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Performance Evaluation of Various Wavelets for Image Compression of Natural and Artificial Images

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ABSTRACT

Recently discrete wavelet transform and wavelet packet has emerged as popular techniques for image compression. The wavelet transform is one of the major processing component of image compression. The results of the compression change as the nature of image and type of the wavelet changes. This paper compares compression performance of Daubechies, Symlets, Coiflets, Biorthogonal, Reverse Biorthogonal & Discrete meyer wavelets along with results for Natural & artificial images. Based on the results, it is proposed that proper selection of wavelet on the basis of nature of images, improve the quality as well as compression ratio remarkably. The prime objective is to select the proper wavelet during the transform phase to compress the image. This paper will provide a good reference for application developers to choose a good wavelet compression system for their application.
Keywords: **Compression, Wavelet, Daubechies, Symlets, Coiflets, Biorthogonal, Reverse Biorthogonal & Discrete Meyer.**

1. INTRODUCTION

Images contain large amount of information that requires much storage space, large transmission bandwidths and long transmission times. Therefore it is advantageous to compress the image by storing only the essential information needed to reconstruct the image. An image can be thought of as a matrix of pixel (or intensity) values. In order to compress the image, redundancies must be exploited, for example, areas where there is little or no change between pixel values. Therefore images having large areas of uniform colour will have large redundancies, and conversely images that have frequent and large changes in colour will be less redundant and harder to compress. We are defining two types of image: Natural image & Artificial image. Natural image refers to the image directly captured by camera with no improvement techniques applied, while artificial image refers to wallpaper with all the image improvement techniques applied. These images are subjected to various wavelet transforms for effective compression. The results are analyzed on the basis of compression ratio & information loss.

2. IMAGE COMPRESSION PRINCIPLES

Image compression reduces the number of bits required to represent the image, therefore the amount of memory required to store the data set is reduced. It also reduces the amount of time required to transmit a data set over a communication link at a given rate. Different methods are developed to perform the image compression. The compression ratio is one of the quantitative parameters to measure the performance of compression methods. Compression ratio is defined as ratio of the size of original data set to the size of the compressed data set.

There are various methods of compressing still images, but every method has three basic steps involved in any of the data compression scheme: Transformation, reduced precision (quantization or thresholding), and minimization of number of bits to represent the image(encoding). The basic block diagram of compression scheme is shown in Fig.1.

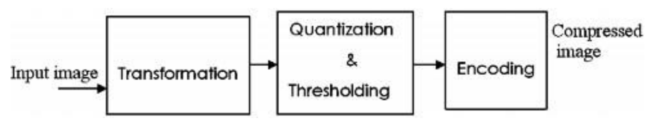


Fig 1: The Block Diagram of Compression Scheme

2.1. Transformation

For image compression, it is desirable that the selection of transform should reduce the size of resultant data set as compared to source data set. Few transformations reduce the number of data items in the data set. Few transformations reduce the numerical size of the data items that allows them to represent by the fewer binary bits. In data compression, transform is intended to decorelate the input signals by transformation. The data represented in the new system has properties that facilitate the compression. Some mathematical transformations have been invented for the sole purpose of data compression; selection of proper transform is one of the important factors in data compression scheme. It still remains an active field of research. The technical name given to these processes of transformation is mapping. Some mathematical transformations have been invented for the sole purpose of data compression, other have been borrowed from various applications and applied to data compression. The partial list includes: Discrete Fourier Transform (DFT), Discrete Cosine Transform (DCT), Hadamard-Haar Transform (HHT), Karhune-Loeve Transforms (KLT), Slant-Haar Transform (SHT), Walsh-Hadamard Transform (WHT), Short Fourier Transforms (SFT), and Wavelet Transforms (WT).

2.2. Quantization/Thresholding

In the process of quantization each sample is scaled by the quantization factor. Where as in the process of thresholding the samples are eliminated if the value of sample is less than the defined threshold value. These two methods are responsible for introduction of error and it leads in degrading the quality. The degradation is based on selection of quantization factor and threshold value. For the high value of threshold the loss of information is more, and for low value of threshold the loss of information is less. By considering the resultant loss of information, the selection of threshold should be low, but for the low value of the threshold there is negligible compression of data. Hence quantization factor, or threshold value should be selected in such a way that it should satisfy the constraints of human visual system for better visual quality, and high compression ratio. Human Visual System is less sensitive to high frequency signal and more sensitive to low frequency signal. By considering this phenomenon, the threshold value or quantization factor is selected and thresholding/ quantization take place in image compression.

In image compression technique two types of thresholding are used as:

- Hard Thresholding;
- Soft Thresholding.

In hard thresholding technique, if the value of the coefficient is less than defined value of threshold, then the coefficient is scaled to zero, otherwise the value of the coefficient is maintained as it is. This process is repeated until all the pixels in the image are exhausted.

In soft thresholding technique, if the value of the coefficient is less than defined value of threshold, then the coefficient value is scaled to zero and otherwise the value of coefficient is reduced by the amount of defined value of threshold. This process is repeated until all the pixels in the image are exhausted.

2.3. Encoding

This phase of compression reduces the overall number of bits needed to represent the data set. An entropy encoder further compresses the quantized values to give better overall compression. This process removes the redundancy in the form of repetitive bit patterns in the output of quantizer. It uses a model to accurately determine the probabilities for each quantized value and produces an appropriate code based on these probabilities so that the resultant output code stream will be smaller than most commonly used entropy encoders are Huffman encoder and the Arithmetic encoder. The Huffman algorithm requires each code to have an integral number of bits, while arithmetic coding methods allow for fractional number of bits per code by grouping two or more such codes together into a block composed of an integral number of bits. This allows arithmetic codes to outperform Huffman codes, and consequently arithmetic codes are more commonly used in wavelet-based algorithm.

3. WAVELET TRANSFORM

Wavelet transform (WT) represents an image as a sum of wavelet functions (wavelets) with different locations and scales. Any decomposition of an image into wavelets involves a pair of waveforms: one to represent the high frequencies corresponding to the detailed parts of an image (wavelet function ø) and one for the low frequencies or smooth parts of an image (scaling function ô). Fig. 2 shows two waveforms of a family discovered in the late 1980s by Daubechies: the right one can be used to represent detailed parts of the image and the left one to represent smooth parts of the image. The two waveforms are translated and scaled on the time axis to produce a set of wavelet functions at different locations and on different scales. 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. The result of WT is a set of wavelet coefficients, which measure the contribution of the wavelets at these locations and scales.

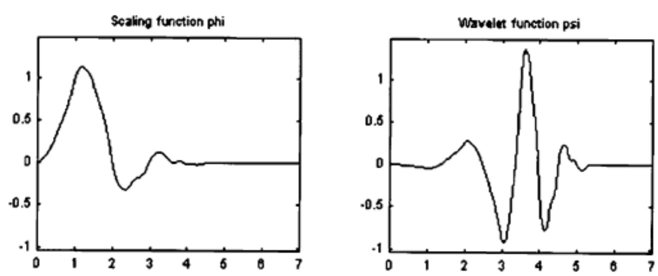


Fig 2: Scaling and Wavelet Function

4. DWT IN IMAGE COMPRESSION

4.1. Image Content

The image content being viewed influences the perception of quality irrespective of technical parameters of the system. Normally, a series of pictures, which are average in terms of how difficult they are for system being evaluated, has been selected. To obtain a balance of critical and moderately critical material we used two types of test images with different frequency content: Nature (Natural Image) & Tabboo (Artificial Image). These images usually contain large number of small details and low spatial redundancy. Choice of wavelet function is crucial for coding performance in image compression. However, this choice should be adjusted to image content. The compression performance for images with high spectral activity is fairly insensitive to choice of compression method (for example, test image Tabboo), On the other hand, coding performance for images with moderate spectral activity (for example, test image nature) are more sensitive to choice of compression method. The best way for choosing wavelet function is to select optimal basis for images with moderate spectral activity. This wavelet will give satisfying results for other types of images.

4.2. Choice of Wavelet Function

Important properties of wavelet functions in image compression applications are compact support (lead to efficient implementation), symmetry (useful in avoiding dephasing in image processing), orthogonality (allow fast algorithm), regularity, and degree of smoothness (related to filter order or filter length). In our experiment, seven types of wavelet families are examined: Haar Wavelet (HW), Daubechies(db), Symlets(sym3), Coiflets (coif1), Biorthogonal (bior 3.1), Reverse Biorthogonal (rbior3.1) & Discrete meyer (dmey). Each wavelet family can be parameterized by integer N that determines filter order. Biorthogonal wavelets can use filters with similar or dissimilar orders for decomposition (Nd) and reconstruction (Nr). In our examples, different filter orders are used inside each wavelet family. Daubechies and Coiflet wavelets are families of orthogonal wavelets that are compactly supported. Compactly supported wavelets correspond to finite-impulse response (FIR) filters and, thus, lead to efficient implementation. Only ideal filters with infinite duration can provide alias-free frequency split and perfect interband decorrelation of coefficients. Since time localization of the filter is very important in visual signal processing, arbitrarily long filters cannot be used. A major disadvantage of DW and CW is their asymmetry, which can cause artifacts at borders of the wavelet subbands. DW is asymmetrical while CW is almost symmetrical. Symmetry in wavelets can be obtained only if we are willing to give up either compact support or orthogonality of wavelet (except for HW, which is orthogonal, compactly supported, and symmetric). If we want both symmetry and compact support in wavelets, we should relax the orthogonality condition and allow nonorthogonal wavelet functions. An example is the family of biorthogonal wavelets that contains compactly supported and symmetric wavelets.

5. EXPERIMENTAL RESULTS

We have taken the test images : Nature & Tabboo Shown in fig. 3. We have used mother wavelet Haar Wavelet (HW), Daubechies(db), Symlets(sym3), Coiflets (coif1), Biorthogonal (bior 3.1), Reverse Biorthogonal (rbior3.1) & Discrete meyer (dmey). Results are observed in terms of Compression ratio achieved for natural & artificial image. The best results are presented in paper (Table1). Fig.4: shows the Natural image & results using (HW), (db), (sym3), (coif1),(bior 3.1), (rbior3.1) & (dmey). Fig. 5: shows the tabboo image & results using (HW), (db), (sym3), (coif1),(bior 3.1), (rbior3.1) & (dmey).

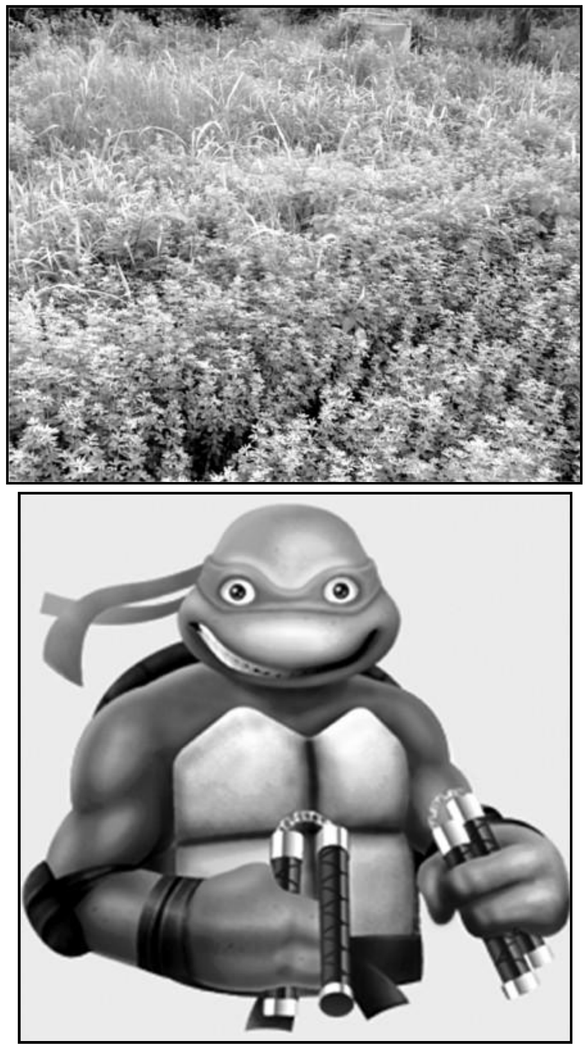
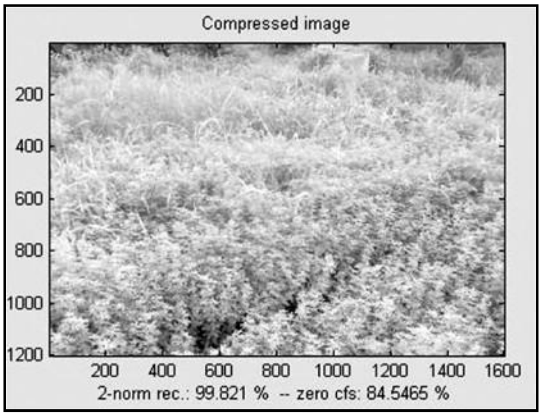
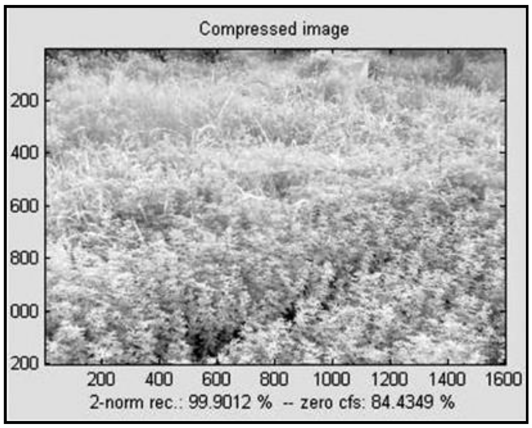


Fig 3: Original Nature & Tabboo Images

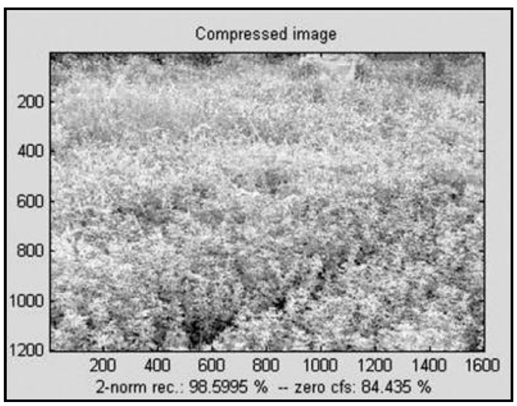
Nature Image



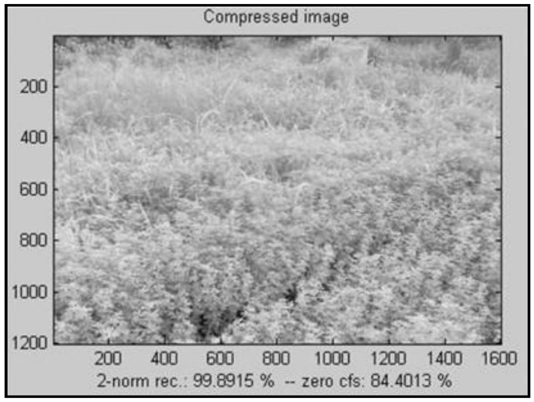
Haar Wavelet



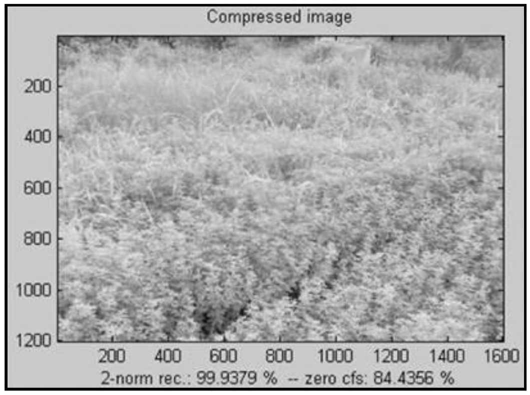
Daubechies



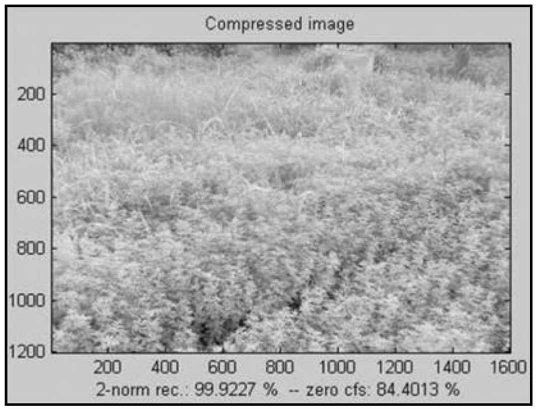
Symlets



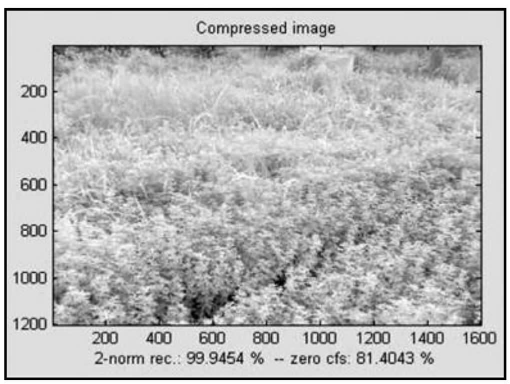
Coiflets



Biorthogonal



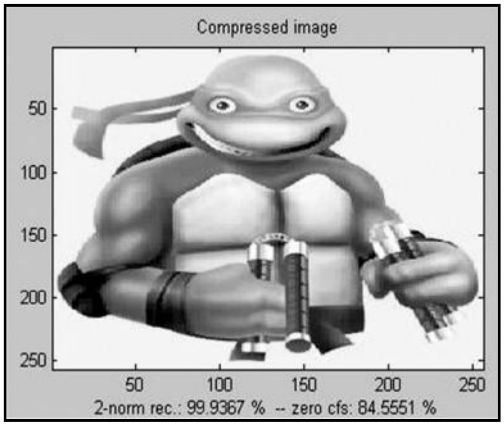
Reverse Biorthogonal



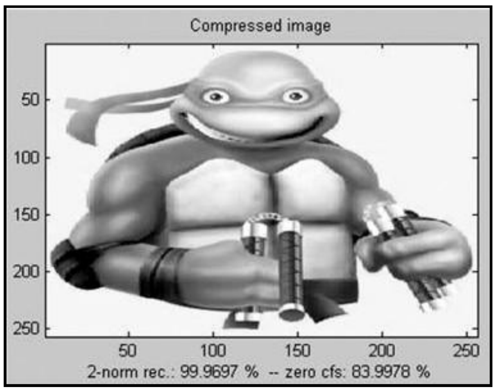
Discrete Meyer

Fig 4: Shows the Nature Image & Results using (HW), (db), (sym3), (coif1),(bior 3.1), (rbior3.1) & (dmey).

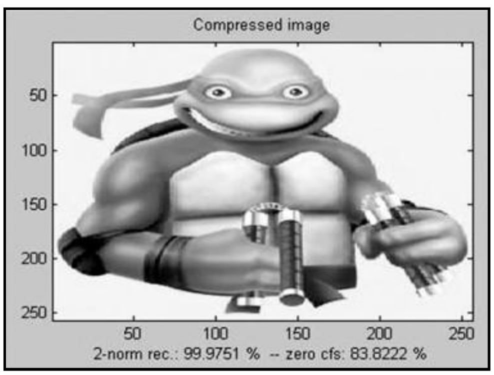
Tabboo Image



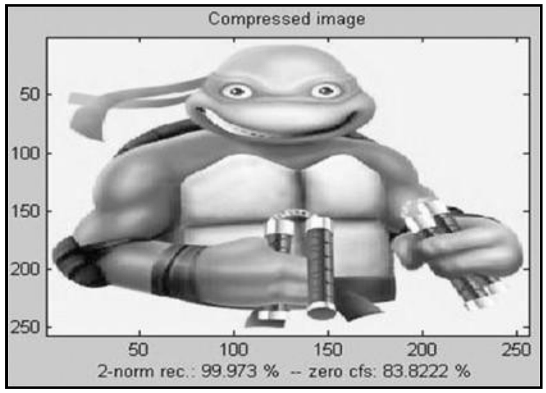
Haar Wavelet



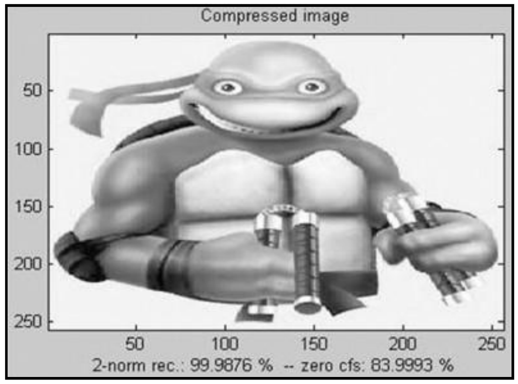
Daubechies



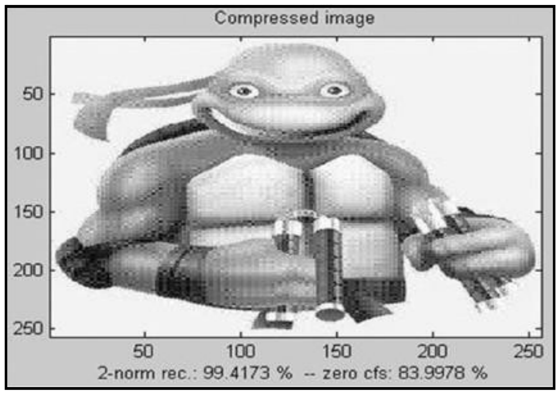
Symlets



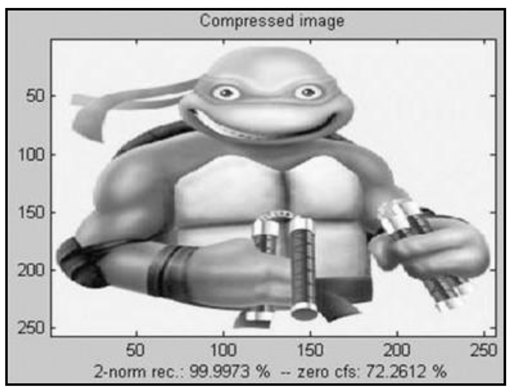
Coiflets



Biorthogonal



Reverse Biorthogonal



Discrete Meyer

Fig 5: Tabboo Image & Results using (HW), (db), (sym3), (coif1),(bior 3.1), (rbior3.1) & (dmey).

Table 1
Experimental Results for Test images

Image	*Wavelet Transforms used*	*Compression Ratio (%)*
Nature	Haar	84.5465
	Daubechies	84.4349
	Symlet	84.4013
	Biortogonal	84.4356
	Reverse biorthogonal	84.4350
	Coiflet	84.4013
	Discrete meyer	81.4043
Tabboo	Haar	84.5551
	Daubechies	83.9978
	Symlet	83.8222
	Biortogonal	83.9993
	Reverse biorthogonal	83.9978
	Coiflet	83.8222
	Discrete meyer	72.2612

6. CONCLUSION

In this paper, selection of mother wavelet on the basis of nature of image has been presented. The input image is first categorized as natural image or artificial image. Extensive result has been taken based on different mother wavelets. The results demonstrate that for Natural & artificial images percentage of zeros is more for Haar wavelet as compared to other wavelets and more energy is retained. It shows that the loss of information is less hence the quality is better.

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