IMAGE COMPRESSION USING DCT &DWT TECHNIQUE

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Abstract: Image compression is one of the most widespread techniques for applications that require transmission and storage of images in databases. In this paper we discuss about the image compression techniques, their need for compression, their characteristics, principles, and classes of compression and various algorithm of image compression. This paper discuss about available image compression algorithms based on Wavelet, JPEG/DCT, Vector Quantizer and Fractal compression. We also sum up the advantages and disadvantages of these algorithms for compression of grayscale images.

I. INTRODUCTION

Image compression is the technique of data compression which is implemented on digital images acquired from almost any source. In effect, the objective of compression algorithm is to reduce redundancy of the image data in order to be able to store or transmit data in an efficient form using minimum storage space and bandwidth. Uncompressed multimedia (graphics, audio and video) data requires considerable storage capacity and transmission bandwidth. Despite of high progress in mass-storage density, processor speeds, and digital communication system performance, demand for data storage capacity and data-transmission bandwidth continues to outstrip the capabilities of available network technologies. The high use of data intensive multimedia-based websites and web based applications have not only demanded the need for more efficient ways to encode signals and images but have made compression of such data essential for storage and communication

Why Compression is needed?

In the last decade, there has been a lot of technological transformation in the way we communicate. This transformation includes the ever present, ever growing internet, the explosive development in mobile communication and ever increasing importance of video communication. Data Compression is one of the technologies for each of the aspect of this multimedia revolution. Cellular phones would not be able to provide communication with increasing clarity without data compression. Data compression is art and science of representing information in compact form. Despite rapid progress in mass-storage density, processor speeds, and digital communication system performance, demand for data storage capacity and data-transmission bandwidth continues to outstrip the capabilities of available technologies. In a distributed environment large image files remain a major bottleneck within systems.

Four Stage model of Data Compression

Almost all data compression systems can be viewed as comprising four successive stages of data processing arranged as a processing pipeline (though some stages will often be combined with a neighboring stage, performed "off-line," or otherwise made rudimentary).

The four stages are

(A) Preliminary pre-processing steps.
(B) Organization by context.
(C) Probability estimation.
(D) Length-reducing code.

The ubiquitous compression pipeline (A-B-C-D) is what is of interest.

With (A) we mean various pre-processing steps that may be appropriate before the final compression engine.

Lossy compression often follows the same pattern as lossless, but with one or more quantization steps somewhere in (A). Sometimes clever designers may defer the loss until suggested by statistics detected in (C); an example of this would be modern zero tree image coding.

• (B) Organization by context often means data reordering, for which a simple but good example is JPEG's "Zigzag" ordering. The purpose of this step is to improve the estimates found by the next step.

• (C) A probability estimate (or its heuristic equivalent) is formed for each token to be encoded. Often the estimation formula will depend on context found by (B) with separate 'bins' of state variables maintained for each conditioned class.

(D) Finally, based on its estimated probability, each compressed file token is represented as bits in the compressed file. Ideally, a 12.5%-probable token should be encoded with three bits, but details become complicated

Coding Redundancy

If the gray levels of an image are coded in a way that uses more code symbols than absolutely necessary to represent each gray level, the resulting image is said to contain coding redundancy. It is almost always present when an image's gray levels are represented with a straight or natural binary code. Let us assume that a random variable r_K lying in the interval [0, 1] represents the gray levels of an image and that each r_K occurs with probability $P_r(r_K)$.

$P_r(r_K) = N_k / n$ where k = 0, 1, 2… L-1

L = No. of gray levels.

N_k =No. of times that gray appears in that image

N = Total no. of pixels in the image

If no. of bits used to represent each value of r_K is $l(r_K)$, the average no. of bits required to represent each pixel is

$L_{avg} = l(r_K)\, P_r(r_K)$

That is average length of code words assigned to the various gray levels is found by summing the product of the no. of bits used to represent each gray level and the probability that the gray level occurs. Thus the total no. of bits required to code an M×N image is $M \times N \times L_{avg}$.

Inter Pixel Redundancy

The Information of any given pixel can be reasonably predicted from the value of its neighbouring pixel. The information carried by an individual pixel is relatively small.

In order to reduce the inter pixel redundancies in an image, the 2-D pixel array normally used for viewing and interpretation must be transformed into a more efficient but usually 'non visual' format. For example, the differences between adjacent pixels can be used to represent an image. These types of transformations are referred as mappings. They are called reversible if the original image elements can be reconstructed from the transformed data set.

Different types of Transforms used for coding are:

1. DCT (Discrete Cosine Transform)
2. DWT (Discrete Wavelet Transform)

The Discrete Cosine Transform (DCT):

The discrete cosine transform (DCT) helps separate the image into parts (or spectral sub-bands) of differing importance (with respect to the image's visual quality). The DCT is similar to the discrete Fourier transform: it transforms a signal or image from the spatial domain to the frequency domain.

Discrete Wavelet Transform (DWT):

The discrete wavelet transform (DWT) refers to wavelet transforms for which the wavelets are discretely sampled. A transform which localizes a function both in space and scaling and has some desirable properties compared to the Fourier transform. The transform is based on a wavelet matrix, which can be computed more quickly than the analogous Fourier matrix. Most notably, the discrete wavelet transform is used for signal coding, where the properties of the transform are exploited to represent a discrete signal in a more redundant form, often as a preconditioning for data compression. The discrete wavelet transform has a huge number of applications in Science, Engineering, Mathematics and Computer Science. Wavelet compression is a form of data compression well suited for image compression (sometimes also video compression and audio compression). The goal is to store image data in as little space as possible in a file. A certain loss of quality is accepted (lossy compression). Using a wavelet transform, the wavelet compression methods are better at representing transients, such as percussion sounds in audio, or high-frequency components in two-dimensional images, for example an image of stars on a night sky. This means that the transient elements of a data. Signal can be represented by a smaller amount of information than would be the case if some other transform, such as the more widespread discrete cosine transform, had been used.

First a wavelet transform is applied. This produces as many coefficients as there are pixels in the image (i.e.: there is no compression yet since it is only a transform). These coefficients can then be compressed more easily because the information is statistically concentrated in just a few coefficients. This principle is called transform coding. After that, the coefficients are quantized and the quantized values are entropy encoded and/or run length encoded.

ENTROPY CODING

Wavelets and threshold help process the signal but up until this point, no compression has yet occurred. One method to compress the data is Huffman entropy coding. With this method, and integer sequence, q, is changed into a shorter sequence, e, with the numbers in e being 8 bit integers. An entropy-coding table makes the conversion. Strings of zeros are coded by the numbers I through 100, 105, and 106, while the non-zero integers in q are coded by 101 through 104 and 107 through 254. In Huffman entropy coding, the idea is to use two or three numbers for coding, with the first being a signal that a large number or long zero sequence is coming. Entropy coding is designed so that the numbers that are expected to appear the most often in q need the least amount of space in e.

Cosine Transform

A discrete cosine transform (DCT) expresses a finite sequence of data points in terms of a sum of cosine functions oscillating at different frequencies. DCTs are important to numerous applications in science and engineering,from lossy compression of audio (e.g. MP3) and images (e.g. JPEG) (where small high-frequency components can be discarded), to spectral methods for the numerical solution of partial differential equations. The use of cosine rather than sine functions is critical for compression, since it turns out (as described below) that fewer cosine functions are needed to approximate a typical signal, whereas for differential equations the cosines express a particular choice of boundary conditions.

In particular, a DCT is a Fourier-related transform similar to the discrete Fourier transform (DFT), but using only real numbers. The DCTs are generally related to Fourier Series coefficients of a periodically and symmetrically extended sequence whereas DFTs are related to Fourier Series coefficients of a periodically extended sequence. DCTs are equivalent to DFTs of roughly twice the length, operating on real data with even symmetry (since the Fourier transform of a real and even function is real and even), whereas in some variants the input and/or output data are shifted by half a sample. There are eight standard DCT variants, of which four are common.

The most common variant of discrete cosine transform is the type-II DCT, which is often called simply "the DCT".[1][2] Its inverse, the type-III DCT, is correspondingly often called simply "the inverse DCT" or "the IDCT". Two related transforms are the discrete sine transform (DST), which is equivalent to a DFT of real and odd functions, and the modified discrete cosine transform (MDCT), which is based on a DCT of overlapping data. Multidimensional DCTs (MD DCTs) are developed to extend the concept of DCT on MD Signals. There are several algorithms to compute MD DCT. A new variety of fast algorithms are also developed to reduce the computational complexity of implementing DCT.

II. RESULTS AND DISCUSSION

5.1 RESULTS

The image on the left is the original image and the image on the right is the compressed one

(The point is that the image on the left you are right now viewing is compressed using Haar wavelet method and the loss of quality is not visible. Of course, image compression using Haar Wavelet is one of the simplest ways.)

Original image

compressed image

III. CONCLUSION

Haar wavelet transform for image compression is simple and crudest algorithm.as compared to other algorithms it is more effective.The quality of compressed image is also maintained. Transform coding is a widely used method of compressing image information. In a transform-based compression system two-dimensional (2-D) images are transformed from the spatial domain to the frequency domain. An effective transform will concentrate useful information into a few of the low-frequency transform coefficients.

The discrete wavelet transform (DWT) is a mathematical tool that has aroused great interest in the field of image processing due to its nice features. Some of these characteristics are: 1) it allows image multi resolution representation in a natural way because more wavelet sub bands are used to progressively enlarge the low frequency subbands; 2) It supports wavelet coefficients analysis in both space and frequency domains, thus the interpretation of the coefficients is not constrained to its frequency behavior and we can perform better analysis for image vision and segmentation; and 3) For natural images, the DWT achieves high compactness of energy in the lower frequency subbands, which is extremely useful in applications such as image compression. The introduction of the DWT made it possible to improve some specific applications of image processing by replacing the existing tools with this new mathematical transform. The JPEG 2000 standard [1] proposes a wavelet transform stage since it offers better rate/distortion (R/D) performance than the traditional discrete cosine transform (DCT). Unfortunately, despite the benefits that the wavelet transform entails, some other problems International Journal of Engineering Research & Technology (IJERT) Vol. 1 Issue 5, July - 2012 ISSN: 2278-0181 www.ijert.org 1 are introduced. Wavelet-based image processing systems are typically implemented by memoryintensive algorithms with higher execution time than other transforms. In the usual DWT implementation [2], the image decomposition is computed by means of a convolution filtering process and so its complexity rises as the filter length increases. Moreover, in the regular DWT computation, the image is transformed at every decomposition level first row by row and then column by column, and hence it must be kept entirely in memory. The lifting scheme [3,4] is probably the best-known algorithm to calculate the wavelet transform in a more efficient way. Since it uses less filter coefficients than the equivalent convolution filter, it provides a faster implementation of the DWT. Other fast wavelet transform algorithms have been proposed in order to reduce both memory requirements and complexity, like line-based [5] and block-based [6] wavelet transform approaches that performs wavelet transformation at image line or block level.

Filters Used to Calculate the DWT and IDWT

For an orthogonal wavelet, in the multiresolution framework (in Using Wavelet Packets), we start with the scaling

function and the wavelet function . One of the fundamental relations is the twin-scale relation (dilation equation or refinement equation):

$$\frac{1}{2}\,\emptyset\left({}^{x}/_{2}\right) = \sum_{n=0}^{N} \mathrm{W_n}\ \emptyset(\mathrm{x}-\mathrm{n})$$

All the filters used in DWT and IDWT are intimately related to the sequence

W_n (x) $\epsilon\, N$

Clearly if $\emptyset$ is compactly supported, the sequence (w_n) is finite and can be viewed as a filter. The filter W,which is called the scaling filter (nonnormalized), is

- Finite Impulse Response (FIR)
- Of length 2N
- Of sum 1
- Of norm

$$\frac{1}{\sqrt{2}}.$$

- A low-pass filter

For example, for the `db3` scaling filter,

- `load db3`
- `db3`

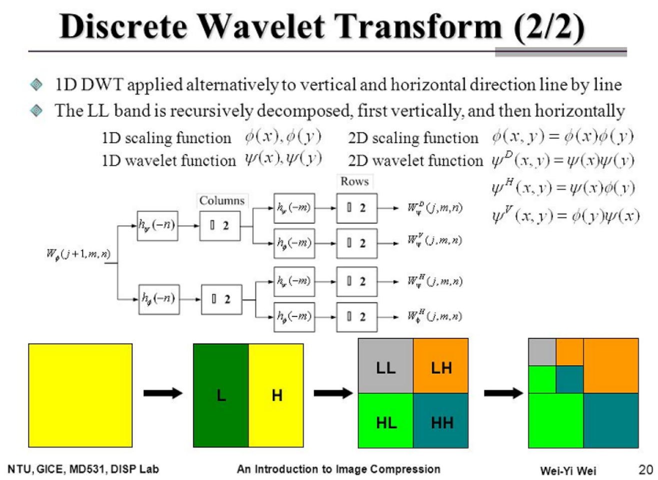
- db3 =
- 0.2352 0.5706 0.3252 -0.0955 -0.0604 0.0249
-
- sum(db3)
- ans =
- 1.0000
-
- norm(db3)
- ans =
- 0.7071

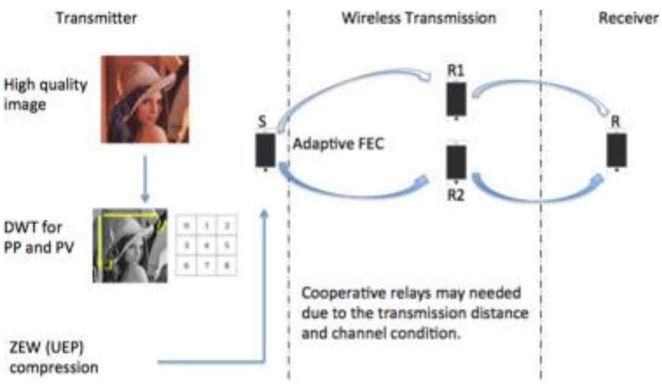
From filter W, we define four FIR filters, of length 2N and of norm 1, organized as follows.

Filters	Low-Pass	High-Pass
Decomposition	Lo_D	Hi_D
Reconstruction	Lo_R	Hi_R

The four filters are computed using the following scheme. where qmf is such that Hi_R and Lo_R are quadrature mirror filters (i.e., Hi_R(k) = (-1) k Lo_R(2N + 1 - k)) for k = 1, 2, ..., 2N.
Note that wrev flips the filter coefficients. So Hi_D and Lo_D are also quadrature mirror filters. The computation of these filters is performed using orthfilt. Next, we illustrate these properties with the db6 wavelet. The plots associated with the following commands are shown in Figure 6-8.

- % Load scaling filter.
- load db6; w = db6;
- subplot(421); stem(w); title('Original scaling filter');
-
- % Compute the four filters.
- [Lo_D,Hi_D,Lo_R,Hi_R] = orthfilt(w);
- subplot(423); stem(Lo_D);
- title('Decomposition low-pass filter Lo{_}D');
- subplot(424); stem(Hi_D);
- title('Decomposition high-pass filter Hi{_}D');
- subplot(425); stem(Lo_R);
- title('Reconstruction low-pass filter Lo{_}R');
- subplot(426); stem(Hi_R);
- title('Reconstruction high-pass filter Hi{_}R');
- % High and low frequency illustration.
- n = length(Hi_D);
- freqfft = (0:n-1)/n;
- nn = 1:n;
- N = 10*n;
- for k=1:N
- lambda(k) = (k-1)/N;
- XLo_D(k) = exp(-2*pi*j*lambda(k)*(nn-1))*Lo_D';
- XHi_D(k) = exp(-2*pi*j*lambda(k)*(nn-1))*Hi_D';
- end
- fftld = fft(Lo_D);
- ffthd = fft(Hi_D);
- subplot(427); plot(lambda,abs(XLo_D),freqfft,abs(fftld),'o');
- title('Transfer modulus: lowpass (Lo{_}D or Lo{_}R')
- subplot(428); plot(lambda,abs(XHi_D),freqfft,abs(ffthd),'o');
- title('Transfer modulus: highpass (Hi{_}D or Hi{_}R')





These approaches increase flexibility when applying wavelet transform and significantly reduce the memory requirements. In this scheme, the 2D-DWT is performed in only one pass, avoiding multiple-layer transpose decomposition operations.

One of the most interesting advantages of this method is that the computation of each wavelet subband is completely independent. An HVS is more sensitive to energy with low spatial frequency than with high spatial frequency. In numerical analysis and functional analysis, a discrete wavelet transform (DWT) is any wavelet transform for which the wavelets are discretely sampled. As with other wavelet transforms, a key advantage it has over Fourier transform is temporal resolution: it captures both frequency and location information.

REFERENCES

[1] Ahmed, N., Natarajan, T., Rao, K. R., "Discrete Cosine Transform", IEEE Trans. Computers, vol. C -23, Jan. 1974, pp. 90-93.
[2] Buccigrossi, R., Simoncelli, E. P., "EPWIC: Embedded Predictive Wavelet Image Coder".
[3] Chan, Y. T., "Wavelet Basics", Kluwer Academic Publishers, Norwell, MA, 1995.
[4] Gersho, A., Gray, R.M., "VectorQuantization and Signal Compression", Kluwer Academic Publishers, 1991.
[5] Malavar, H. S., "Signal Processing with Lapped Transforms", Norwood, MA, Artech House, 1992.
[6] Mallat, S.G., "A Theory for Multiresolution Signal Decomposition: The Wavelet Representation", IEEE Trans. PAMI, vol. 11, no. 7, July 1989, pp. 674-693.
[7] [Onlineat] ftp.uu.net:/graphics/jpeg/jpegsrc.v6a.tar.gz
[8] J.M. Shapiro, "Embedded image coding using zero tree of wavelet coefficients", IEEE Trans. on Signal Processing, vol. 41, 3445-3462, 1993.
[9] A. Said, W.A. Pearlman, "A new, fast, and efficient image codec based on set partitioning in hierarchical trees", IEEE Trans. on Circuits and Systems for Video Technology, vol. 6, 243-250, 1996.[10]
[10] Rao, K. R., Yip, P., "Discrete Cosine Transforms - Algorithms, Advantages, Applications", Academic Press, 1990.
[11] N.M. Nasrabadi, R.A. King, "Image coding using vector quantization: a review", IEEE Trans. On Communications,vol. 36, 957-571, 1988.
[12] Y. Linde, A. Buzo, R. M Gray, "An algorithm for vector quantizer design", IEEE Trans. on Communications, vol. 36, 84-95, 1980.
[13] Vetterli, M., Kovacevic, J. Wavelets, "Subband Coding", Englewood Cliffs,NJ, Prentice Hall, 1995, [Online] Available :http://cm.bell-labs.com/who/jelena/Book/home.html
[14] Wallace, G. K. "The JPEG Still Picture Compression Standard", Comm. ACM, vol. 34, no. 4, April 1991, pp. 30-44.
[15] M.F. Barnsley, L.P. Hurd, "Fractal Image Compression", AK Peters, Ltd. Wellesley, Massachusetts, 1993.
[16] Y.W. Chen, "Vector Quantization by principal component analysis", M.S. Thesis, National Tsing Hua University, June, 1998.
[17] H.S.Chu, "A very fast fractal compression algorithm", M.S. Thesis, National Tsing Hua University, June, 1997.
[18] Y. Fisher, "Fractal Image Compression", SIGGRAPH Course Notes, 1992.
[19] Y. Fisher, Editor, "Fractal Image Compression: Theory and Applications", Springer-Verlag, 1994.
[20] A.E. Jacquin, "Image coding based on a fractal theory of iterated contractive image transformations". IEEE Trans. on Image Processing, vol. 1, pp.18-30, 1992.

