Performance Measure Of Different Wavelets For A Shuffled Image Compression Scheme

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ABSTRACT

In the modern world of technologies, the main constraint of limitation is the memory of the system. Memory plays a key role in the multimedia devices and the data storage devices, where the images are considerably bulky. To compress the image, the previously used technologies include Discrete Cosine Transform wherein there are more Blocking Artifacts and floor operator loss due to which the quality of reconstructed image is degraded and utilizes more Bandwidth. The paper discusses the important features of wavelet transform in compression of still images, including the extent to which the image quality is degraded by compression and decompression process. In this paper, the optimum method of wavelet transformation is explored. Performance Measure of different Wavelets is compared with and without shuffling scheme . By using these wavelets and compression, we can achieve an optimum balance between the performance metrics like Peak Signal to Noise Ratio and Compression Ratio and also reduces the Mean Square Error. Our results provide a good reference for application developers to choose a good wavelet compression system for their application.

1. Introduction

Image compression is the application of Data compression on digital images. In effect, the objective is to reduce redundancy of the image data in order to be able to store or data in an efficient form.

Image compression can be lossy or lossless. Lossless compression is sometimes preferred for artificial images such as technical drawings, icons or comics. This is because lossy compression methods, especially when used at low bit rates, introduce compression artifacts(11). Lossless compression methods may also be preferred for high value content, such as medical imagery or image scans made for archival purposes. Lossy methods are especially suitable for natural images such as photos in applications where minor (sometimes imperceptible) loss of fidelity is acceptable to achieve a substantial reduction in bit rate.

A lossy compression method is one where compressing data and then decompressing it retrieves data that may well be different from the original, but is close enough to be useful in some way (12). Lossy compression is most commonly used to compress multimedia data (audio, video, still images), especially in applications such as streaming media and internet telephony. On the other hand lossless compression is preferred for text and data files, such as bank records, text articles, etc.

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2. WAVELET IMAGE COMPRESSION

The foremost goal is to attain the best compression performance possible for a wide range of image classes while minimizing the computational and implementation complexity of the algorithm. For a compression algorithm to be widely useful, it must perform well on a wide variety of image content while maintaining a practical compression/ decompression time on modest computers. In order to allow a broad range of implementation, an algorithm must be amenable to both software and hardware implementation.

A wavelet is a kind of mathematical function used to divide a given function or continuous-time signal into different frequency components and study each component with a resolution that matches its scale

2.1 TYPICAL IMAGE CODER

(a)
Fig. 1 (a) Wavelet Coder

A typical image compression system consisting of three closely connected components namely (a) Source Encoder (b) Quantizer, and (c) Entropy Encoder is shown in Fig.1(a). Compression is accomplished by applying a linear transform to decorrelate the image data, quantizing the resulting transform coefficients, and entropy coding the quantized values.

The source coder decorrelates the pixels. A variety of linear transforms have been developed which include Discrete Fourier Transform (DFT), Discrete Cosine Transform (DCT), Discrete Wavelet Transform

(DWT) and many more, each with its own advantages and disadvantages.

The most commonly used entropy encoders are the Huffman encoder and the arithmetic encoder, although for applications requiring fast execution, simple run-length encoding (RLE) has proven very effective. It is important to note that a properly designed quantizer and entropy encoder are absolutely necessary along with optimum signal transformation to get the best possible compression.

PROPOSED IMAGE CODER

Fig.2 Proposed coder

2.2. WAVELETS

HAAR WAVELET

The Haar wavelet is the first known wavelet and was proposed in 1909 by Alfred Haar. The Haar wavelet is also the simplest possible wavelet. The disadvantage of the Haar wavelet is that it is not continuous and therefore not differentiable (12).

The Haar Wavelet's mother wavelet function ψ (*t*) can be described as

$$\psi(t) = \begin{cases} 1 & 0 \le t < 1/2, \\ -1 & 1/2 \le t < 1, \\ 0 & \text{otherwise.} \end{cases}$$

And its scaling function φ (*t*) can be described as

$$\varphi(t) = \begin{cases} 1 & 0 \le t < 1, \\ 0 & \text{otherwise.} \end{cases}$$

$$((s_0, d_0), \ldots, (s_n, d_n))$$

DAUBECHIES WAVELET

Named after Ingrid Daubechies, the Daubechies wavelets are a family of orthogonal wavelets defining a discrete wavelet transform and characterized by a maximal number of vanishing moments for some given support. With each wavelet type of this class, there is a scaling function (also called father wavelet) which generates an orthogonal multiresolution analysis.

COIFLET WAVELET

Coiflet is a discrete wavelet designed by Ingrid Daubechies to be more symmetrical than the Daubechies wavelet. Whereas Daubechies wavelets have $N / 2 - 1$ vanishing moments, Coiflet scaling functions have $N / 3 - 1$ zero moments and their wavelet functions have $N / 3$.

COIFLET CO – EFFICIENTS

Both the scaling function (low-pass filter) and the wavelet function (High-Pass Filter) must be normalized by a factor $1/\sqrt{2}$. Below are the coefficients for the scaling functions for C6-30. The wavelet coefficients are derived by reversing the order of the scaling function coefficients and then reversing the sign of every second one. (i.e. C6 wavelet = {−0.022140543057, 0.102859456942, 0.544281086116, −1.205718913884, 0.477859456942, 0.102859456942}) Mathematically, this looks like $B_k = (-1)^k C_{N-1-k}$ where k is the coefficient index, B is a wavelet coefficient and C a scaling function coefficient. N is the wavelet index, ie 6 for C6.

BI – ORTHOGONAL WAVELET

A biorthogonal wavelet is a wavelet where the associated wavelet transform is invertible but not necessarily orthogonal. Designing biorthogonal wavelets allows more degrees of freedoms than orthogonal wavelets. One additional degree of freedom is the possibility to construct symmetric wavelet functions. In the biorthogonal case, there are two scaling functions, which may generate different multiresolution analyses, and accordingly two different wavelet functions . So the numbers M, N of coefficients in the scaling sequences may differ. The scaling sequences must satisfy the following biorthogonality condition. Then the wavelet sequences can be determined as , n=0,...,M-1 and , n=0,....,N-1.

SYMLETS

The symlets are nearly symmetrical wavelets proposed by Daubechies as modifications to the db family. The properties of the two wavelet families are similar.

3. MULTIPLE LEVEL DECOMPOSITION

The decomposition process can be iterated, with successive approximations being decomposed in turn, so that one signal is broken down into many lower resolution components. This is called the wavelet decomposition tree and is depicted as in Fig. 3.

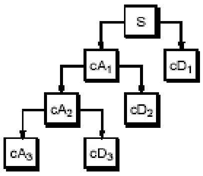


Fig. 3 Multilevel decomposition

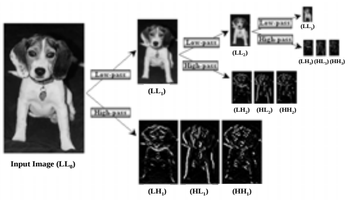
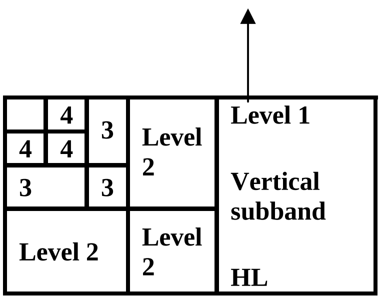


Fig. 3.1 Decomposition Levels

The process of 2-D wavelet transform applied through three transform levels

To obtain a two-dimensional wavelet transform, the one-dimensional transform is applied first along the rows and then along the columns to produce four subbands: low-resolution, horizontal, vertical, and diagonal. (The vertical subband is created by applying a horizontal high-pass, which yields vertical edges.) At each level, the wavelet transform can be reapplied to the low-resolution subband to further decorrelate the image. Fig.3.2 illustrates the image decomposition, defining level and subband conventions used in the AWIC algorithm. The final configuration contains a small low-resolution subband. In addition to the various transform levels, the phrase level 0 is used to refer to the original image data. When the user requests zero levels of transform, the original image data (level 0) is treated as a low-pass band and processing follows its natural flow (10).

Low Resolution Subband



Level 1 **Horizontal Subband** **LH**	**Level 1** **Diagonal Subband** **HH**

Fig. 3.2 Image Decomposition Using Wavelets

4. SHUFFLING

The quantization method is used to generate the result in this paper is the SPIHT zerotree quantizer. The SPIHT and other quantizer achieve better performance by exploiting the spatial dependence of pixel in different subband of a scalar wavelet transform. It has been noted that there exists a spatial dependence between pixels in different subbands in the form of a children-parent relationship. In particular, each pixels in a smaller subband has four children in the next larger subband in the form of 2×2 block adjacent pixels. This relationship illustrated in this fig.4.1.In this figure each small square represent a pixel and each narrow points from a particular pixel to its 2×2 group of children. The importance of parent-child relation in quantization is this: if the parent coefficient is small value, then the children will most likely have small values: conversely, if the parent has a large coefficient one or more of the children might also.

This observation suggests the following procedure: rearrange the coefficient in each 2×2 block so that coefficients corresponding to the same spatial locations are place together. This new procedure will referred to as shuffling. A clear picture of this is given in Fig.4.2.Fig.4.2 (a) shows one of 2×2 blocks resulting from the wavelet decomposition. Eight pixels (two from each subband) are highlighted and given a unique numeric label. Fig.4.2 (b) shows a same set of pixels after shuffling. Note that pixel 1-4 map to 2×2set of adjacent pixels as do pixels 5-8.This shuffling procedure restore the some of the spatial dependence of the pixels by moving those pixels that corresponds to a particular part of image to the position that they would have been located had a scalar wavelet decomposition been performed (12).

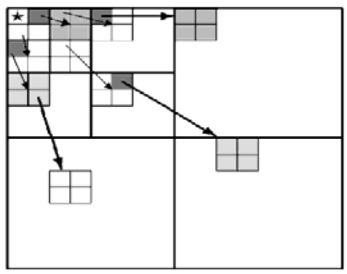


Fig.4.1 Parent-Child Relationship.

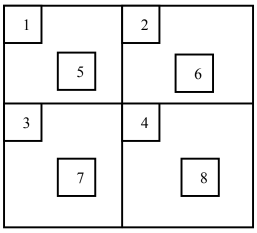


Fig.4.2(a) Before shuffling

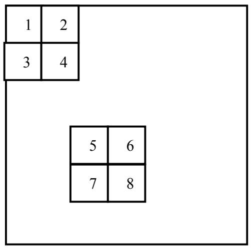


Fig.4.2 (b) After shuffling

5.ENCODING

Encoding is the process of transforming information from one format into another.

5.1 ENTROPY ENCODING

An entropy encoding is a lossless data compression scheme that is independent of the specific characteristics of the medium.

There are many ways of compressing images. One of the main types of entropy coding assigns codes to symbols so as to match code lengths with the probabilities of the symbols. Typically, these entropy encoders are used to compress data by replacing symbols represented by equal-length codes with symbols represented by codes where the length of each codeword is proportional to the negative logarithm of the probability. Therefore, the most common symbols use the shortest codes.

5.2 RUN LENGTH ENCODING (RLE)

One relatively simple way to compress an image is called Run Length Encoding (RLE), which describes the image as a list of "runs", where a run is a sequence of horizontally adjacent pixels of the same color. It codes the data by measuring the length of runs of the values (3).

The simplest form of compression technique which is widely supported by most bitmap file formats such as TIFF, BMP, and PCX. RLE performs compression regardless of the type of information stored, but the content of the information does affect its efficiency in compressing the information.

5.3 HUFFMAN ENCODING

Huffman Coding – Compression:

We use this coding to encode/compress a text file. Steps:

– Read the file.

– Calculate the probability of each symbol (since we use an ASCII file, there are 256 possible symbols). Instead of actual probability we can use instance count.

– Use the Huffman coding algorithm to find the coding for each symbol. Need to apply only on subset of symbols that actually appear in the file.

- Encode the file, and write it out.

The out file must also include the encoding table, so as to permit decoding.

5.4 ARITHMETIC ENCODING

The principles of arithmetic coding describe an arithmetic coding engine that will produce a compliant bit stream when used in conjunction with the correct methods for binarization and context selection (described below).

Arithmetic coding is employed on integer-valued wavelet coefficients and uses a two-stage process as shown in figure5.1. First, integer values are binarized into a sequence of bits or boolean values. At the same time a "context" is generated for each of these bits. These boolean values, together with the corresponding context, are then coded by the binary arithmetic coding engine.

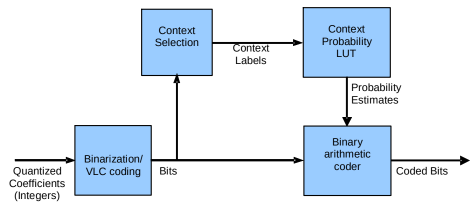


Figure 5.1. Arithmetic encoding process

6. SIMULATION RESULTS

INPUT :

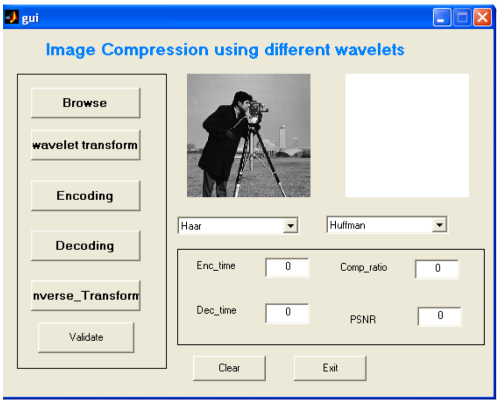


Fig.6.1 Input Image

TRANSFORMED IMAGE:

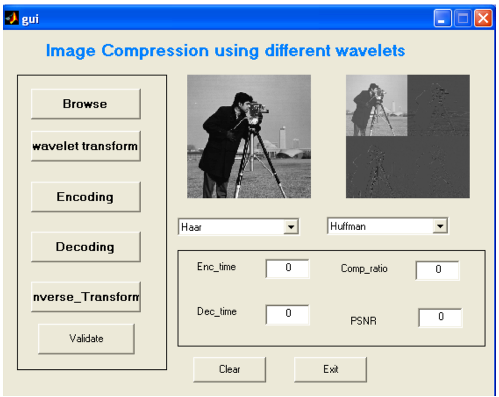


Fig.6.2 Transformed Image

ENCODING:

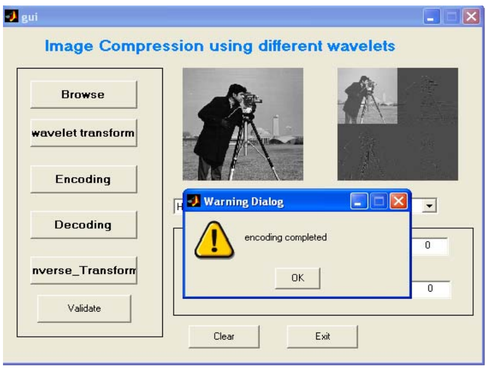


Fig.6.3 Encoding

DECODING:

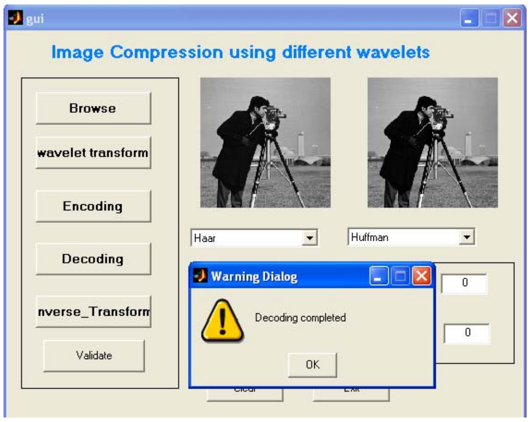


Fig.6.4 Decoding

VALIDATION:

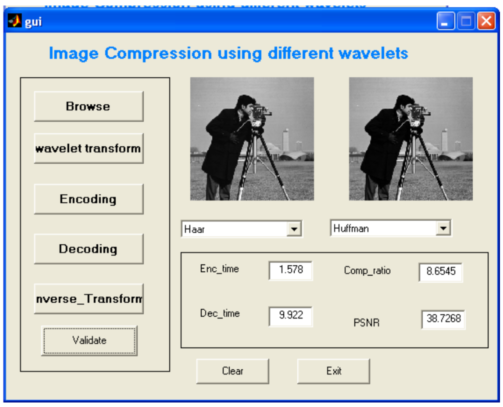


Fig.6.5 Validation

6.1 PERFORMANCE METRICS

The proposed image codec utilizes three image compression parameters that can be used to minimize computation and communication energy consumed. The three parameters are transform level, quantization level and elimination level. These parameters can be used to effect the desired trade-off between energy consumed, image quality obtained and bandwidth. The energy savings, bandwidth and compression has a direct relationship with these parameters.

6.2 COMPARISON TABLE

Table 1: Comparison of Different Wavelets with Huffman and RLE Encoding with and without shuffling

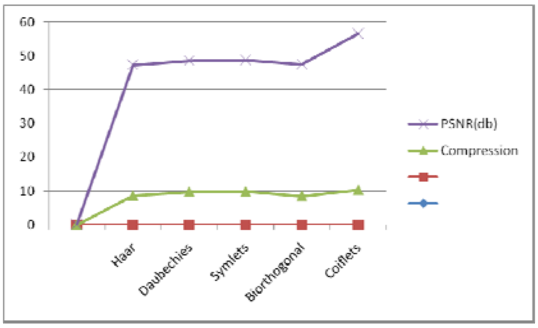
Wavelets	With Shuffling				Without Shuffling	
	Encoding Time(s)	Decoding Time(s)	Compression Ratio(db)	PSNR(db)	Compression Ratio(db)	PSNR(db)
Haar	1.578	9.922	8.6545	38.7268	8.2	32.46
Daubechies	2.39	11.406	9.8404	38.7959	9.5	36.73
Symlets	1.594	21.563	9.8667	38.9756	9.3	36.47
Biorthogonal	1.734	12.11	8.5417	39.5051	7.6	40.20
Coiflets	1.562	38.188	19.3718	47.8725	18.7	45.37

Table2: Comparison of Different Wavelets with Arithmetic and RLE Encoding with and without shuffling

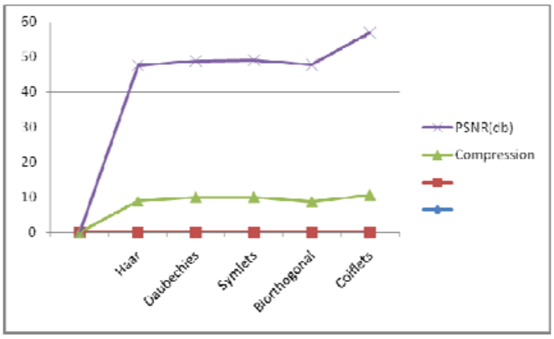
Wavelets	With Shuffling				Without Shuffling	
	Encoding Time(s)	Decoding Time(s)	Compression Ratio	PSNR (db)	Compression Ratio(db)	PSNR(db)
Haar	5.203	11.484	8.9121	38.7296	7.9	30.27
Daubechies	4.547	18.656	10.0599	38.7759	9.2	35.67
Symlets	4.906	25.516	10.0998	38.9444	9.0	36.52
Biorthogonal	5.094	15.281	8.7792	39.0051	7.9	42.43
Coiflets	5.063	41.891	19.6512	46.2872	17.5	43.86

6.3 COMPARISON GRAPHS

HUFFMAN ENCODING



ARITHMETIC ENCODING



7. CONCLUSION

In this paper we have discussed the method of wavelet transformation with various wavelets with and without shuffling and thus we conclude that Haar and Coiflet wavelet gives best reconstructed image and also better CR and PSNR than other wavelets. Arithmetic gives better CR whereas Huffman gives better PSNR.

8. FUTURE ENHANCEMENTS

Wavelet compression is a lossy method. To make it lossless and more efficient, we go in for adaptive schemes in various factors for the transform.
For example, we have different algorithms like Genetic algorithm, Lifting schemes, Directional Qucinix Lifting, Adaptive filters etc

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