Evaluation of factors affecting the selection of mother wavelet to improve image compression of Artificial & Natural Images

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Abstract
Image compression is essential for applications such as transmission and storage of databases. Artificial and Natural images are inherently voluminous. Therefore, efficient data compression techniques are essential for their archival and transmission of data. The standards use Discrete Cosine Transform (DCT) to reduce the spatial redundancy present in the images or video frames. The DCT has the main drawback of blocking artifacts. In recent time, wavelet transform (WT) has emerged as a popular technique for image compression applications. The wavelet transform has high de-correlation and energy compaction efficiency. The blocking artifacts is absent in a wavelet-based coder due to their overlapping basis functions. The wavelet transform can be composed of any function that satisfies requirements of multi-resolution analysis. In wavelet-based image compression, the compression performance depends on the choice of wavelets. A review of the wavelet family used for compression is given in the literature. We have examined and compared various wavelet families such as Haar, Daubechies, Symlets, Coiflets, Biorthogonal and Reverse Biorthogonal using artificial and natural images. The results are measured in terms of PSNR considering as subjective quality measures.

Keywords
Wavelet Transform, Artificial Image, Natural Image, Peak Signal to Noise Ratio, Haar, Daubenchies, symlet, Coieflet, Biortogonal, Reverse biorthogonal.

I. Introduction

In the modern digital age, computer storage technology continues at a rapid pace, a means for reducing the storage requirements of an image is still needed in most situations. In images, the neighboring pixels are correlated and therefore contain redundant information. Before compressing an image, we first find out the pixels which are correlated. The fundamental components of compression is redundancy i.e. duplication. The redundancy can be removed to achieve compression of the image data. The two types of redundancy can be identified in still images: Spatial Redundancy i.e. correlation between neighboring pixel values and Spectral Redundancy i.e. correlation between different color planes or spectral bands. Most of the current methods of image compression are transform based methods such as DCT or DWT. The transform based compression has become the standard paradigm in image compression such as JPEG [03] [04] and video compression such as MPEG-2 [05] and H.263 [06], where the Discrete Cosine Transform (DCT) is used because of its de-correlation and energy compaction properties [07]. In the case of DCT based image compression, image is divided into blocks of uniform size. But, the block-based segmentation of source image has a fundamental limitation of the DCT-based compression system [08] [09]. The degradation is known as the "blocking effect" and depends on block size.

Wavelets provide good compression ratios [24] [25], especially for high resolution images. Wavelets perform much better than competing technologies like JPEG [03], both in terms of signal-to-noise ratio and visual quality. Unlike JPEG, it shows no blocking effect but allow for a graceful degradation of the whole image quality, while preserving the important details of the image. Recently, Discrete Wavelet Transform (DWT) has emerged as a popular technique for image compression applications with excellent compression performance [02] [10]. In DWT the image is transformed and compressed as a single data object rather than block by block. This technique allows a uniform distribution of compression error across entire image. Discrete wavelet transform have higher decorreltaion and frequency, gives it potentiality for good representation of image with fewer coefficients [11]. The basic measure of the performance of a compression algorithm is the compression ratio, which is defined by the ratio between original data size and compressed data size. Higher compression ratios will produce lower image quality and the vice versa is also true.
In DWT, there exist very wide choice of wavelet functions. The choice of wavelet depends on contents and resolution of image. Here we are defining two images viz. Artificial and Natural Image Fig 1(a & b). Artificial image stand for image on which enhancement techniques have been applied e.g Wallpaper whereas Natural image is an image on which no enhancement technique has been applied e.g image captured by camera directly.

II. Wavelet Transform Based Image Compression:

Fig.1. a. Tabboo (Artificial Image)

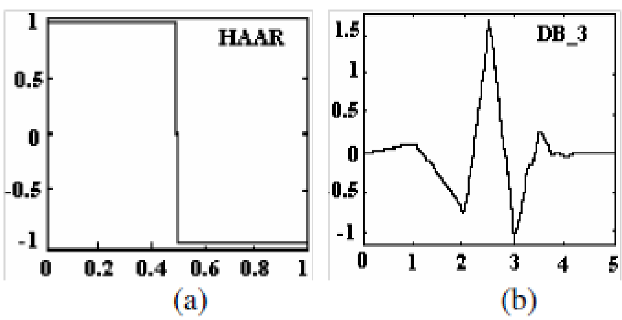
Fig.1. b. Field (Natural Image)

With the growth of technology and the entrance into the digital age, the world has found itself in a situation where it needs to deal with vast amount of information. Dealing with such enormous amount of information can often present difficulties. Digital information must be stored and retrieved in an efficient manner, in order for it to be put to practical uses. Compression is one way to deal with this problem. The basic goal of the image compression is to find such a representation for an image that only a minimal number of bits are used. This both allows one to store more image data on a limited storage space as well as makes it possible to transfer images faster over a channel with limited bandwidth.

A. Wavelet Transform:

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 also suited for non-stationary signals, such as very brief signals and signals with interesting components at different scales. [12].

Wavelet transform represents an image as a sum of wavelet functions with different locations and scales [02]. Any decomposition of an image into wavelets involves a pair of waveforms [13] [22], one to represent the high frequencies corresponding to the detailed parts of an image (wavelet function) and one for the low frequencies or smooth parts of an image (scaling function). Each wavelet contains the same number of cycles, such that, as the frequency reduces, the wavelet gets longer. High frequencies are transformed with short functions (low scale). Low frequencies are transformed with long functions (high scale). During computation, the analyzing wavelet is shifted over the full domain of the analyzed function. Thus the result of Wavelet Transform is a set of wavelet coefficients, which measure the contribution of the wavelets at these locations and scales. The wavelet based compression is more robust under transmission and decoding errors. As well as wavelets can provides high compression ratio with no blocking artifacts. It can also provide an efficient decomposition of signals prior to compression. These factors provide upper hand to wavelets for compression of image and video data in comparison to other compression techniques.



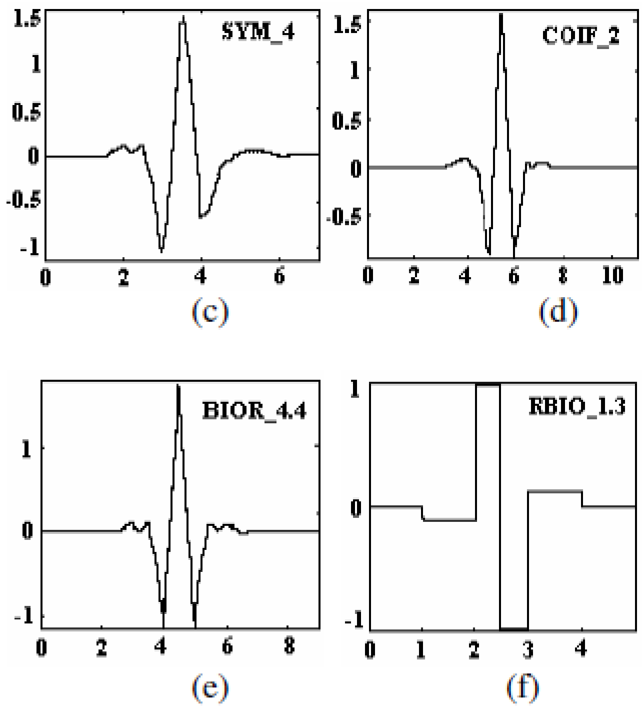


Figure-2: Wavelet families (a) Haar (b) DB_3 (c) SYM_4 (d) COIF_2 (e) BIOR_4.4 (f) RBIO_1.3

Choice of Wavelets for Image Compression

In wavelet-based image compression the choice of wavelets is crucial and determines the compression performance. A large choice of wavelet families exists depending on the choice of wavelet function. The choice of wavelet functions depends on the content and resolution of image. So, the “best" wavelet choice is dependent on the specific image to be compressed. To determine optimal wavelet, we compare the compression performance of various wavelets on to test images set.

In this paper, we have considered two test images and the six wavelets namely: Daubechies, Symlets, Coiflets, Biorthogonal, R. Biorthogonal and Dmey [19] [20]. Fig. -2 illustrates the families of wavelet used in our experiments. The waveforms shown can be used to represent detailed parts of the image. A brief introduction of these wavelets is as follows: Haar wavelet is one of the oldest and simplest wavelet. Therefore, any discussion of wavelets starts with the Haar wavelet. Haar wavelet is discontinuous, and resembles a step function. Daubechies, one of the brightest stars in the world of wavelet research, invented what are called compactly supported orthonormal wavelets with six coefficients and biorthogonality. The names of the Daubechies family wavelets are written dbN, where N is the order, and db the "surname" of the wavelet. The Daubechies, bior, rbior and Coiflets are compactly supported orthogonal wavelets [19]. Coiflet wavelet function has 2N moments equal to 0 and the scaling function has 2N-1 moments equal to 0. Biorthogonal wavelet exhibits the property of linear phase, which is needed for signal and image reconstruction. The interesting properties can be derived by using two wavelets, one for decomposition and the other for reconstruction instead of the same single one [21]. The Meyer wavelets are symmetric in shape. The wavelets are chosen based on their shape and their ability to compress the image in a particular application.

III. Evaluation of Image Compression Technique

In order to quantitatively evaluate the quality of the compressed image the Peak Signal-to- Noise Ratios (PSNR) of the images are computed. PSNR provides a measurement of the amount of distortion in a signal [22], with a higher value indicating less distortion. For n-bits per pixel image, PSNR is defined as:

$$PSNR = 20 \log_{10} \frac{2^n - 1}{RMSE}$$

Where, RMSE is the root mean square difference between two images. The Mean Square Error (MSE) is defined as follows [21]:

$$MSE = \frac{1}{MN} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} |y(m,n) - x(m,n)|^2$$

Where, x (m, n), y (m, n) are, respectively, the original and recovered pixel values at the mth row and nth column for the image of size MXN. PSNR is normally quoted in decibels (dB), which measure the ratio of the peak signal and the difference between two images (error image). Logically, a higher value of PSNR is good because it means that the ratio of Signal to Noise is higher. So, if we find a compression scheme having a high PSNR, we can recognize that it is a better one. For an 8-bit grayscale image, the peak signal value is 255. Therefore, the PSNR of 8-bit grayscale image and its reconstructed image is calculated as [22],

$$PSNR = 10 \log_{10} \left(\frac{255^2}{MSE} \right)$$

IV. Result Analysis

We have performed the experiments and analyzed different wavelets. Six wavelets are choosen from the different wavelet families namely: HAAR, DB_3, SYM_4, COIF_2, BIOR_4.4 and RBIO_1.3 for the evaluation of the test images. The test images are Tabboo (256x256), Field (512x512), The compression performance is the basis for the choice of these wavelets among the different wavelet families in terms of PSNR and visual quality. The experimental results for all the six wavelet family have been analyzed for the test images. The results are shown in the Tables-I, Tables-II, measured in terms of PSNR (Peak Signal to Noise Ratio) and Compression Ratio (CR).

Table-1 (Tabboo Image)

Compression Ratio	Wavelet	HAAR	DB_3	SYM_4	COIF_2	BIOR_4.4	RBIO_1.3
2:1	PSNR(db)	50.66	51.33	51.37	51.36	51.30	51.38
16:1	PSNR(db)	33.15	33.34	33.49	33.32	33.66	33.74
50:1	PSNR(db)	26.84	27.00	26.98	26.83	26.95	27.22
100:1	PSNR(db)	24.50	24.49	24.40	23.89	24.12	24.70
200:1	PSNR(db)	22.82	22.73	22.47	21.67	22.07	22.67

Table-2 (Field Image)

Compression Ratio	Wavelet	HAAR	DB_3	SYM_4	COIF_2	BIOR_4.4	RBIO_1.3
2:1	PSNR(db)	40.74	42.26	42.55	42.49	43.22	42.48
16:1	PSNR(db)	23.75	24.69	24.85	24.50	25.01	24.85
50:1	PSNR(db)	20.55	21.11	21.14	20.92	21.17	21.20
100:1	PSNR(db)	19.18	19.57	19.53	19.31	19.51	19.64
200:1	PSNR(db)	18.07	18.35	18.22	17.95	18.14	18.39

The Fig. -3 presented the results of compression performance of the wavelets in terms of PSNR (in dB). The wavelet BIOR_ 4.4 gives the better compression performance (in terms of PSNR) at lower compression ratios for the Field image. The wavelet RBIO_1.3 gives better compression performance at all compression ratios for the image Tabboo. It is also noticeable that the wavelet SYM_4 and RBIO_1.3 gives approximately the same value of PSNR for the image Field. The Fig. -4: (a & b) PSNR for different number of decompositions. We also found that if the decomposition level was increased the compression performance improves but the quality of image degrades.

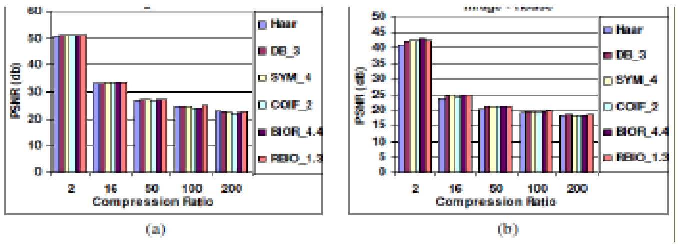


Fig.3 Performance of wavelets in terms of PSNR (in dB) a. Tabboo Image b. Field Image

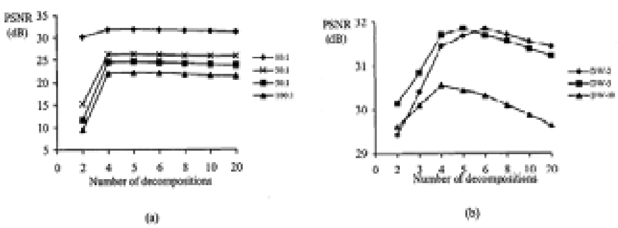


Fig. 4 (a & b) PSNR for different number of decompositions.

V. Conclusion

In this paper, a comparative study of different wavelet family on to test images set has been done using PSNR and Compression ratio. This study gives the choice of optimal wavelet for image compression. The effects of Haar, Daubechies, Symlets, Coiflets, Biorthogonal and R. Biorthogonal wavelet family on two different test images have been examined. The Compression Ratios and Visual Image Quality are also presented. We used, Peak signal to noise ratio (PSNR) as the objective quality measure. We analyzed results for a wide range of wavelets and found that wavelet RBIO_1.3 provides the better compression performance for the test images. The wavelet BIOR_4.4 also provides competitive compression performance at lower compression ratios for the test images. Therefore, conclusively we can say that the “best wavelet” choice of wavelet in the image compression of images dependent on to the image content and desired image quality.

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