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Performance Analysis and Comparison of Wavelet Families Using for Image Compression

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Abstract: The aim of this study is to analyze and compare a set of wavelet families using for image compression. The study discusses important features of wavelet transform in compression of images. The wavelet transform is a fast developing tool for image compression and provides efficient compression performance. Especially for high compression ratios, wavelets perform much better than competing technologies both in terms of signal-to-noise ratio and visual quality. Wavelet transformation provides both spatial and frequency domain information of image. Wavelet Transform (WT) decomposes an image into wavelet function (wavelets) at different resolution levels. Therefore, the wavelet transform can be composed of function that satisfies requirements of multiresolution analysis. Depending on the application, different aspects of wavelets can be emphasized. The selection of wavelet for image compression depends on the image application and image contents. A review of the wavelet families using for image compression is given here. In this study we have analyzed various wavelets of different wavelet families (such as Biorthogonal, Daubechies, Reverse Biorthogonal, Symlets and Coiflets) performing image compression on variety of test images. The test images are of different frequency content, size and resolution. We have also analyzed effects of wavelet functions belonging to each of these wavelet families at a compression ratio of 100:1 at decomposition level 5 on the variety of test images. The results of compression performance for different wavelets of different wavelet family, image contents, compression ratios and resolutions are given. The image quality is measured, objectively peak signal-to-noise ratio and subjectively visual quality of image.

Key words: Wavelets, wavelet families, wavelet transform, Image compression, compression performance, peak signal to noise ratio

INTRODUCTION

During the past decades, with the birth of wavelet theory and multiresolution analysis, wavelet based image compression techniques have been extensively studied and tremendously improved. An overview of wavelets has brought to the fields as diverse as videoconferencing, remote sensing, biomedical imaging and computer graphics or turbulence, is given in[1]. From a historical point of view, Joseph Fourier in the nineteenth century laid the foundation of wavelet analysis with his theory of frequency analysis, which proved to be enormously powerful and important[2]. The first citation of "wavelet" seems to be in 1909, by Alfred Haar. In the late nineteen-eighties, Daubechies[3], Mallat[4] and Meyer[5] explored and applied the ideas of wavelet transforms. There was a great amount of literature addressing the wavelet based signal processing techniques such as compression.

Wavelet transforms have received significant attention recently due to their suitability for a number of image processing tasks including image compression. The principle behind the wavelet transform is to hierarchically decompose an input signal into a series of successively lower-resolution reference signals and their associated detail signals[6-8]. At each level, the reference signal and detail signal (or signals in the separable multidimensional case) contain the information needed to reconstruct the reference signal at the next higher resolution level. Wavelets are functions that satisfy certain mathematical demands in multiresolution analysis. The name wavelet comes from the requirement that the function magnitude should integrate to zero and the function has to be well localized[9]. Efficient image compression is enabled by allocating bandwidth according to the relative importance of information in the reference and detail signals and then applying scalar or vector quantization to the transformed data values[10,11]. The recent growth of data intensive

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digital image and video applications, have not only sustained the need for more efficient ways to compress images but have made compression, keeping in mind image-storage technology and digital communications. Image compression has become a topic of increasing importance in order to achieve cost-effective solutions. Image compression means reducing the volume of data needed in order to represent an image. Hence, image compression is the representation of an image in digital form with as few bits as possible while maintaining an acceptable level of image quality[12]. A typical still image contains a large amount of spatial redundancy in plain areas where adjacent pixels have almost the same values. It means that the pixels are highly correlated. The redundancy can be removed to achieve compression of the image data i.e. the fundamental components of compression is redundancy reduction.

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. Usually, higher compression ratios will produce lower image quality and the vice versa is also true. Current standards for compression of images use DCT[13,14], which represent an image as a superposition of cosine functions with different discrete frequencies[15]. Most existing compression systems use square DCT blocks of uniform size[13,16]. The use of uniformly sized blocks simplified the compression system, but it does not take into account the irregular shapes within real images. The block-based segmentation of source image is a fundamental limitation of the DCT-based compression system[17]. The degradation is known as the "blocking effect" and depends on block size.

Wavelets provide good compression ratios[18,19], especially for high resolution images. Wavelets perform much better than competing technologies like JPEG[20], both in terms of signal-to-noise ratio and image 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. In a wavelet compression system, the entire image is transformed and compressed as a single data object rather than block by block as in a DCT-based compression system. It allows a uniform distribution of compression error across the entire image. It can provide better image quality than DCT, especially on a higher compression ratio[21]. However, the implementation of the DCT is less expensive than that of the DWT. For example, the most efficient algorithm for 2-D 8X8 DCT requires only 54 multiplications[22], while the complexity of calculating the DWT depends on the length of wavelet filters. A wavelet image compression system can be consists of wavelet function, quantizer and an encoder. In our study, we analyzed various wavelet families using for image compression on variety of test images and then compare the performance of wavelets. According to this analysis, we show the selection of the optimal wavelet for image compression taking into account Peak Signal-to-Noise Ratio (PSNR) as objective and visual quality of image as subjective quality measures.

METRIALS AND METHODS

The objective of the image compression is to find such a representation for an image that only a minimal number of bits are used while maintaining a desirable quality. This allows one to store more image data on a limited storage space as well as makes it possible to transfer images faster over a limited bandwidth channel. A number of methods have been presented over the years to perform image compression. Generally, the image compression methodologies can be classified into two categories: Lossless and Lossy compression. If the image compression is completely reversible, it is said to be lossless. If the decompressed image is only an approximation of the original image, the compression is said to be lossy. Lossless image compression techniques achieve generally compression ratios in range 1-5 on natural images[23,24], while lossy methods typically achieve several times better compression ratios. For example the compression ratio for a comic image on the page 68 is 1.8 when using lossless GIF[25] compression. Lossy compression techniques JPEG[26] and SPIHT[27] achieve compression ratios of 8 and 16, respectively with good image quality.

Transform based compression is one of the most useful applications. Combined with other compression techniques, this technique allows the efficient transmission, storage and display of images that otherwise would be impractical[28]. A wavelet image compression system can be composed by selecting a type of wavelet function for transformation, quantizer and coder. The transform based image compression scheme is shown in Fig. 1. This generalized transform based image compression method works as follows:

Image transform: In this step, divide the source image into blocks and apply the transformations to the blocks using transform, such as DCT or Wavelet Transform (WT)[29]. This step is intended to "decorrelate" the input signal by transforming to a representation in which the set of data values is sparser, thereby compaction of the information content of the signal into a smaller number of coefficients. The selection of transform used depends on a number of factors, in particular, computational complexity and coding gain.

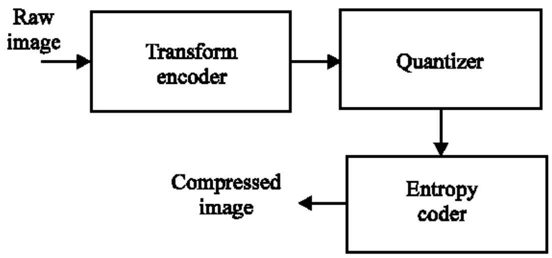


Fig. 1: Transform based image compression system

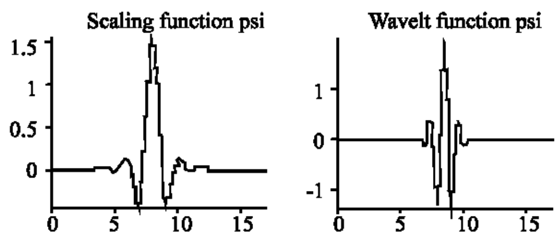


Fig. 2: Scaling and Wavelet functions

Quantization: This step represents the information within the new domain by reducing the amount of data. This step is not reversible and represents the lossy stage in the process. A good quantizer tries to assign more bits for coefficients with more information content or perceptual significance and fewer bits for coefficients with less information content, based on a given fixed bit budget. The choice of a quantizer depends on the transform that is selected. While transforms and quantizers can be "mixed and matched" to a certain degree, some quantization methods perform better with particular transform methods[30,21]. Also, perceptual weighting of coefficients in different subbands can be used to improve subjective image quality[31]. Quantization methods used with wavelet transforms fall into two general categories: embedded and non-embedded[27,32].

Encoding: This last step removes redundancy from the output of the quantizer. This process removes redundancy in the form of repeated bit patterns in the output of the quantizer. The most common entropy coding techniques are Run-Length Encoding (RLE), Huffman coding, arithmetic coding and Lempel-Ziv (LZ) algorithms. The arithmetic coder is more effective than others[33], this allows arithmetic codes to outperform Huffman codes and consequently arithmetic codes are more commonly used in wavelet-based algorithms[27,32,34].

OVERVIEW OF WAVELET TRANSFORM

Wavelet Transform[15,21] has emerged as a powerful mathematical tool in many areas of science and engineering specifically for image compression[17,18,32]. It has provided a promising vehicle for image processing applications, because of its flexibility in representing images. It is mainly used to decorrelate the image data, so the resulting coefficients can be efficiently coded by discarding redundant data. Therefore a "dense" signal is converted to a "sparse" signal and most of the information is concentrated on a few significant coefficients. It also has good energy compaction capabilities, which results in a high compression ratio. Wavelets were developed during the last decades to facilitate many applications, such as image compression, de-noising, human vision, radar, etc. Also, it is being used in many areas of science and engineering such as: signal processing, fractal analysis, numerical analysis, statistics and astronomy[17,35]. Wavelets were determined to be the best way to compress a huge library of fingerprints[36].

Since the wavelet basis functions have short support for high frequencies and long support for low frequencies, smooth area of an image may be represented with very few bits. It is known that most of the energy is concentrated in low frequency information and for the remaining high frequency components of the image, most energy is spatially concentrated around edges. High frequency details are added where they are needed. A perfect reconstruction can be achieved if the compression of difference signals is lossless by simply predicting the original image and adding back the predicted image and the difference. Wavelet transform using in compression research concentrated on the hope of more efficient compaction of energy into a few numbers of low frequency. This generated some of wavelet based coding algorithms[1,37] which were designed to exploit the energy compaction properties of the wavelet transform by applying scalar or vector quantizers for the statistical of each frequency band of wavelet coefficients.

Wavelet Transform (WT) represents an image as a sum of wavelet functions with different locations and scales[38]. Decomposition of an image into wavelets results in a pair of waveform, represents the wavelet function (high frequencies corresponding to the detailed parts of an image) and scaling function (for the low frequencies or smooth parts of an image)[39]. Figure 2 shows two waveforms of Biorthogonal wavelet. The scaling function (left one) represents smooth parts of the image and the wavelet function (right one) can be used to represent detailed 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[38]. 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. WT performs multiresolution image analysis. The result of multiresolution analysis is simultaneous image representation on different resolution (and quality) levels[4].

The greatest problem associated with the transform coding techniques such as DCT based image compression[17] is the presence of visually annoying “blocking artifact” in the compressed image. This has caused an inclination towards the use of Discrete Wavelet Transform (DWT) for all image and video compression standards. DWT offers adaptive spatial-frequency resolution (better spatial resolution at high frequencies and better frequency resolution at low frequencies)[40]. DWT now becomes a standard tool in image compression applications because of their data reduction capabilities[38,41]. The basis of Discrete Cosine Transform (DCT) is cosine functions[20], while the basis of Discrete Wavelet Transform (DWT) is wavelet function that satisfies requirement of multi-resolution analysis[42]. Discrete wavelet transform have certain properties that makes it better choice for image compression. It is especially suitable for images having higher resolution. Since, DWT can provide higher compression ratios with better image quality due to higher decorrelation property. Therefore, DWT has potentiality for good representation of image with fewer coefficients[43].

Wavelet families: We analyzed five wavelet families for image compression and compare their results. The compression results of wavelets are analyzed on the variety of test images of different contents. The fundamental difficulty in selection of an optimal wavelet for image compression system is how to select a wavelet for image compression. According to this analysis, we show the selection of the optimal wavelet for image compression taking into account PSNR objectively and visual quality of image subjectively as quality measures. The image content being viewed influences the perception of image quality irrespective of technical parameters of the system[44]. To obtain a balance we used four types of test images with different frequency content, different resolution and different size: Elaine (256×256), House (512×512), Lion (800×800) and Saturn (1024×1024). Spectral characteristics of test images are calculated, by using DFT applied to test images. Images have low frequency content in the center of the image. Moving away from the center of the image, frequency contents increases. Images with high spectral characteristics are more difficult for a compression system to handle. These images usually contain a large number of small details and low spatial redundancy. The frequency contents of the test images are shown in Fig. 3.

The selection of wavelet function is crucial for performance in image compression[45]. There are a number of basis that decides the selection of wavelet for image

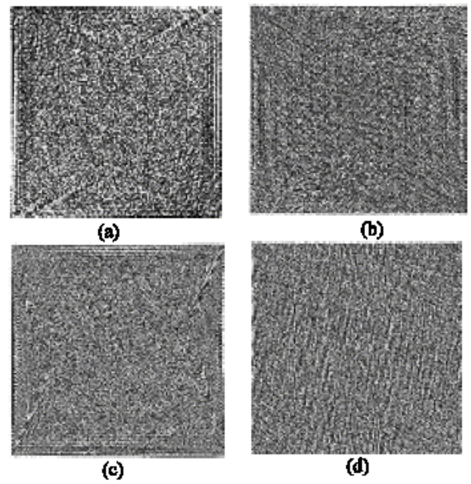


Fig. 3: Frequency contents of test Images (a) Elaine (256×256) (b) House (512×512) (c) Lion (800×800) (d) Saturn (1024×1024)

compression. Since the wavelet produces all wavelet functions used in the transformation through translation and scaling, it determines the characteristics of the resulting wavelet transform. Therefore, the details of the particular application should be taken into account and the appropriate wavelet should be selected in order to use the wavelet transform effectively for image compression. The compression performance for images with different spectral characteristics will decide the wavelet function from wavelet family. Important properties of wavelet functions in image compression applications are compact support, symmetry, orthogonality, regularity and degree of smoothness.

In our experiment, five wavelet families are examined: Daubechies Wavelet (DB), Biorthogonal Wavelet (BIOR), Reverse Biorthogonal Wavelet (RBIO), Coiflet Wavelet (COIF) and Symlet (SYM). The DB, BIOR, RBIO and COIF wavelets are families of orthogonal wavelets that are compactly supported[46]. These wavelets are capable of perfect reconstruction. Daubechies is asymmetrical while Coiflet is almost symmetrical. Scaling and wavelet functions for decomposition and reconstruction in the BIOR family can be similar or dissimilar. Daubechies wavelets are the most popular wavelets and represent the foundations of wavelet signal processing and are used in numerous applications. Daubechies wavelet function will give satisfying results for images with moderate spectral activity[47]. By using two wavelets, one for decomposition and the other for reconstruction instead of the same single one, interesting properties can be derived The wavelets are selected based on their shape and their ability to compress the image in a particular application. Figure 4 illustrates some of the commonly used wavelet functions used in our experiment.

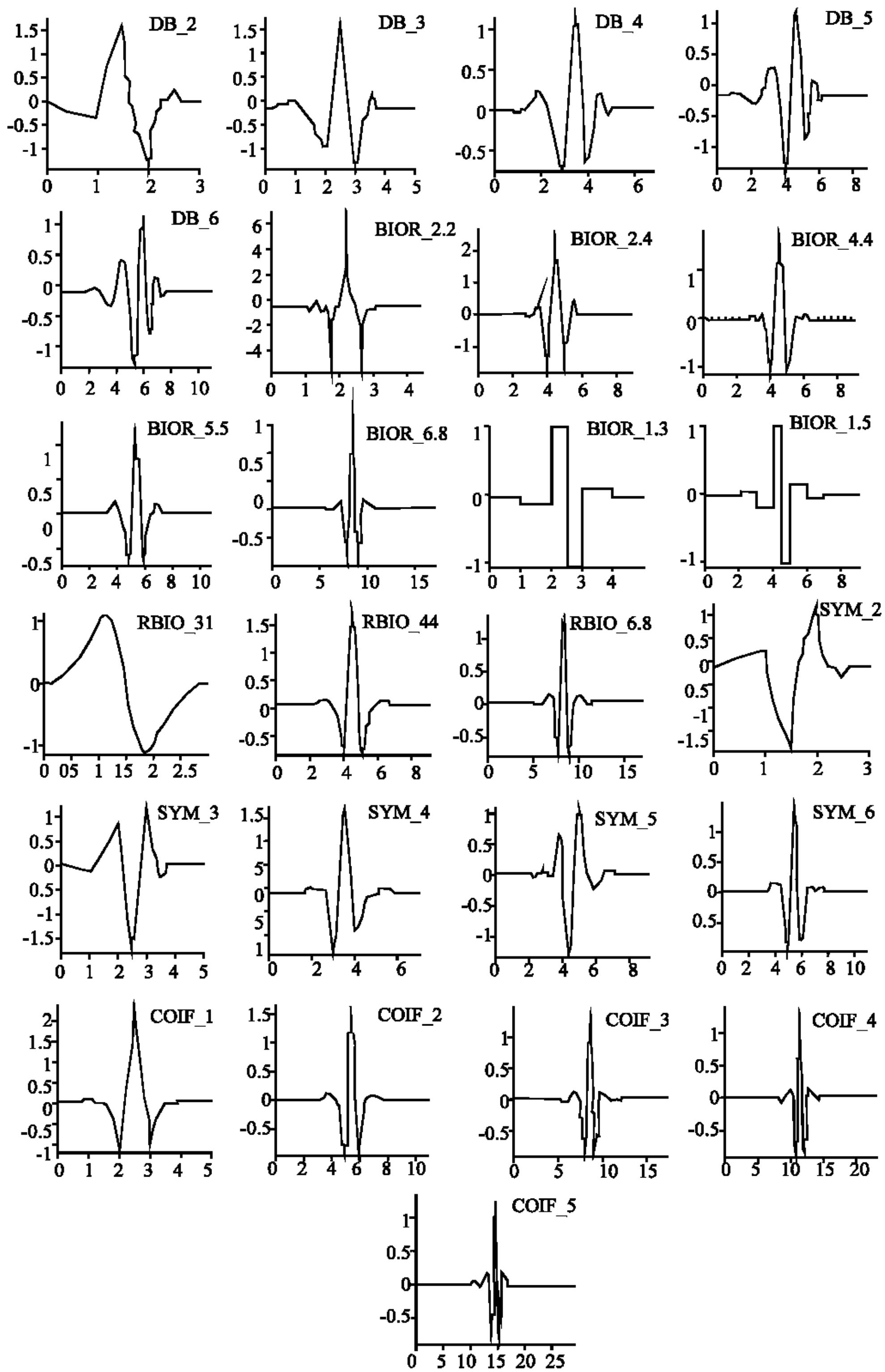


Fig. 4: Different wavelets families used in our experiment

Quality measures: The performance of image compression techniques are mainly analyzed on the basis of two measures: Compression Ratio (CR) and the magnitude of error introduced by the encoding. The compression ratio is defined as:

$$C.R. = \frac{\text{The number of bits in the original image}}{\text{The number of bits in the compressed image}}$$

For error evaluation, two error metrics are used to compare the various image compression techniques: Mean Square Error (MSE) and the Peak Signal to Noise Ratio (PSNR). In order to quantitatively analyze 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[48], 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[45]:

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

Where x(m, n), y(m,n) are respectively the original and recovered pixel values at the m^{th} row and n^{th} column for M X N size image. The PSNR is given in decibel units (dB), which measure the ratio of the peak signal and the error signal (difference between two images). A higher value of PSNR is good because it means that the ratio of Signal to Noise is higher. Here, the 'signal' is the original image and the 'noise' is the error in reconstruction. Therefore, a compression scheme having a lower MSE (or a high PSNR) recognize that it is a better one. The PSNR value provides the quality objectively. While, visual quality of image is considered as subjective quality measures.

Experimental results, analysis and comparison: In our experiment, we have analyzed the various wavelet families such as: Biorthogonal, Reverse Biorthogonal, Daubechies, Coiflet and Symlet using for image compression on to four different test images: Elaine (256×256), House (512×512), Lion (800×800) and Saturn (1024×1024). The test images are of different frequency contents, different size and different resolution.

The frequency contents of the test images are computed by using DFT. The compression results are measured in terms of Peak Signal to Noise Ratio (PSNR), Compression Ratio (CR) and visual quality of compressed image. We have performed the experiment for all the wavelet functions in each wavelet family. Table 1-5 shown below provides the experimental results of PSNR in terms of decibels for the test images compressed with wavelets.

Table 1: Wavelet family: Biorthogonal

		PSNR (in dB)				
Image	C R	2.2	2.4	4.4	5.5	6.8
Elaine	2:1	42.66	42.58	43.37	42.65	42.94
	16:1	30.50	30.31	26.21	25.33	24.47
	50:1	26.61	26.10	26.21	25.33	24.47
	100:1	24.15	23.17	23.25	22.17	20.71
	200:1	21.48	20.25	20.11	18.92	18.53
House	2:1	42.43	42.27	43.22	42.35	42.85
	16:1	24.68	24.50	25.01	24.48	24.47
	50:1	21.07	20.93	21.17	20.74	20.65
	100:1	19.49	19.35	19.52	19.16	18.91
	200:1	18.27	18.08	18.14	17.76	17.30
Lion	2:1	42.39	42.39	43.07	42.31	42.92
	16:1	29.34	29.32	29.70	29.30	29.50
	50:1	26.77	26.75	27.03	26.74	26.80
	100:1	25.71	25.70	25.89	25.66	25.64
	200:1	24.89	24.87	24.98	24.76	24.63
Saturn	2:1	78.79	78.90	80.34	79.23	80.51
	16:1	50.53	50.58	51.12	50.67	51.05
	50:1	46.76	46.74	47.15	46.67	46.89
	100:1	44.53	44.38	44.74	44.10	44.22
	200:1	42.15	41.83	42.01	41.22	40.93

Table 2: Wavelet family: Reverse biorthogonal

		PSNR (in dB)				
Image	C R	2.2	2.4	4.4	5.5	6.8
Elaine	2:1	43.24	43.01	42.57	42.07	42.56
	16:1	30.58	30.42	29.66	29.49	29.10
	50:1	26.50	26.06	25.15	25.35	29.11
	100:1	23.94	23.22	22.43	22.56	20.45
	200:1	21.57	20.05	19.85	19.33	18.50
House	2:1	42.48	42.50	41.44	44.38	41.90
	16:1	24.85	24.80	24.12	32.66	24.10
	50:1	21.20	21.08	20.65	30.30	20.41
	100:1	19.64	19.41	19.20	28.07	18.76
	200:1	18.39	18.10	17.90	25.11	17.23
Lion	2:1	42.86	42.68	42.17	41.21	42.44
	16:1	29.75	29.59	29.22	24.02	29.28
	50:1	27.11	26.98	26.67	20.72	26.66
	100:1	25.97	25.84	25.60	19.28	25.52
	200:1	25.04	24.91	24.75	17.95	24.54
Saturn	2:1	80.16	79.68	78.74	42.00	79.64
	16:1	50.90	50.90	50.48	29.17	50.66
	50:1	46.82	46.83	46.38	26.65	46.44
	100:1	44.47	44.44	43.72	25.61	43.70
	200:1	41.79	41.72	40.81	24.76	40.38

Table 3: Wavelet family: Daubechies

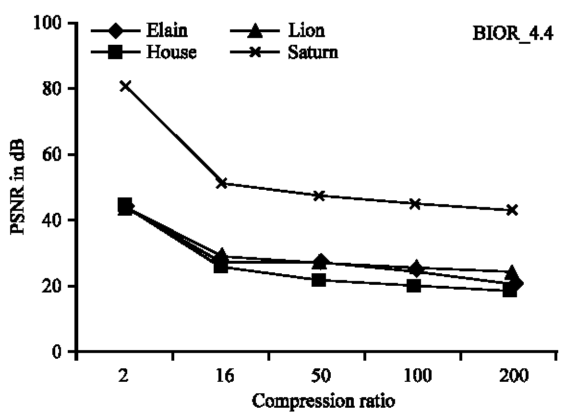
		PSNR (in dB)				
Image	C R	2.2	2.4	4.4	5.5	6.8
Elaine	2:1	43.03	43.09	43.15	43.10	42.93
	16:1	30.24	30.39	30.30	29.94	29.64
	50:1	26.37	26.25	25.90	25.15	24.63
	100:1	24.10	23.59	23.30	22.23	21.54
	200:1	21.89	21.37	20.47	19.83	18.98
House	2:1	41.83	42.26	42.52	42.54	42.45
	16:1	24.46	24.69	24.68	24.57	24.42
	50:1	21.04	21.11	21.04	20.86	20.76
	100:1	19.59	19.57	19.49	19.31	19.21
	200:1	18.41	18.35	18.26	18.02	17.88
Lion	2:1	42.71	42.77	42.79	42.73	42.61
	16:1	29.62	29.58	29.47	29.33	29.21
	50:1	25.99	26.97	26.87	26.77	26.66
	100:1	25.87	25.88	25.79	25.72	25.62
	200:1	24.99	25.01	24.92	24.87	24.78
Saturn	2:1	80.09	79.11	79.04	78.92	79.31
	16:1	50.58	50.81	50.98	51.03	50.96
	50:1	46.44	46.83	46.89	46.85	46.75
	100:1	43.96	44.43	44.41	44.20	44.03
	200:1	41.23	41.66	41.46	41.18	40.85

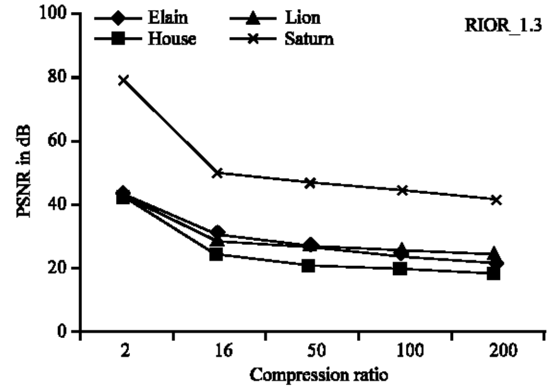
Table 4: Wavelet Family: Coiflets

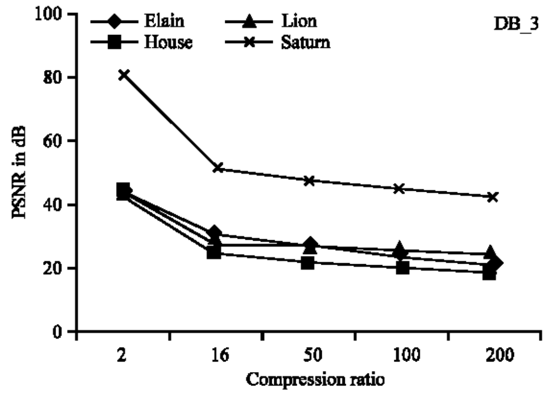
Image	C R	PSNR (in dB) 2.2	2.4	4.4	5.5	6.8
Elaine	2:1	43.10	43.07	42.97	42.36	41.93
	16:1	30.15	30.01	29.36	28.11	26.90
	50:1	26.08	25.34	24.05	22.23	20.86
	100:1	23.63	22.32	20.31	18.60	18.35
	200:1	21.39	19.03	18.46	18.40	
House	2:1	41.97	42.49	42.50	42.13	41.82
	16:1	24.51	24.64	24.36	23.81	23.41
	50:1	20.98	20.92	20.52	20.09	19.65
	100:1	19.45	19.31	18.83	18.43	17.88
	200:1	18.24	17.95	17.31	16.60	16.03
Lion	2:1	42.73	42.84	42.81	42.66	42.58
	16:1	29.60	29.58	29.45	29.26	29.13
	50:1	26.97	26.91	26.77	26.57	26.42
	100:1	25.84	25.78	25.64	25.43	25.24
	200:1	24.93	24.85	24.66	24.36	24.02
Saturn	2:1	80.98	80.36	80.48	80.71	80.91
	16:1	50.84	51.01	51.03	50.91	50.82
	50:1	46.35	46.84	46.77	46.47	46.22
	100:1	43.54	44.29	44.08	43.56	43.04
	200:1	40.45	41.38	40.78	39.77	38.52

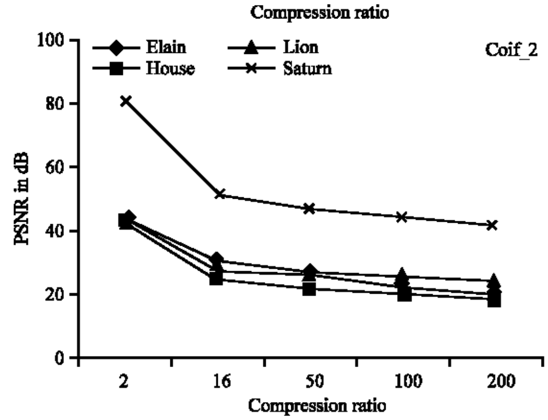
Table 5: Wavelet family: Symlet

Image	C R	PSNR (in dB) 2.2	2.4	4.4	5.5	6.8
Elaine	2:1	43.03	43.10	43.22	43.21	43.11
	16:1	30.24	30.39	30.41	30.35	30.06
	50:1	26.36	26.25	26.22	25.96	25.46
	100:1	24.02	23.59	23.60	23.23	22.46
	200:1	21.89	21.37	20.75	20.16	19.05
House	2:1	41.83	42.26	42.55	42.52	42.63
	16:1	24.46	24.69	24.85	24.82	24.72
	50:1	21.04	21.11	21.14	21.10	20.98
	100:1	19.59	19.57	19.53	19.49	19.35
	200:1	18.41	18.35	18.22	18.12	17.99
Lion	2:1	42.71	42.77	42.87	42.86	42.86
	16:1	29.62	29.58	29.65	29.59	29.55
	50:1	26.99	26.97	27.00	26.95	26.89
	100:1	25.88	25.88	25.87	25.83	25.78
	200:1	24.99	25.01	24.97	24.92	24.87
Saturn	2:1	80.09	79.11	80.20	80.08	80.18
	16:1	50.58	50.81	51.04	51.18	51.08
	50:1	46.40	46.83	46.94	46.91	46.89
	100:1	43.96	44.43	44.49	44.42	44.32
	200:1	41.23	41.66	41.80	41.60	41.33









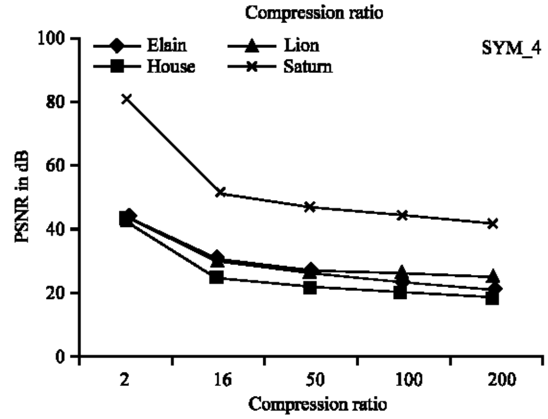


Fig. 5: Comparison of compression performance in terms of PSNR values with wavelets provides better results in their respective wavelet family on test image

Here, we have given the experimental results for the wavelets which provide better PSNR in their corresponding wavelet families. The comparison of PSNR values of five wavelet families for wavelet functions provides better compression performance for test images are shown in Fig. 5. We are also presenting compression results of test images in terms of visual quality for different wavelet functions for wavelet Families. The visual quality results of image are shown in Fig. 6.

All of these images shown have been compressed at the compression ratio of 100:1 each at decomposition level of 5. The presented results shown that wavelet function RBIO_1.3, DB_3, and SYM_4 provides the better compression results in terms of peak signal to noise ratios (PSNR) values in their respective families for the test images. While BIOR_2.2 and BIOR_4.4 in Biorthogonal family and COIF_1 and COIF_2 in Coiflet family gives the competitive PSNR results in their families. When we

Fig. 6 (a): Compression Results of image Elaine (i) original image (ii) Reconstructed image using wavelet BIOR_2.2 (iii) Reconstructed image using wavelet RBIO_3.1, each at compression ratio of 100:1 and decomposition level 5

Fig. 6 (b): Compression Results of image House (i) original image (ii) Reconstructed image using wavelet RBIO_1.3 (iii) Reconstructed image using wavelet RBIO_3.1, each at compression ratio of 100:1 and decomposition level 5

Fig. 6 (c): Compression Results of image Lion (i) original image (ii) Reconstructed image using wavelet RBIO_1.3 (iii) Reconstructed image using wavelet RBIO_3.1, each at compression ratio of 100:1 and decomposition level 5

Fig. 6 (d): Compression Results of image Saturn (i) original image (ii) Reconstructed image using wavelet BIOR_4.4 (iii) Reconstructed image using wavelet RBIO_3.1, each at compression ratio of 100:1 and decomposition level 5.

analyze the results, it found that the wavelet function RBIO_1.3 gives the better compression performance for the small size images and the wavelet function BIOR_4.4 gives the better compression performance for large size images in terms of PSNR values. While both wavelet functions BIOR_4.4 and RBIO_1.3 shown the competitive compression performance for the medium size images. The analysis and comparison of the results shown that not only in the RBIO family, the wavelet function RBIO_1.3 gives the better compression performance (in terms of PSNR) in all the wavelet families considered in our experiment. It is also noticed in the experimental results that wavelets Haar, DB_1, BIOR_1.1 and RBIO_1.1 are giving exactly the same PSNR values at each of the compression ratios for all the test images. The wavelet Dmey shows the poorest compression performance both in terms of PSNR and visual quality of image. For the compression performance in terms of visual image quality, the wavelet BIOR_2.2 provides the better results for the test image Elaine. While, the wavelet RBIO_1.3 for the images House and Lion and wavelet BIOR_4.4 for the image Saturn gives the better compression performance in terms of visual image quality. The wavelet RBIO_3.1 gives the poorest compression performance in terms of image quality. In all the studies, if the decomposition level increased the compression performance improves but the quality of image deteriorates. Further, it is also observed that the BIOR & RBIO wavelet families take much more computational time in comparison to other wavelet Families considered in our experiment.

CONCLUSION

This study presented an analysis and comparison of the wavelet families using for image compression considering PSNR and visual quality of image as quality measure. A comparative study of various wavelet families using for image compression on variety of test images has been done. The effects of Biorthogonal, Reverse Biorthogonal, Daubechies, Coiflets and Symlets wavelet families on test images have been examined. The compression ratio, PSNR and visual image quality for wavelet functions of each family is also presented. The Peak signal to noise ratio (PSNR) is taken as the objective measure for performance analysis of wavelets using for images compression. We analyzed the results for a wide range of wavelet families and found that the wavelet RBIO_1.3 provides best compression performance for all variety of images almost at all the compression ratio among all the families we have considered. The computational time required for the Biorthogonal & Reverse Biorthogonal wavelet families is more in comparison to other wavelet families. As far as the Image quality is concerned we got a fair image quality with wavelet RBIO_1.3 at the compression ratio 100:1 and decomposition level 5 for the test images. Hence, compression performance of wavelet function depends not only on the size of the image but also on the content and resolution of the images. Finally, we can conclude that the selection of wavelet for image compression depends on size, contents and resolution of the images for desired image quality.

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