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An Overview of Image Compression

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Abstract: This paper presents an introduction about Image compression techniques. Image compression is an application of data compression that encodes the original image with few bits. The objective of image compression is to reduce the redundancy of the image and to store or transmit data in an efficient form. In recent years, the development and demand of multimedia product grows increasingly fast, contributing to insufficient bandwidth of network and storage of memory device. Therefore, the theory of data compression becomes more and more significant for reducing the data redundancy to save more hardware space and transmission bandwidth. In computer science and information theory, data compression or source coding is the process of encoding information using fewer bits or other information-bearing units than an unencoded representation. Compression is useful because it helps reduce the consumption of expensive resources such as hard disk space or transmission bandwidth.

Keywords: data redundancy; lossless; losssy; Huffman; arithmetic; DCT; subband; wavelet;

I. HISTORY OF COMPRESSION

This introduction part specify the history of compression. Morse code, invented in 1838 for use in telegraphy, is an early example of data compression based on using shorter code words for letters such as "e" and "t" that are more common in English. Modern work on data compression began in the late 1940s with the development of information theory. In 1949 Claude Shannon and Robert Fano devised a systematic way to assign codewords based on probabilities of blocks. An optimal method for doing this was then found by David Huffman in 1951. Early implementations were typically done in hardware, with specific choices of codewords being made as compromises between compression and error correction. In the mid-1970s, the idea emerged of dynamically updating codewords for Huffman encoding, based on the actual data encountered and in the late 1970s, with online storage of text files becoming common, software compression programs began to be developed, almost all based on adaptive Huffman coding. In 1977 Abraham Lempel Ziv and Jacob Ziv suggested the basic idea of pointer-based encoding.

II. DATA REDUNDANCY

Compression is achieved by removal of one or more of the three basic data redundancies.

Types:

A. Coding redundancy
B. Inter pixel Redundancy
C. Psychovisual redundancy

A. Coding Redundancy:

Code is a list of symbols(letters,numbers,bits etc.)[1] . codeword is a sequence of symbols used to represent a piece of information or an event .Code word length is calculated by counting the number of symbols in each code word.

Let the discrete random variable rk for k=1,2,…L with associated probabilities Pr(rk)=nk/n where k=1,2,…L, nk is the number of times that the kth gray level appears in the image and n is the total number of pixels in the image. If the number of bits required to represent each value of rk is (rk), then the average number of bits required to represent each pixel [1] is

$$Lavg= \sum_{K=1}^{L} l(r_k)p_r(r_k)$$

The average length of the code words assigned to the various gray level values is found by summing the product of the number of bits used to represent each gray level and the probability that the gray level occurs.

Table 1:Coding redundancy

Rk	Pr(rk)	Code1	L1(rk)	Code2	L2(rk)
R1	0.1875	00	2	011	3
R2	0.5	01	2	1	1
R3	0.1250	10	2	010	3
R4	0.1875	11	2	00	2

Lavg=2 for code1;Lavg=1.81 for code 2.

Coding redundancy is almost always present when the gray levels of an image are coded using a natural binary code. In the table, both a fixed and variable –length encoding of a four level image whose gray level distribution is shown in column 2 is given. The 2-bit binary encoding (code1)in column 3 has an average length of 2 bits. The average number of bits required by code2 (in column 5) is

$$Lavg=\sum^{4} l_2(k)p_r(r_k)$$

=3(0.1875)+1(0.5)+3(0.125)+2(0.1875)=1.8125 and the resulting compression ratio is

Cr =2/1.8125=1.103.

B. Inter Pixel Redundancy:

In order to reduce inter pixel redundancy, the 2-D pixel [1] array normally used for human viewing and interpretation must be transformed into a more efficient format. For example, the difference between adjacent pixels can be used to represent an image. It is called mapping. A simple mapping procedure is lossless predictive coding , eliminates the inter pixel redundancies of closely spaced pixels by extracting and coding only the new information in each pixel. The new information of a pixel is defined as the difference between the actual and predicted value of that pixel.

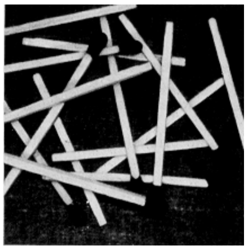

Figure 1:sample(a)

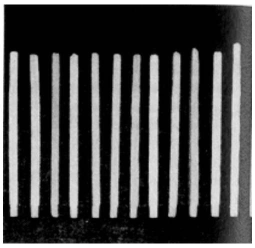

Figure 2: sample(b)

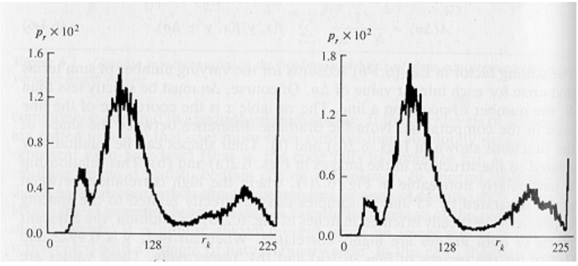

Figure 3: Histogram of Fig 1 & 2

These observations highlight the fact that variable –length coding is not designed to take advantage of the structural relationship s between the aligned matches in Fig2.Although the pixel to pixel correlations are more important in the Fig 1. Because the values of the pixels in either image can be predicted by their neighbors, the information carried by individual pixels is relatively small. visual contribution of a single pixel to an image is redundant; it could be predicted by their neighbors.

C. Psycho visual redundancy:

In general, an observer searches for distinguishing features such as edges or textual regions and mentally combines them into recognizable groupings. The brain then correlates these groupings with prior knowledge in order to complete the image interpretation process. Thus eye does not respond with equal sensitivity to all visual information. Certain information simply has less relative importance than other information in normal visual processing. This information is said to be psycho visually redundant. Unlike coding and inter pixel redundancy psycho visual redundancy is associated with real or quantifiable visual information. Its elimination is desirable because the information itself is not essential for normal visual processing. Since the elimination of psycho visually redundant data results in a loss of quantitative information, it is called quantization.



Figure 4: Original Figure 5: 16 gray level Figure 6: 16 gray levels/random noise

Consider the image in In fig 4. shows a monochrome image with 256 gray levels. Fig 5 : is the same image after the uniform quantization to four bits or 16 possible levels. Fig 6 is called improved gray-scale quantization. It recognizes the eye's inherent sensitivity to edges and breaks them up by adding to each pixel a pseudorandom number, which is generated from the low-order bits of neighboring pixels, before quantizing the result. In fig 6 removes a great deal of psycho visual redundancy with little impact on perceived image quality.

III. IMAGE COMPRESSION TECHNIQUES

The image compression techniques are broadly classified into two categories depending whether or not an exact replica of the original image could be reconstructed using the compressed image [2] .These are:

A. Lossless technique
B. Lossy techniqhe

A. Lossless compression techniques:

In lossless compression techniques, the original image can be perfectly recovered form the compressed (encoded) image. These are also called noiseless since they do not add noise to the signal (image).It is also known as entropy coding since it use statistics/decomposition techniques to eliminate/minimize redundancy. Lossless compression is used only for a few applications with stringent requirements such as medical imaging. Following techniques are included in lossless compression:

a. Run length encoding
b. Huffman encoding
c. Dictionary Techniques
   a)LZ77
   b)LZ78
   c)LZW
d. Arithmetic coding
e. BitPlane coding

B. Lossy compression technique:

Lossy schemes provide much higher compression ratios than lossless schemes. Lossy schemes are widely used since the quality of the reconstructed images is adequate for most applications. By this scheme, the decompressed image is not identical to the original image, but reasonably close to it. Following techniques are included in lossy compression:

a. Lossy Predictive coding
   a) DPCM
   b)ADPCM
   c)Delta Modulation
b. Transform Coding
   a)DFT
   b)DCT
   c)Haar
   d)Hadamard
c. Subband Coding
d. Wavelet Coding
e. Fractal Coding
f. vector Quantization

IV. LOSSLESS TECHNIQUES

A. Run length Encoding :

Run length encoding store the data with count value.In gray scale system $\{V_i, R_i\}$ where V_i is intensity of pixel and R_i is number of consecutive pixels.It is mainly used in fax machines.

Example :

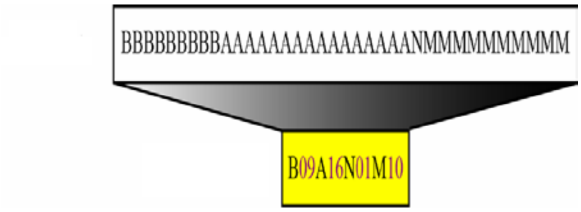

Figure 7

Fig 7 shows the example of run length encoding .

B. *Huffman Encoding :*

This technique was developed by David Huffman. The code generated using this technique or procedure are called Huffman Codes[3]. It is entropy encoding .It is back end of many compression algorithms. The pixels in the image are treated as symbols. Symbols which occur more frequency assigned less number of bits, less frequency assigned a large number of bits.

STEPS :

a. Arrange the symbol probabilities Pi in a decreasing order and consider them as leaf nodes of a tree.
b. While there is more than one node
   a) Merge the two nodes with smallest probability to form a new node whose probability is the sum of the two merged nodes.
   b) Arbitrarily assign 1 and 0 to each pair of branches merging into a node.
c. Read sequentially from the root node to the leaf node where the symbol is located.

Table 2 : Huffman Reduction

Orginal Source		Source Reduction	
Symbol	Probability	1	2
A2	0.5	0.5	0.5
A4	0.1875	0.3125	0.5
A1	0.1875	0.1875	
A3	0.125		

In table 2 initial source symbols and their probabilities are ordered from top to bottom in terms of decreasing probabilities, to form the first source reduction 0.125 & 0.1875 are combined to form a compound symbol with probability 0.3125 [4]. This compound symbol & its probabilities are placed in the first source reduction column & the probabilities are ordered based on the most to least probable values. This process is repeated until a source reduction with two symbols.

C. *Dictionary Techniques :*

This technique was developed by Abraham Lempel Ziv. Build a list of commonly occurring patternsto a dictionary.When these patterns appear in the source output,they are encoded with a reference to the dictionary. If the patterns does not appear in the dictionary, then it can be encoded using some other, less efficient, method. In effect we are splitting the input into two classes, frequently occurring patterns and infrequently occurring patterns.

D. *LZ77 :*

In the LZ77 approach, the dictionary is simple a portion of the previously encoded sequence. The encoder examines the input sequence through a sliding window. The window consists of two parts, a search buffer that contains a portion of the recently encoded sequence, and a look-ahead buffer that contains the next portion of the sequence to be encoded [5]. The encoder then examines the symbols following the symbol at the pointer location to see if they match consecutive symbols in the look-ahead buffer. The number of consecutive symbols in the search buffer that match consecutive symbols in the look-ahead buffer, starting with the first symbol, is called the length of the match. The encoder searches the search buffer for the longest match. Once the longest match has been found, the encoder encode it with a triple<o,l,c> where o is offset, l is the length of the match, and c is the codeword corresponding to the symbol in the look-ahead buffer that follows the match.

E. *LZ78:*

LZ77 have the drawback of finite view of the past. LZ78 algorithm to solve this problem by dropping the reliance on the search buffer and keeping an explicit dictionary. This dictionary has to be built at both the encoder and decoder. The input are coded as a double<i,c> with I being an index corresponding to the dictionary entry that was the longest match to the input, and c being the code for the character in the input following the matched portion of the input.

F. *LZW :*

LZW encoding is an example of a category of algorithms called *dictionary*- based encoding [3] . The idea is to create a dictionary (a table) of strings used during the communication session. If both the sender and the receiver have a copy of the dictionary, then previously-encountered strings can be substituted by their index in the dictionary to reduce the amount of information transmitted. In this phase there are two concurrent events: building an indexed dictionary and compressing a string of symbols. The algorithm extracts the smallest substring that cannot be found in the dictionary from the remaining uncompressed string. It then stores a copy of this substring in the dictionary as a new entry and assigns it an index value. Compression occurs when the substring, except for the last character, is replaced with the index found in the dictionary. The process then inserts the index and the last character of the substring into the compressed string. Decompression is the inverse of the compression process. The process extracts the substrings from the compressed string and tries to replace the indexes with the corresponding entry in the dictionary, which is empty at first and built up gradually. The idea is that when an index is received, there is already an entry in the dictionary corresponding to that index.

G. *Arithmetic Encoding :*

Arithmetic coding yields better compression because it encodes a message as a whole new symbol instead of separable symbols .Most of the computations in arithmetic coding use floating-point arithmetic. However, most hardware can only support finite precision. While a new symbol is coded, the precision required to present the range grows**.** Context-Based Adaptive Binary Arithmetic Coding (CABAC) as a normative part of the new ITU-T/ISO/IEC standard [6]. By combining an adaptive binary arithmetic coding technique with context modeling, a high degree of adaptation and redundancy reduction is achieved. The CABAC framework also includes a low-complexity method for binary arithmetic coding and probability estimation that is well suited for efficient hardware and software implementations.

Example :

The message a1,a2,a3,a3,a4 is encoded using 3 decimal digits or 3/5 = 0.6 decimal digits per source symbol.

- The entropy of this message is:

$$H = -\sum_{k=0}^{3} P(r_k) log(P(r_k))$$

(3X0.2log10(0.2)+0.4log10(0.4))=0.578 digits/symbol

Table 3 : Example Source Symbol

Source Symbol	Probability	Initial Subinterval
a_1	0.2	[0.0, 0.2)
a_2	0.2	[0.2, 0.4)
a_3	0.4	[0.4, 0.8)
a_4	0.2	[0.8, 1.0)

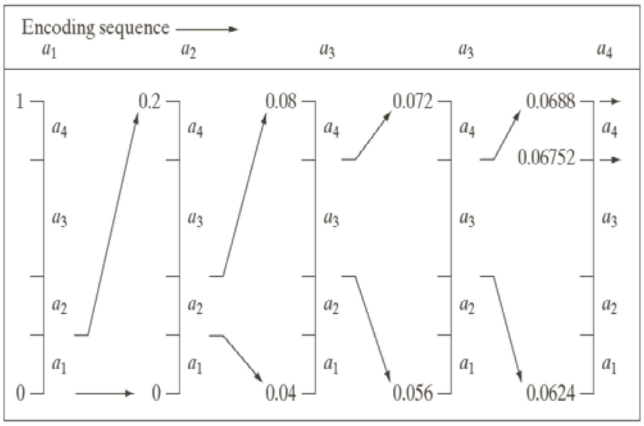

Figure 8:Arithmetic encoding

ENCODE

a1,a2,a3,a3,a4

[0.06752, 0.0688)

H. *BitPlane Encoding :*

It is used to process each bit plane individually[7].

a. Decompose an image into a series of binary images.

b. Compress each binary image (e.g., using run-length coding)

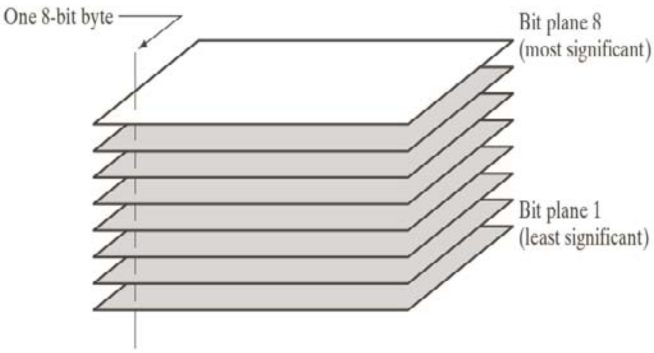

Figure 9 :Example bitpalne

V. LOSSY TECHNIQUES

A. *Difference Pulse Code Modulation(DPCM):*

DPCM system was developed at Bell Laboratories a few years after World War II.It is most popular as a speech-encoding system and is widely used in telephone communications.

B. *Delta Modulation:*

A very simple form of DPCM that has been widely used in a number of speech codig applications is the delta modulator (DM). The DM can be viewed as a DPCM system with a 1 bit (two-level) quantize.

C. *Discrete Fourier Transform(DFT):*

The procedure that we gave for obtaining the Fourier series and transform were based on the assumption that the signal we were examining could be represented as a continuous function of time.

D. *Discrete Cosine Transform :*

The discrete cosine transform (DCT) gets its name from the fact that the rows of the NXN transform matrix C are obtained as a function of Cosines[8]. The DCT is closely related to DFT. In terms of compression the DCT performs better than DFT. Set of basis functions for a 4x4 image (i.e., cosines of different frequencies).

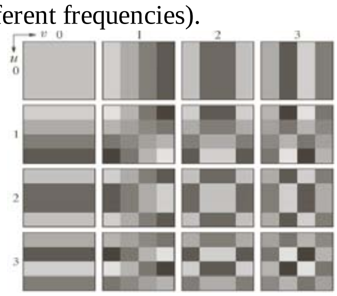

Figure 10 : 4X4 image(cosines of different frequencies)

E. *Karhunen-Loeve Transform :*

One can remove the correlation between a group of random variables using an orthogonal linear transform called the Karhunen-Loµeve transform (KLT), also known as the Hotelling transform.Let X be a random vector that we assume has zero-mean and autocorrelation matrix RX. The Karhunen-Loµeve transform is the matrix A that will make the components of Y = AX uncorrelated. It can be easily veri¯ed that such a transform matrix A can be constructed from the eigenvectors of RX, the autocorrelation matrix of X. Without loss of generality, the rows of A are ordered so that RY = diag(¸0; ¸1; : : : ; ¸N¡1) where ¸0 ¸ ¸1 ¸ ::: ¸ ¸N¡1 ¸ 0.The rows of the discrete karhunen Loeve transform, also known as the Hotelling transform, consist of the eigenvectors of the autocorrelation matrix.

a. Attributions

b. Kari Karhunen 1947, Michel Loève 1948

c. a.k.a Hotelling transform (Harold Hotelling, discrete formulation 1933)

d. a.k.a. Principle Component Analysis (PCA, estimate Rx from samples)

F. *Subband coding :*

The source output can be decomposed into its constituent parts using digital filters. Each of these constituent parts will be different bands of frequencies which make up the source.In subband compression approach where digital filters are used to separate the source output into different bands of frequencies[9]. Each part then can be encoded separately. A *filter* is system that isolates certain frequencies.

a. Low Pass Filters
b. High Pass Filters
c. Band Pass Filters

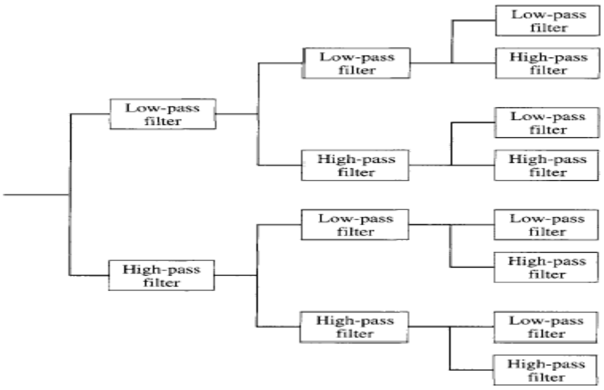

Figure 11 : An eight band filter bank

The most frequently used filter banks in subband coding consists of a cascade of stages where each stage consists of a low-pass filter and a high pass filter as shown in the figure.The subband coding algorithm has applications in –

a. Speech Coding
b. Audio Coding
c. Image Compression

Figure 12 : Decomposition of sinan image using the eight-tap Johnston filter

G. *Wavelets :*

All other functions were obtained by changing the size of the function or scaling and translating this single function [10].This function is called the mother wavelet. Wavelet-based coding such as JPEG 2000 on the other hand provides substantial improvement in picture quality at low bit rates because of overlapping basis functions and better energy compaction property of wavelet transforms. Because of the inherent multi-resolution nature, wavelet-based coders facilitate progressive transmission of images thereby allowing variable bit rates.

We also briefly introduce the technique that utilizes the statistical characteristics for image compression.

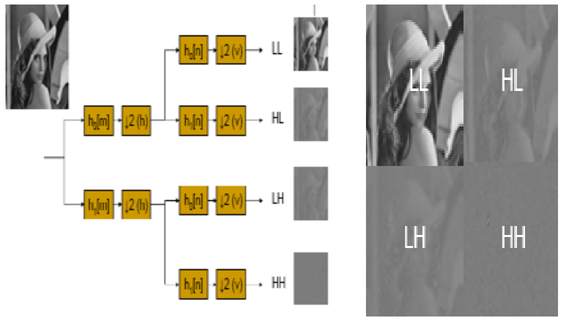

Figure 14 : Wavelet Decomposition

Application :

a. enhancement and denoising
b. compression and MR approximation
c. fingerprint representation with wavelet packets
d. bio-medical image classification
e. subdivision surfaces “Geri’s Game”, “A Bug’s Life”, “Toy Story 2”

H. *Vector Quantization :*

Vector quantization (VQ) is the generalization of scalar quantization to the case of a vector. The basic structure of a VQ is essentially the same as scalar quantization, and consists of an encoder and a decoder. The encoder determines a partitioning of the input vector space and to each partition assigns an index, known as a codeword. The set of all codewords is known as a codebook. The decoder maps the each index to a reproduction vector. Combined, the encoder and decoder map partitions of the space to a discrete set of vectors. Vector Quantization is a very important concept[11] in compression: In 1959 Shannon delineated fundamental limitations of compression systems through his Source coding theorem with a ¯delity criterion." While this is not a con- structive result, it does indicate, loosely speaking, that fully elective compression can only be achieved when input data samples are encoded in blocks of increasing length, i.e. in large vectors. Optimal vector quantizers are not known in closed form except in a few trivial cases. However, two optimality conditions are known for VQ (and for scalar quantization as a special case) which lead to a practical algorithm for the design of quantizers. These conditions were discovered independently by Lloyd [12 , 13] and Max [14] for scalar quantization, and were extended to VQ by Linde, Buzo, and Gray [15].

VI. CONCLUSION

This paper presents the different types of image compression techniques. These techniques are basically classified into two.Lossy compression techniques and lossless compression techniques.As the name indicates in lossless technique the image can be decoded without any loss of information.But in case of lossy compression it cause some form of information loss. These techniques are good for various applications.Huffman algorithm is best for variable length code.Arithmetic coding is better than Huffman.LZWmost commonly used for file compression.RLE is required for sequential data that contains repetitive information.Subband codingis best for speech & Audio coding.DPCMis commonly used for Audio compression.Wavelet-Bset algorithm is used for finger print compression.Fractal compression-Best for digital images.

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