) = \alpha(u)\alpha(v) \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} f(x, y) cos(\frac{(2x+1)u\pi}{2N}) cos(\frac{(2y+1)v\pi}{2N}),$$
$$u, v=0,1,...,N-1$$

#### inverse

$$f(x,y) = \sum_{u=0}^{N-1} \sum_{v=0}^{N-1} \alpha(u) \alpha(v) C(u,v) cos(\frac{(2x+1)u\pi}{2N}) cos(\frac{(2y+1)v\pi}{2N}),$$

x, y=0,1,...,N-1

$$\alpha(u) = \begin{cases} \sqrt{1/N} & \text{if } u=0\\ \sqrt{2/N} & \text{if } u>0 \end{cases} \quad \alpha(v) = \begin{cases} \sqrt{1/N} & \text{if } v=0\\ \sqrt{2/N} & \text{if } v>0 \end{cases}$$

# DCT (cont'd)

### Basis set of functions for a 4x4 image (i.e.,cosines of different frequencies).



# DCT (cont'd)

8 x 8 subimages

64 coefficients per subimage

50% of the coefficients truncated



**Advanced Image/Video Processing Image Compression**
# DCT (cont'd)

DCT minimizes "blocking artifacts" (i.e., boundaries between subimages do not become very visible).

#### DFT

i.e., n-point periodicity gives rise to discontinuities!

DCT i.e., 2n-point periodicity prevents discontinuities!



### DCT (cont'd)

#### Subimage size selection





## JPEG Compression

# JPEG uses DCT for handling interpixel redundancy.

#### Modes of operation:

- (1) Sequential DCT-based encoding
- (2) Progressive DCT-based encoding
- (3) Lossless encoding
- (4) Hierarchical encoding

#### JPEG Compression (Sequential DCT-based encoding)



### **JPEG Steps**

- Divide the image into 8x8 subimages;
  For each subimage do:
- 2. Shift the gray-levels in the range [-128, 127]
- 3. Apply DCT (64 coefficients will be obtained: 1 DC coefficient F(0,0), 63 AC coefficients F(u,v)).
- 4. Quantize the coefficients (i.e., reduce the amplitude of coefficients that do not contribute a lot).

$$C_q(u, v) = Round[\frac{C(u, v)}{Q(u, v)}]$$
 Quantization  
Table

# JPEG Steps (cont'd)

#### 5. Order the coefficients using zig-zag ordering

- Place non-zero coefficients first
- Create long runs of zeros (i.e., good for run-length encoding)
- See next slide
- 6. Encode coefficients.

DC coefficients are encoded using predictive encoding

All coefficients are converted to a binary sequence:

6.1 Form intermediate symbol sequence

6.2 Apply Huffman (or arithmetic) coding (i.e., entropy coding)

#### JPEG Steps (cont'd)

✤ AC coefficients are arranged into a zig-zag sequence:



## Shifting and DCT

(a) Original 8	8 block	(b) Shifted block	(c) Block after FDCT Eqn. (5)
140 144 1471140 140 144 152 140 147 140 152 155 136 167 163 168 145 156 160 152 162 148 156 148 140 147 167 140 155 155 136 156 123 167 162	0 155 179 175 148 167 179 162 152 172 155 136 160 136 147 162 140 136 162 144 140 147	12 16 19 12 11 27 51 47 16 24 12 19 12 20 39 51 24 27 8 39 35 34 24 44 40 17 28 32 24 27 8 32 34 20 28 20 12 8 19 34 19 39 12 27 27 12 8 34 8 28 -5 39 34 16 12 19	185 - 17    14    -8    23    -9    -13    -18      20    -34    26    -9    -10    10    13    6      -10    -23    -1    6    -18    3    -20    0      -8    -5    14    -14    -8    -2    -3    8      -3    9    7    1    -11    17    18    15      3    -2    -18    8    8    -3    0    -6      8    0    -2    3    -1    -7    -1    -1
148 155 136 155 152	2 147 147 136	20 27 8 27 24 19 19 8	0

(non-centered spectrum)

#### Quantization

#### Quantization Table Example







#### Quantization (cont'd)



#### Zig-Zag Ordering (cont'd)





#### Intermediate Coding (cont'd)



AC (0,2) (-3)



If RUN-LENGTH > 15, then symbol (15,0) means RUN-LENGTH=16

# Entropy Encoding (cont'd)



End of Block

See Table 8.17-8.19, page 500, 501, 501

# **Entropy Encoding**

#### **Symbol\_1** (Variable Length Code (VLC))

(Runlength, size)	Code word
(0,,0) EOB	1010
(0,1)	00
, (0,2)	01
(0,3)	100
(1,2)	11011
(2,1)	11100
(3,1)	111010
(4,1)	111011
(5,2)	11111110111
(6,1)	1111011
(7,1)	11111010

#### **Symbol\_2** (Variable Length Integer (VLI))

	Amplitude range
Size	Ampitude range
1	(-1, 1)
2	(-3, -2) (2,3)
3	(-74) (47)
4	(-158) (815)
5	(-3116) (1631)
6	(-6332) (3263)
7	(-12764) (64127)
8	(-255128) (128255)
9	(-511256) (256511)
12	( 1022 512) (512 1023)

(1,2)(12) → (11011 1100) See Table 8.17-8.19, page 500, 501, 501 VLC VLI

#### **JPEG Examples**



worst quality,

highest compression

best quality,

lowest compression

#### Results

Table 6. Results of JPEG Compression for Grayscale Image 'Lisa' (320 ×240 pixels)

Quality factors	Original number of bits	Compressed number of bits	Compression ratio (Cr)	Bits/pixel (Nb)	RMS error
1	512,000	48,021	10.66	0.75	2.25
2	512,000	30,490	16.79	0.48	2.75
4	512,000	20,264	25.27	0.32	3.43
8	512,000	14,162	36-14	0.22	4.24
15	512,000	10,479	48.85	0.16	5.36
25	512,000	9,034	56-64	0.14	6-40
					1

### **Progressive JPEG**

The image is encoded in multiple scans, in order to produce a quick, rough decoded image when transmission time is long.



✤ Each scan, codes a subset of DCT coefficients.

Let's look at three methods:

(1) Progressive spectral selection algorithm
 (2) Progressive successive approximation algorithm
 (3) Combined progressive algorithm

(1) Progressive spectral selection algorithm
 Group DCT coefficients into several spectral bands
 Send low-frequency DCT coefficients first
 Send higher-frequency DCT coefficients next

Band 1: DC coefficient only Band 2:  $AC_1$  and  $AC_2$  coefficients Band 3:  $AC_3$ ,  $AC_4$ ,  $AC_5$ ,  $AC_6$ , coefficients Band 4:  $AC_7$ .... $AC_{63}$ , coefficients

(2) Progressive successive approximation algorithm

All DCT coefficients are sent first with lower precision

**Refine them in later scans** 

Band 1: All DCT coefficients (divided by four) Band 2: All DCT coefficients (divided by two) Band 3: All DCT coefficients (full resolution)

# (3) Combined progressive algorithm Combines spectral selection and successive approximation.



#### Results using spectral selection

	Spectral selection
Scan 1	DC, AC1, AC2
Scan 2	AC3-AC9
Scan 3	AC10-AC35
Scan 4	AC 36-AC 63

Table 8. Progressive spectral selection JPEG. (Image 'Cheetah': 320 × 240 pixels -> 512,000 bits)

Scan number	Bits transmitted	Compression ratio	Bits/pixel	RMS error
1	29,005	17-65	0.45	19-97
2	37,237	7.73	1-04	13-67
3	71,259	3.72	2.15	7.90
4	32,489	3-01	2-66	4.59
Sequential JPEG	172,117	2.97	2.69	4-59

# Results using successive approximation

Successive

approximation

Table 9. Progressive successive approximation JPEG. (Image 'Cheetah': 320 × 240 pixels -> 512,000 bits)

Scan number	Bits transmitted	Compression ratio	Bits/pixel	RMS error
1	26,215	19-53	0.41	22.48
2	34,506	8-43	0.95	12-75
3	63,792	4-11	1.95	7-56
4	95,267	2.33	2-43	4-59
Sequential JPEG	172,117	2.97	2-69	4.59

ocan +	All $D_{C} = -$
	full resolution

# Example using successive approximation



after 3.6s

after 1.6s



after 7.0s



#### Lossless JPEG

#### Use a predictive algorithm instead of DCT-based



# **Fingerprint Compression**

An image coding standard for digitized fingerprints, developed and maintained by:
 FBI

- >>> Los Alamos National Lab (LANL)
- National Institute for Standards and Technology (NIST).
- The standard employs a discrete <u>wavelet</u> transform-based algorithm (*Wavelet/Scalar Quantization or WSQ*).

### **Memory Requirements**

- FBI is digitizing fingerprints at 500 dots per inch with 8 bits of grayscale resolution.
- A single fingerprint card turns into about 10 MB of data!



A sample fingerprint image 768 x 768 pixels =589,824 bytes

# **Preserving Fingerprint Details**



The "white" spots in the middle of the black ridges are *sweat pores* 

They're admissible points of identification in court, as are the little black flesh "islands" in the grooves between the ridges

#### These details are just a couple pixels wide!

# What compression scheme should be used?

Better use a lossless method to preserve every pixel perfectly.

Unfortunately, in practice lossless methods haven't done better than 2:1 on fingerprints!

Does JPEG work well for fingerprint compression?

## **Results using JPEG compression**

file size 45853 bytes compression ratio: 12.9



The fine details are pretty much history, and the whole image has this artificial "blocky" pattern superimposed on it.

The <u>blocking artifacts</u> affect the performance of manual or automated systems!

### **Results using WSQ compression**

file size 45621 bytes compression ratio: 12.9



The fine details are preserved better than they are with JPEG.

NO blocking artifacts!

## WSQ Algorithm



### Varying compression ratio

FBI's target bit rate is around 0.75 bits per pixel (bpp)

This target bit rate is set via a "knob" on the WSQ algorithm.

Si.e., similar to the "quality" parameter in many JPEG implementations.

## Varying compression ratio (cont'd)

In practice, the WSQ algorithm yields a higher compression ratio than the target because of unpredictable amounts of lossless entropy coding gain.

Si.e., mostly due to variable amounts of blank space in the images.

Fingerprints coded with WSQ at a target of 0.75 bpp will actually come in around 15:1

# Varying compression ratio (cont'd)

Original image 768 x 768 pixels (589824 bytes)


## Varying compression ratio (cont'd) 0.9 bpp compression

WSQ image, file size 47619 bytes, compression ratio 12.4



JPEG image, file size 49658 bytes, compression ratio 11.9



## Varying compression ratio (cont'd) 0.75 bpp compression

WSQ image, file size 39270 bytes compression ratio 15.0



JPEG image, file size 40780 bytes, compression ratio 14.5



## Varying compression ratio (cont'd) 0.6 bpp compression

WSQ image, file size 30987 bytes, compression ratio 19.0



JPEG image, file size 30081 bytes, compression ratio 19.6

