Comparison of DCT and Wavelet based Image Compression Techniques

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***Abstract*- Image compression defines as reducing the amount of data required to represent digital image. Transform coding, on the other hand, first transforms the image from its spatial domain representation to a different type of representation using some well-known transform and then codes the transformed values (coefficients). Image compression is urgently needed for very large medical or satellite images, both for reducing the storage requirements and for improving transmission efficiency. Fourier based transforms (e.g. DCT and DFT) are efficient in exploiting the low frequency nature of an image. The high frequency coefficients are coarsely quantized, and hence the reconstructed quality of the image at the edges will have poor quality. On the other hand, wavelets are efficient in representing nonstationary signals because of the adaptive time-frequency window. So the Discrete Wavelet Transform (DWT) is applied to an image and the energy compaction performance of both Discrete Cosine Transform (DCT) and DWT is compared. It is observed that both transforms provide comparable energy compaction performance.**

***Keywords*-Image Compression, DCT, DWT, Energy Compaction**

I. INTRODUCTION

Image compression defines as reducing the amount of data required to represent digital image. However, image information contains a large of information, which brings a lot of difficulties for storage, processing and transmission. Thus image compression is very importance and necessity. There are two way to image compression (1) lossless compression and (2) lossy compression. Lossy image compression algorithms are applicable whenever the exact reconstruction of an image is not expected. These algorithms are usually based on transform methods. In recent years, a considerable effort have been made to design image compression method in which the main goal is to obtain good quality of decompressed images even at very low bit rates. Due to the great use of digital information, image compression becomes imperative in different areas such as image storage, transmission and processing. At these areas the representation of the information needs to be efficient. The goal of image coding is to reduce the bit rate for signal transmission or storage while maintaining an acceptable image quality for different purposes.

Fourier-based transforms (e.g. DCT and DFT) are efficient in exploiting the low frequency nature of an image. However, a major disadvantage of these transforms is that the basis functions are very long. If a transform coefficient is quantized, the effect is visible throughout the image. This does not create much problem for the low frequency coefficients that are coded with higher precision [2]. However, the high frequency coefficients are coarsely quantized, and hence the reconstructed quality of the image at the edges will have poor quality. A sharp edge in an image is represented by many transform coefficients (that cancel each other outside the edge area) that must be preserved intact and in the same relationship to one another to achieve good fidelity of the reconstructed image. Second, an image is generally a nonstationary signal where different parts of an image have different statistical properties. If the transform is calculated over the entire image, this nonstationarity will be lost, resulting in a poor compression performance.

JPEG is the first international still image compression standard for continuous-tone image. The JPEG baseline system is based on DCT. The JPEG sequential DCT-based mode has been very successful in coding images of high and medium bit rates. For low bits rates, the quantization step size needs to be increased in order to get more compression ratio. This leads to a high degree of artificial blocking in the reconstructed image. This is a standard problem for most block-based transform techniques [4]. The DWT has recently emerged as a powerful technique for image compression because of the multi-resolution property. The advantages of using DWT over the DCT lies in the fact that the DWT projects high-detail image components onto shorter basis functions with higher resolution, while lower detail components are projected onto larger basis functions, which correspond to narrower sub-bands, establishing a trade-off between time and frequency resolution.

II. DISCRETE COSINE TRANSFORM

The Discrete Cosine Transform (DCT) algorithm is well known and commonly used for image compression. DCT converts the pixels in an image, into sets of spatial frequencies. It has been chosen because it is the best approximation of the Karhunen_loeve transform that provides the best compression ratio [5]. The DCT work by separating images into the parts of different frequencies. During a step called Quantization, where parts of compression actually occur, the less important frequencies are discarded, hence the use of the lossy. Then the most important frequencies that remain are used retrieve the image in decomposition process. As a result, reconstructed image is distorted. Compared to other input dependent transforms, DCT has many advantages [6]:

1. It has been implemented in single integrated circuit.

2. It has the ability to pack most information in fewest coefficients.
3. It minimizes the block like appearance called blocking artifact that results when boundaries between sub-images become visible.

The DCT can be extended to the transformation of 2D signals or images. This can be achieved in two steps: by computing the 1D DCT of each of the individual rows of the two-dimensional image and then computing the 1D DCT of each column of the image. If represents a 2D image of size x(n_1 , n_2) N × N , then the 2D DCT of an image is given by:

$$Y[j,k] = C[j]C[k]\sum_{m=0}^{N-1}\sum_{n=0}^{N-1} x[m,n]\cos\left(\frac{(2m+1)j\pi}{2N}\right)\cos\left(\frac{(2n+1)k\pi}{2N}\right)$$

……eq.2.1

Where j, k, m, n = 0, 1, 2..., N −1 and

$$C[j] \;\; and \;\; C[k] = \begin{bmatrix} \sqrt{\frac{1}{N}} & \text{for j,k} = 0 \\ \sqrt{\frac{1}{N}} & \text{for j,k} = 1,2,\dots,\text{N-1} \end{bmatrix}$$

Similarly the 2D IDCT can be defined as

$$x[m,n] = \sum_{j=0}^{N-1}\sum_{k=0}^{N-1} C[j]C[k]Y[j,k]\cos\left(\frac{(2m+1)j\pi}{2N}\right)\cos\left(\frac{(2n+1)k\pi}{2N}\right)$$

…eq. 2.2

The DCT is a real valued transform and is closely related to the DFT. In particular, a N × N DCT of x(n_1,n_2) can be expressed in terms of DFT of its even-symmetric extension, which leads to a fast computational algorithm. Because of the even-symmetric extension process, no artificial discontinuities are introduced at the block boundaries. Additionally the computation of the DCT requires only real arithmetic. Because of the above properties the DCT is popular and widely used for data compression operation.

In the DCT compression algorithm

- The input image is divided into 8-by-8 or 16-by-16 blocks
- The two-dimensional DCT is computed for each block.
- The DCT coefficients are then quantized, coded, and transmitted.
- The receiver (or file reader) decodes the quantized DCT coefficients, computes the inverse two-dimensional DCT (IDCT) of each block.
- Puts the blocks back together into a single image.

III. DISCRETE WAVELET TRANSFORM

Another method of decomposing signals that has gained a great deal of popularity in recent years is the use of wavelets. Decomposing a signal in terms of its frequency content using sinusoids results in a very fine resolution in the frequency domain, down to the individual frequencies. However, a sinusoid theoretically lasts forever; therefore, individual frequency components give no temporal resolution. In other words, the time resolution of the Fourier series representation is not very good. In a wavelet representation, we represent our signal in terms of functions that are localized both in time and frequency [3]. Recently, wavelets have become very popular in image processing, specifically in coding applications for several reasons [4]. First, wavelets are efficient in representing nonstationary signals because of the adaptive time frequency window. Second, they have high decorrelation and energy compaction efficiency. Third, blocking artifacts and mosquito noise are reduced in a wavelet based image coder. Finally, the wavelet basis functions match the human visual system characteristics, resulting in a superior image representation. Compared with DCT, DWT uses more optimal set of functions to represent sharp edges than cosines. Wavelets are finite in extent as opposed to sinusoidal functions.

Here, the whole image is first transformed by wavelet transform, then the actual encoding is applied on the complete wavelet coefficients, as shown in the Figure 1.Although these methods effectively overcome the blocking artifact problem, it is not possible to encode the image during the transform stage.

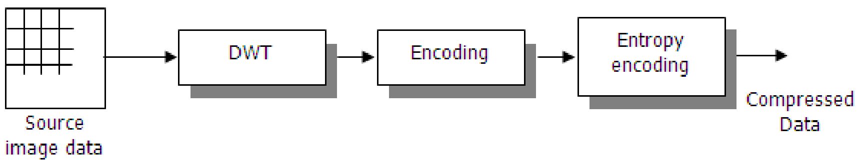


Figure 1. The typical DWT based Image coding

The fundamental idea behind wavelets is to analyze the signal at different scales or resolutions, which is called multi resolution. Wavelets are a class of functions used to localize a given signal in both space and scaling domains. A family of wavelets can be constructed from a mother wavelet. Compared to Windowed Fourier analysis, a mother wavelet is stretched or compressed to change the size of the window. In this way, big wavelets give an approximate image of the signal, while smaller and smaller wavelets zoom in on details. Therefore, wavelets automatically adapt to both the high-frequency and the low-frequency components of a signal by different sizes of windows. Any small change in the wavelet representation produces a correspondingly small change in the original signal, which means local mistakes will not influence the entire transform. The wavelet transform is suited for non-stationary signals, such as very brief signals and signals with interesting components at different scales.

A. Why wavelet based compression?

As discussed earlier, for image compression, loss of some information is acceptable. Among all of the above lossy compression methods, vector quantization requires many computational resources for large vectors; fractal compression is time consuming for coding; predictive coding has inferior compression ratio and worse reconstructed image quality than those of transform based coding. So, transform based compression methods are generally best for image compression.

For transform based compression, JPEG compression schemes based on DCT (Discrete Cosine Transform) have some advantages such as simplicity, satisfactory performance, and availability of special purpose hardware for implementation. However, because the input image is blocked, correlation across the block boundaries cannot be eliminated. This results in noticeable and annoying “blocking artifacts"' particularly at low bit rates as shown in figure 2. wavelet-based schemes achieve better performance than other coding schemes like the one based on DCT. Since there is no need to block the input image and its basis functions have variable length, wavelet based coding schemes can avoid blocking artifacts. Wavelet based coding also facilitates progressive transmission of images.

IV. COMPARISON OF DCT AND WAVELETS

The DCT and DWT are the two most important transforms in image coding. Although the block DCT and wavelet coding may look different, there are some similarities. Like wavelets provide both spatial and frequency (or scale) information, we demonstrate that DCT also provides similar information [2]. The main difference between the DCT and DWT coefficients lies in the highpass bands. The highpass DCT bands provide higher frequency resolution, but lower spatial resolution. As a result, there are more frequency bands, but it is difficult to recognize the spatial information. On the other hand, the wavelet subbands provide higher spatial resolution, and lower frequency resolution. As a result, the number of subbands is few, but the spatial resolution is superior.

V. EXPERIMENTAL RESULTS

1. DCT Results

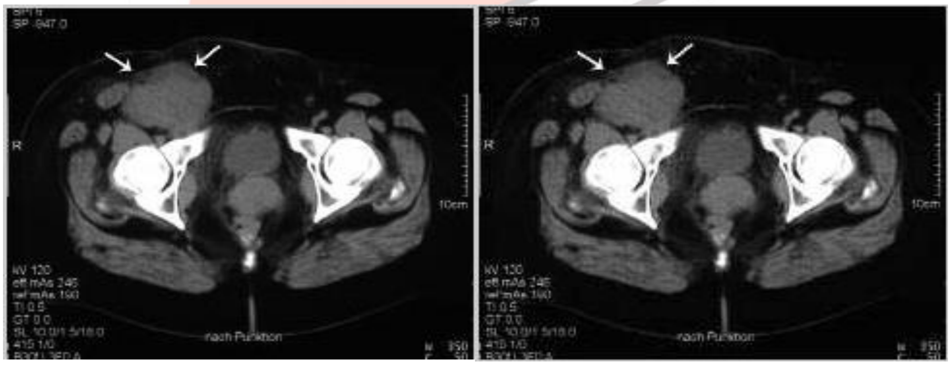
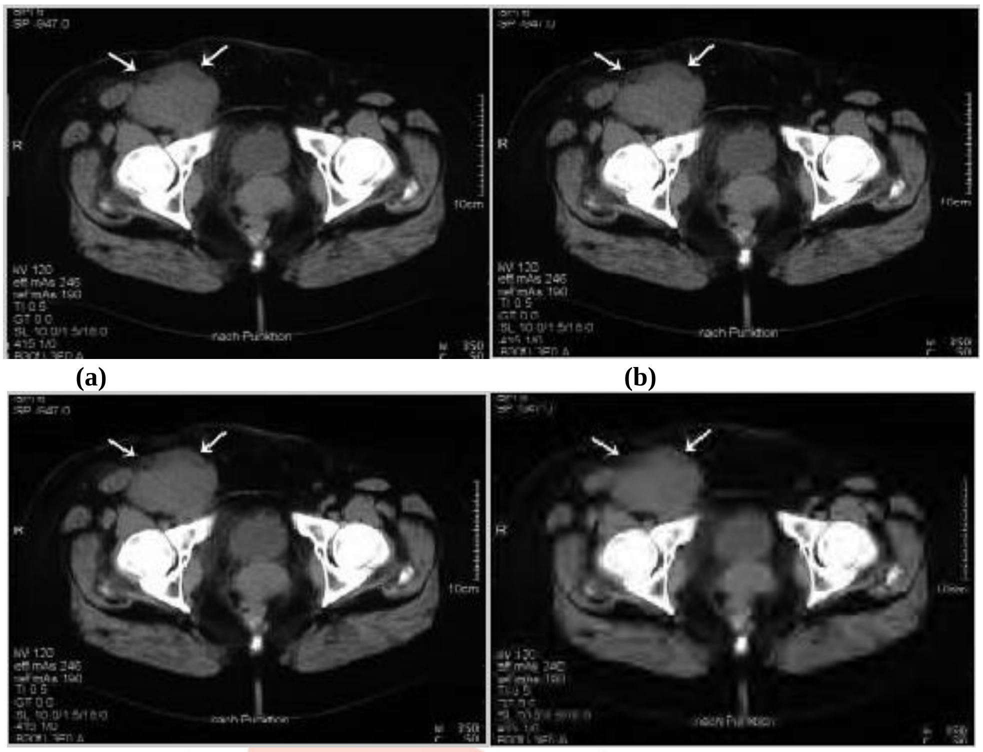


Fig 5.1: (a) Original CT Scan Image (b) Compressed Image

Table 5.1: performance evaluation parameters:

Compression Ratio	42.15
PSNR	31.6760
MSE	43.5157

2. DWT results:



(a) (b) (c) (d)

Fig 5.2: (a) Original CT Scan Image (b) Compressed image with decomposition level 1 (c) Compressed image with decomposition level 2 (d) Compressed image with decomposition level 3

TABLE 5.1: CR, MSE, PSNR values of wavelet transform for decomposition level 1

WAVELET FILTER	COMPRESSION RATIO (CR)	MSE	PSNR
Daubechies (db1)	51.39	0.49	51.15
db4	51.13	0.61	50.26
db15	51.13	0.85	48.81
Coiflets (coif1)	51.13	0.601	50.33
coif5	51.13	0.68	49.76
Discrete meyer (dmey)	51.13	0.75	49.35
Symlets (sym2)	51.14	0.60	50.28
Sym8	51.13	0.65	49.95
Sym25	51.13	0.75	49.36
Biothogonal (bior 1.1)	51.39	0.49	51.15
Bior 2.2	51.14	0.58	50.48
Bior 6.8	51.13	0.62	50.16
Reverse (rbior 1 .1)	51.39	0.49	51.15

TABLE 5.2: CR, MSE and PSNR values of wavelet transform for decomposition level 2

WAVELET FILTER	COMPRESSION RATIO (CR)	MSE	PSNR
Daubechies (db1)	84.50	14.41	36.54
db4	83.99	13.32	36.88
db15	80.00	12.06	37.31
Coiflets (coif1)	83.82	13.31	36.88
coif5	80.00	10.30	38.00
Discrete meyer(dmey)	72.26	6.22	40.18
Symlets (sym2)	83.99	13.32	36.88
Sym8	81.96	11.56	37.50
Sym25	77.36	9.32	38.43
Biothogonal (bior 1.1)	83.50	14.41	36.54
Bior 2.2	83.82	11.84	37.39
Bior 6.8	81.81	10.89	37.75
Reverse (rbior 1 .1)	84.55	14.41	36.54

Summary of Research

- Fourier based transforms (e.g. DCT) are efficient in exploiting the low frequency nature of an image. The high frequency coefficients are coarsely quantized, and hence the reconstructed quality of the image at the edges will have poor quality.
- High MSE is measured with lower Compression Ratio.
- DCT-based image coders perform very well at moderate bit rates, higher compression ratios, and image quality degrades because of the artifacts resulting from the block-based DCT scheme.
- The effects of different wavelet functions, filter orders, number of decompositions, image contents, and compression ratios are examined. The final choice of optimal wavelet in image compression application depends on image quality and computational complexity.
- A suitable number of decompositions should be determined by means of image quality and less computational operation. choice of optimal wavelet depends on the method, which is used for picture quality evaluation. We used objective and subjective picture quality measures.
- Increasing the decomposition level increasing the MSE and Compression Ratio and lower the PSNR.
- Higher order filter shows the low compression ratio, low MSE with high PSNR
- Wavelet based compression scheme can avoid blocking artifacts that is noticeable in DCT technique, but it has limitations in capturing geometric curves.so need new technique for image compression.

VI. CONCLUSION

We demonstrated an analysis and comparison of image compression using DCT and DWT. Since information loss implies some tradeoff between error and bitrate, the measure of distortion (square error) is calculated. It is observed that different bands provide lowpass information, and horizontal, vertical and diagonal edges. It is also observed that both transforms provide comparable energy compaction performance. This work further can extended to Embedded zerotree wavelet (EZW) coding and Set Partitioning in Hierarchical Trees (SPIHT).

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