ALGORITHM FOR IMPROVED IMAGE COMPRESSION AND RECONSTRUCTION PERFORMANCES

G.Chenchu Krishnaiah[1], T.Jayachandra Prasad[2], M.N. Giri Prasad[3]

[1]Department of ECE, GKCE, Sullurpet, AP, India
krishna.rakesh4@gmail.com
[2]Department of ECE, RGMCET, Nandyal, AP, India
[3]Department of ECE, JNTUCE, Anantapur, AP, India

ABSTRACT

Energy efficient wavelet image transform algorithm (EEWITA) which is capable of evolving non-wavelet transforms consistently outperform wavelets when applied to a large class of images subject to quantization error. An EEWITA can evolve a set of coefficients which describes a matched forward and inverse transform pair that can be used at each level of a multi-resolution analysis (MRA) transform to minimize the original image size and the mean squared error (MSE) in the reconstructed image. Simulation results indicate that the benefit of using evolved transforms instead of wavelets increases in proportion to quantization level. Furthermore, coefficients evolved against a single representative training image generalize to effectively reduce MSE for a broad class of reconstructed images. In this paper an attempt has been made to perform the comparison of the performances of various wavelets and non-wavelets.

Experimental results were obtained using different types of wavelets and non-wavelets for different types of photographic images (color and monochrome). These results concludes that the EEWITA method is competitive to well known methods for lossy image compression, in terms of compression ratio (CR), mean square error (MSE), peak signal to noise ratio (PSNR), encoding time, decoding time and transforming time or decomposition time. This analysis will help in choosing the wavelet for decomposition of images as required in a particular applications.

KEYWORDS

Wavelets, EEWITA, Quantization, Multi-resolution Analysis, Image Processing, Evolved wavelets, Image compression, Algorithms, Performances and Reconstruction

1. INTRODUCTION

Since the late 1980s, engineers, scientists, and mathematicians have used wavelets [1] to solve a wide variety of difficult problems, including fingerprint compression, signal denoising, and medical image processing. The adoption of the joint photographic experts group's JPEG2000 standard [2] has established wavelets as the primary methodology for image compression and reconstruction [3]. Wavelets may be described by four sets of coefficients:

1. hl is the set (collection) of wavelet numbers for the forward discrete wavelet transform (DWT).
2. gl is the set (collection) of scaling numbers for the DWT.
3. h2 is the set (collection) of wavelet numbers for the inverse DWT (DWT^{-1}).
4. g2 is the set (collection) of scaling numbers for the DWT^{-1}.

For the Daubechies – 4 (D4) wavelet, these sets consist of the following floating point coefficients:

DOI : 10.5121/sipij.2012.3206

h1={-0.1294, 0.2241, 0.8365, 0.4829}

g1={-0.4830, 0.8365, -0.2241, -0.1294}

h2={0.4830, 0.8365, 0.2241, -0.1294}

g2={-0.1294, -0.2241, 0.8365, -0.4830}

A two- dimensional (2D) DWT [4]of a discrete input image *f* with M rows and N columns is computed by first applying the one-dimensional (1D) subband transform defined by the coefficients from sets h1 and g1 to the columns of *f*, and then applying the same transform to the rows of the resulting signal [2]. Similarly, a 2D DWT^{-1} is performed by applying the 1D inverse wavelet transform defined by sets h2 and g2 first to the rows and then to the columns of a previously compressed signal.

A one-level DWT decomposes f into M/2-by-N/2 subimages h^1, d^1, a^1, and v^1, where a^1 is the trend subimage of *f* and h^1, d^1, and v^1 are its first horizontal, diagonal, and vertical fluctuation subimages, respectively. Using the multi-resolution analysis (MRA) scheme [3], a one-level wavelet transform may be repeated $k \leq \log_2(\min(M, N))$ times. The size of the trend signal a^i at level i of decomposition is $1/4^i$ times the size of the original image *f* (e.g., a three level transform produces a trend subimage a^3 that is $1/64^{th}$ the size of *f*). Nevertheless, the trend subimage will typically be much larger than any of the fluctuation subimages; for this reason, the MRA scheme computes a k-level DWT by recursively applying a one-level DWT to the rows and columns of the discrete trend signal a^{k-1}. Similarly, a one-level DWT^{-1} is applied k times to reconstruct an approximation of the original M-by-N signal *f*.

Quantization is the most common source of distortion in lossy image compression systems. Quantization refers to the process of mapping each of the possible values of given sampled signal y onto a smaller range of values Q(y). The resulting reduction in the precision of data allows a quantized signal q to be much more easily compressed. The corresponding dequantization step, $Q^{-1}(q)$, produces signal $\hat{y}$ that differs from the original signal y according to a distortion measure ρ. Different kinds of techniques may be used to quantify distortion; however, if quantization errors are uncorrelated, then the aggregate distortion $\rho(y, \hat{y})$ in the dequantized signal may be computed as a linear combination of MSE for each sample.

2. RELATED WORK

Joseph Fourier invented a method to represent a signal with a series of coefficients based on an analysis function in 1807. He laid the mathematical basis on which the wavelet theory is developed. The first mention of wavelets was by Alfred Haar in 1909 in his PhD thesis. In the 1930's, Paul Levy found the scale-varying Haar basis function superior to Fourier basis functions. Again in 1981, the transformation method of decomposing a signal into wavelet coefficients and reconstructing the original signal was derived by Jean Morlet and Alex Grossman. The Discrete Wavelet Transform (DWT) has become a very versatile signal processing tool over the last two decades.

In fact, it has been effectively used in signal and image processing applications ever since 1986 when Mallat [5] proposed the multiresolution representation of signals based on wavelet decomposition. They mentioned the scaling function of wavelets for the first time; allowing researchers and mathematicians to construct their own family of wavelets. The main advantage of DWT over the traditional transformations is that it performs multiresolution analysis of signals with localization both in time and frequency. Today, the DWT is being increasingly used for image compression since it supports many features like progressive image transmission (by quality, by resolution), ease of compressed image manipulation, region of interest coding, etc.

Wavelets being the basic, a number of algorithms such as EZW (Shapiro 1993) and Adaptive and energy efficient wavelet image compression are becoming popular. In around 1998, Ingrid Daubechies used the theory of multiresolution wavelet analysis to construct her own family of wavelets using the derived criteria. This set which consist of wavelet orthonormal basis functions have become the cornerstone of wavelet applications today. She worked to the most extremes of theoretical treatment of wavelet analysis.

Recently, a new mathematical formulation for wavelet transformation has been proposed by Swelden [6] based on spatial construction of the wavelets and a very versatile scheme for its factorization has been suggested in [7]. This approach is called the lifting-based wavelet transform or simply lifting. The main feature of the lifting-based DWT scheme is to break up the high-pass and low-pass wavelet filters into a sequence of upper and lower triangular matrices, and convert the filter design into banded matrix multiplications [7]. This scheme often requires far fewer computations compared to the convolution based DWT [6,7] and offers many other advantages. In this paper an attempt has been made to evaluate the performance of Lifting based and Non-lifting based wavelet transforms.

2.1 Lifting Based Wavelet Transforms: 9/7 and 5/3

There are two operational modes of the JPEG 2000 standard: Loss-less and Lossy [2]. In the loss-less mode, the reconstruction of the compressed imagery is an exact replica of the original image. For lossy modes perfect reconstruction of the original image is sacrificed for compression gain. For most applications, the lossy mode is preferred because of its added compression gain and comparable visual image quality at low-to- moderate compression ratios. In each of the JPEG 2000 operational modes, there exists a separate wavelet transform. The integer 5/3 transform is used in the lossless mode, and the lossy mode utilizes the Cohen-Daubechies- Feauvea (CDF) 9/7 transform.

The CDF 9/7 transform uses floating-point coefficients in its transform filters, which donot lend themselves to a straight forward computational architecture for embedded parallel processing. In addition, proper quantization of the CDF 9/7 wavelet coefficients is not an integer operation [2]. In [8] integers transforms are investigated in the context of image compression, investigating specifically both the 5/3 and CDF 9/7 wavelet transforms. Also, [9] investigates a different computational process for the lifting implementation of several wavelet transforms, including the CDF 9/7 transform, and integer implementation of the transforms. Additionally, [10] develops a different method to lifting of the CDF 9/7 transform for efficient integer computation as well. Bi-orthogonal CDF 5/3 wavelet for lossless compression and a CDF 9/7 wavelet for lossy compression are the standards in JPEG 2000 [11].

3. Energy Efficient Wavelet Image Transform Algorithm (EEWITA)

In this section, we present *EEWITA* [12], a wavelet-based transform algorithm which aims to minimize computation energy (by reducing the number of arithmetic operations and correspondingly memory accesses) and communication energy (by reducing the quantity of transmitted data). The algorithm also aims at effecting energy savings while minimally impacting the quality of the reconstructed image [13]. *EEWITA* exploits the numerical distribution of the high-pass filter coefficients to judiciously eliminate a large number of samples from consideration in the image compression process. Fig. 1 illustrates the distribution of high-pass filter coefficients after applying a 2 level wavelet transform to the 512 X 512 Lena image sample [14].

We observe that the high-pass filter coefficients are generally represented by small integer values. For example, 80 % of the high-pass filter coefficients for level 1 are less than 5. Because of the numerical distribution of the high-pass filter coefficients and the effect of the quantization step on small valued coefficients, we can estimate the high-pass filter coefficients to be zeros (and hence avoid computing them) and incur minimal image quality loss.

This approach has two main advantages [15]. First, as the high pass filter coefficients need not be calculated, *EEWITA* helps to reduce the *computation energy* consumed during the wavelet image compression process by reducing the number of executed operations. Second, because the encoder and decoder know the estimation technique, no information needs to be transmitted across the wireless channel regarding the technique, thereby reducing the *communication energy* required.

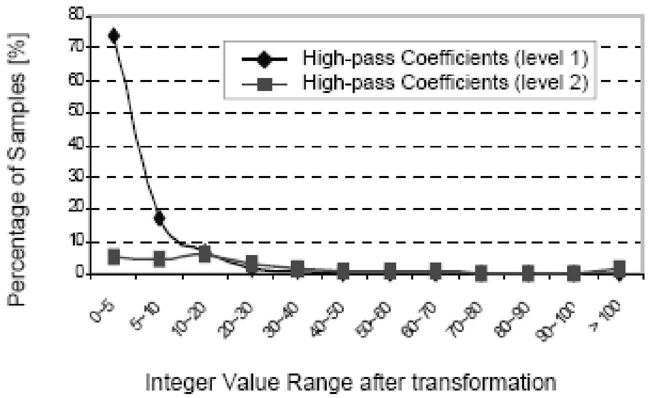

Fig. 1. Numerical distribution of high-pass filter coefficients after wavelet transform through level 2.

Using the estimation technique, which was presented, we have developed our *EEWITA* which consists of two techniques attempting to conserve energy by avoiding the computation and communication of high-pass filter coefficients: The first technique attempts to save energy by eliminating the least significant subband. Among the four subbands, we find that the diagonal subband (HHi) is least significant (Fig. 1), so that it will be the best candidate for elimination during the wavelet transform step.

We call this technique "*HH elimination*". In the second scheme, only the most significant subband (low-resolution information, LLi) is preserved and all high-pass subbands (LHi, HLi, and HHi) are eleminated. We call this as "*H* elimination*", because all high-pass subbands are removed in the transform step. We next present details of the HH and H* elimination techniques, and compare the energy efficiency of these techniques with the original AWIC algorithm [16] which refers to the wavelet transform algorithm.

3.1Energy Efficiency of HH Elimination Techniques

To implement the HH and H* elimination or elimination techniques (*EEWITA*), we modify the wavelet transform step as shown in Fig. 2. During the wavelet transform, each input image goes through the row and column transform by which the input image can be decomposed into four subbands (LL, LH, HL, HH). However, to implement the HH elimination technique, after the row transform, the high-pass filter coefficients are only fed into the low-pass filter, and not the high-pass filter in the following column transform step (denoted by the lightly shaded areas in Fig. 2 under <HH Elimination>). This process avoids the generation of a diagonal subband (HH).

To implement the H* elimination or removal technique, the input image is processed through only the low-pass filter during both the row and column transform steps (shown by the lightly shaded areas under <H* Elimination>). We can therefore remove all high-pass decomposition steps during the transform by using the H* elimination technique (*EEWITA*) to estimate the energy efficiency of the elimination techniques (*EEWITA*) presented, we measure the computational and data access loads using the same method. We assume the elimination techniques are applied to the first E transform levels out of the total L transform levels. This is because the advantage of eliminating high-pass filter coefficients is more significant at lower transform levels. In the HH elimination technique, the computation load during the row transform is the same as the computation load with the AWIC algorithm [16].

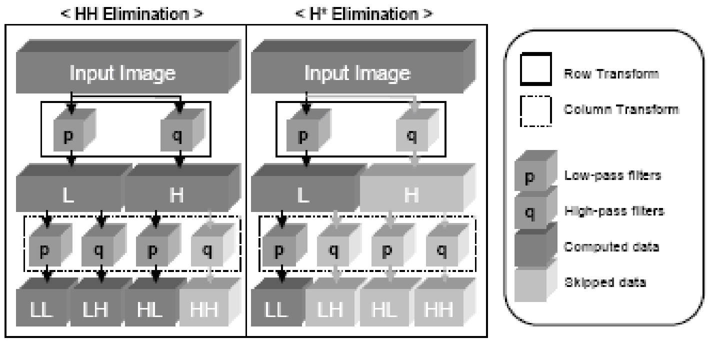

Fig. 2. Data flow of the wavelet transform step with HH/H*.

However, during the column transform of the high-pass subband resulting from the previous row transform, the high-pass subband (HH) is not calculated. The results show that this leads to a savings of 1/4MN(4A+2S) operation units of computational load (7.4 % as compared to the AWIC algorithm). Therefore, the total computational load when using HH elimination is represented as:

$$\text{Computational load } C_{HH} = \frac{MN(22A+19S)}{2}\sum_{i=1}^{E}\frac{1}{4^{i-1}} + MN(12A+10S)\sum_{i=E+1}^{L}\frac{1}{4^{i-1}}$$

Because the high-pass subband resulting from the row transform is still required to compute the HL subband during the column transform, we cannot save on “read” accesses using the HH removal technique. However, we can save on a quarter of “write” operations (12.5 % savings) during the column transform since the results of HH subband are pre-assigned to be zeros before the transform is calculated. Thus, the total data-access load is given by:

$$\text{Data-access load } C_{READ\_HH} = C_{READ\_AWTC},\ C_{WRITE\_HH} = \frac{7}{4}MN\sum_{i=1}^{E}\frac{1}{4^{i-1}} + 2MN\sum_{i=E+!}^{L}\frac{1}{4^{i-1}}$$

4. ONE TRANSFORM FOR ALL MRA LEVELS

Evolving coefficients for an inverse non-wavelet transform ([17][18]) or a matched forward and inverse non-wavelet transform pair [19] that reduced mean square error (MSE) relative to the performance of a standard wavelet transform applied to the same images under conditions subject to a quantization . The resulting transforms consistently reduced MSE by as much as 25% when applied to images from both the training and test sets. Unfortunately, none of these previous studies involved MRA; instead, coefficients were optimized only for one-level image decomposition and/or reconstruction transforms. Subsequent testing demonstrated that the performance of these transforms degraded substantially when tested in a multi-resolution environment.

In practice, virtually all wavelet-based compression schemes entail several stages of decomposition. Typical wavelet-based MRA applications compress a given image by recursively applying the h1 and g1 coefficients a defining single DWT at each of k levels. Image reconstruction requires k recursive applications of the h2 and g2 coefficients defining the corresponding DWT^{-1}. The JPEG2000 standard allows between 0< k< 32 DWT stages; near-optimal performance on full-resolution images is reported for D = 5 levels [2].

The first goal of this research effort was to determine whether an EEWITA could evolve a single set of coefficients for a matched evolved forward and inverse transform pair satisfying each of the following conditions:

1. The evolved coefficients were intended for use at each and every level of decomposition by a matched multi-level transform pair.
2. The evolved forward transform produced compressed files whose size was less than or equal to those produced by the DWT.
3. When applied to the compressed file produced by the matching evolved forward transform, the evolved inverse transform produced reconstructed images whose MSE was less than or equal to the MSE observed in images reconstructed by the DWT^{-1} from files previously compressed by the DWT.

5. SIMULATION RESULTS

In this work, different types of wavelets are considered for image compression. Here the major concentration is to verify the comparison between Hand designed wavelets and Lifting based wavelets. Hand designed wavelets considered in this work are Haar wavelet, Daubechie wavelet, Biorthognal wavelet, Demeyer wavelet, Coiflet wavelet and Symlet wavelet. Lifting based wavelet transforms considered are 5/3 and 9/7. Wide range of images, including both color and gray scale images were considered. The algorithms are implemented in MATLAB. The GUI used in the work was given in the figures 3, 4, 5, 6, 7, 8, 9 and 10 respectively. In the tables 1 to 11 respectively, the performance of hand designed and lifting based wavelet transform is presented. The performance of Hand designed and lifting based wavelet transforms on Rice images was analysed and plotted in figures 11to 16 respectively.

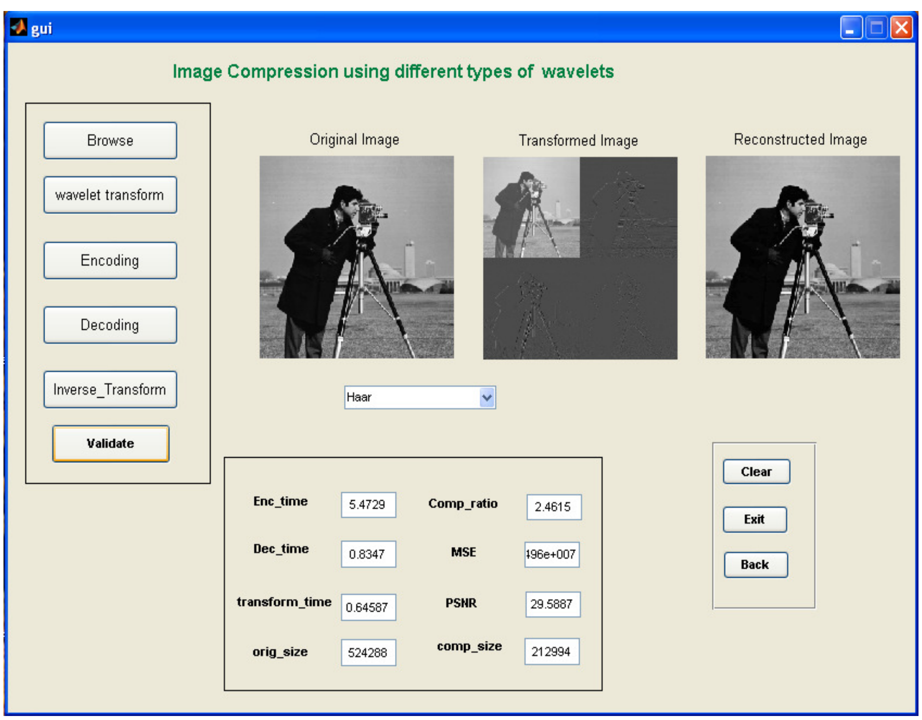

Figure 3. Sample Screen Shot of Haar Wavelet.

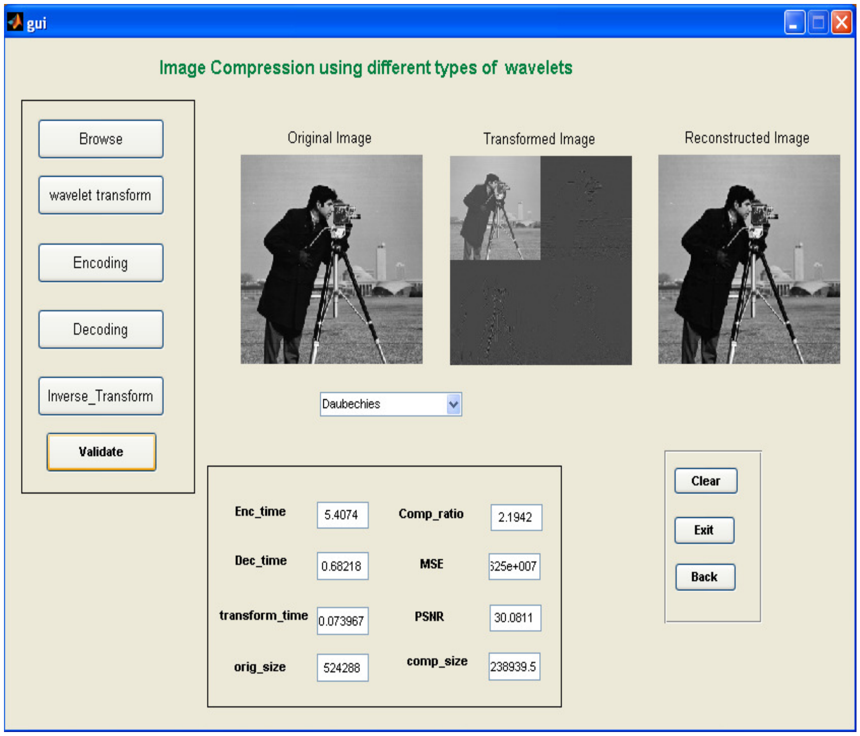

Figure 4. Sample Screen Shot of Daubechie Wavelet.

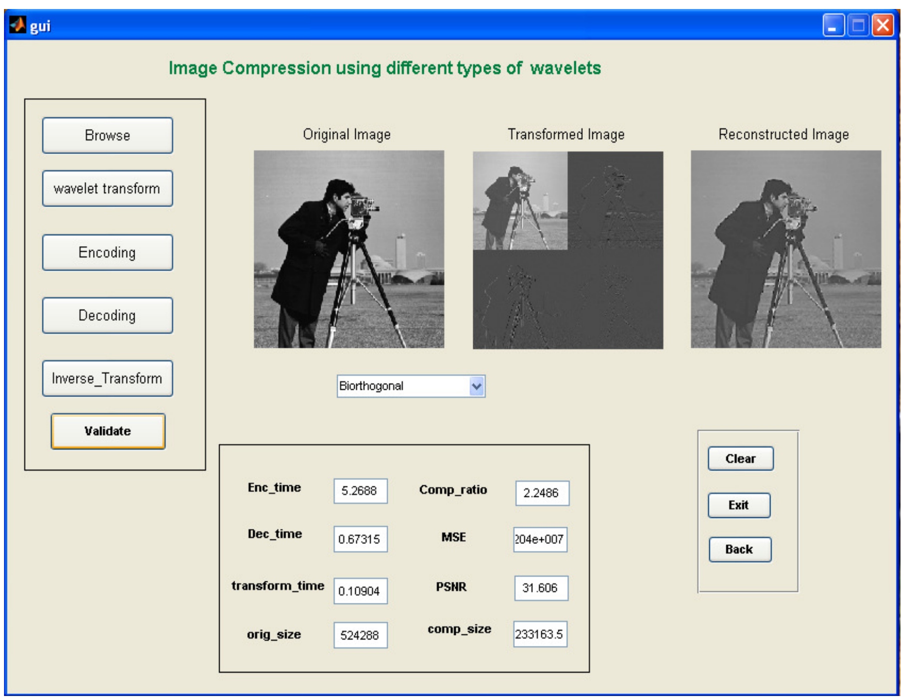

Figure 5. Sample Screen Shot of Biorthogonal Wavelet.

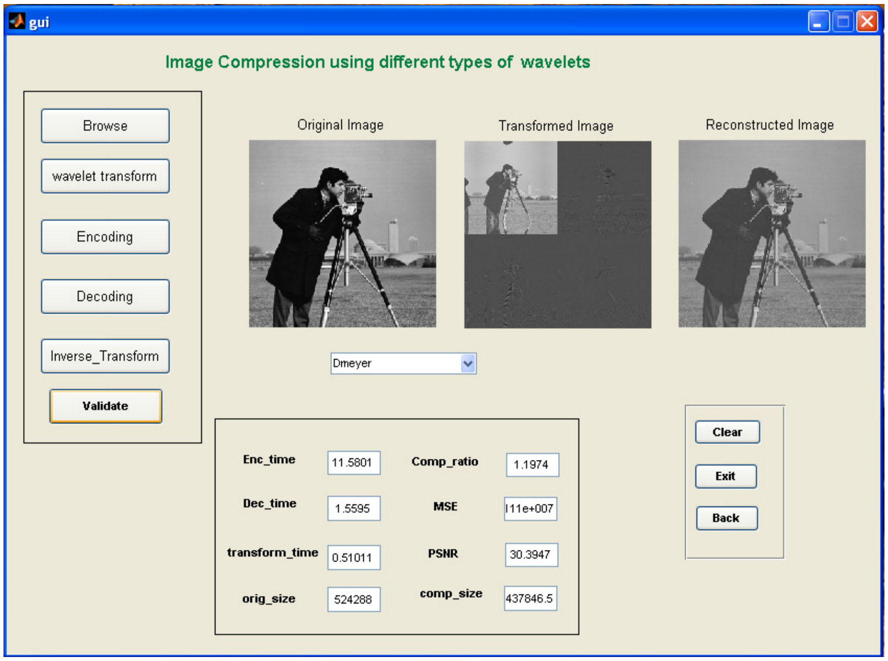

Figure 6. Sample Screen Shot of Demeyer Wavelet.

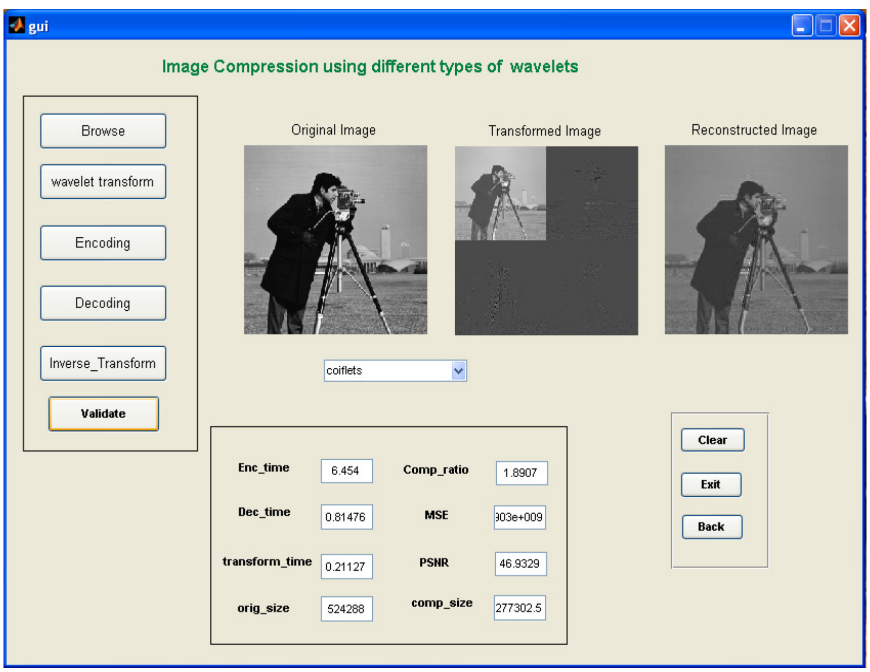

Figure 7. Sample Screen Shot of Coiflet Wavelet.

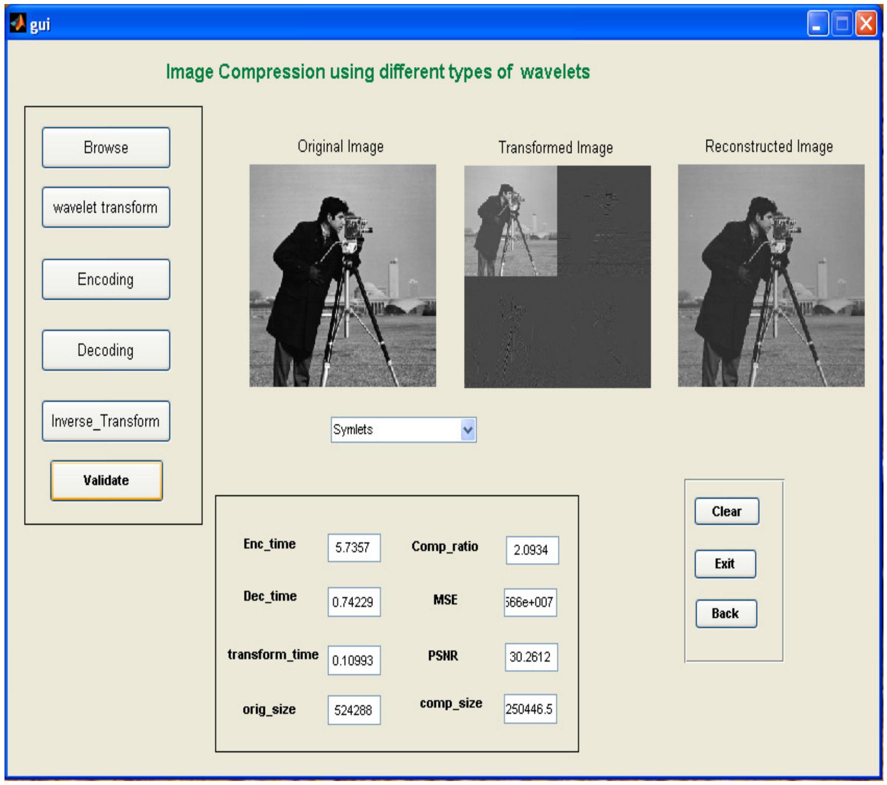

Figure 8. Sample Screen Shot of Symlet Wavelet.

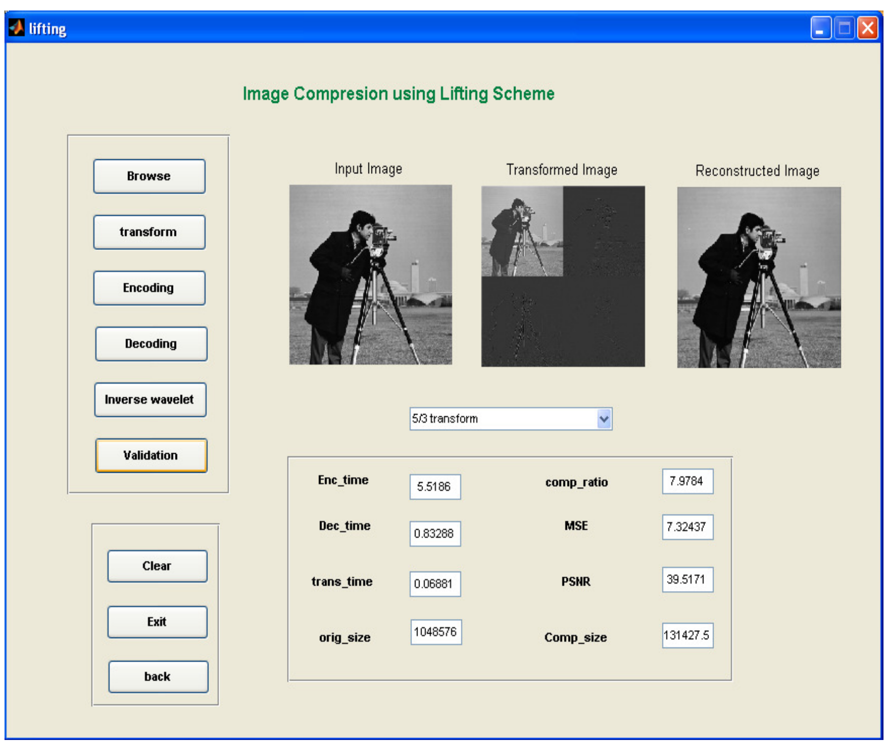

Figure 9. Sample Screen Shot of 5/3 Lifting based Wavelet transform.

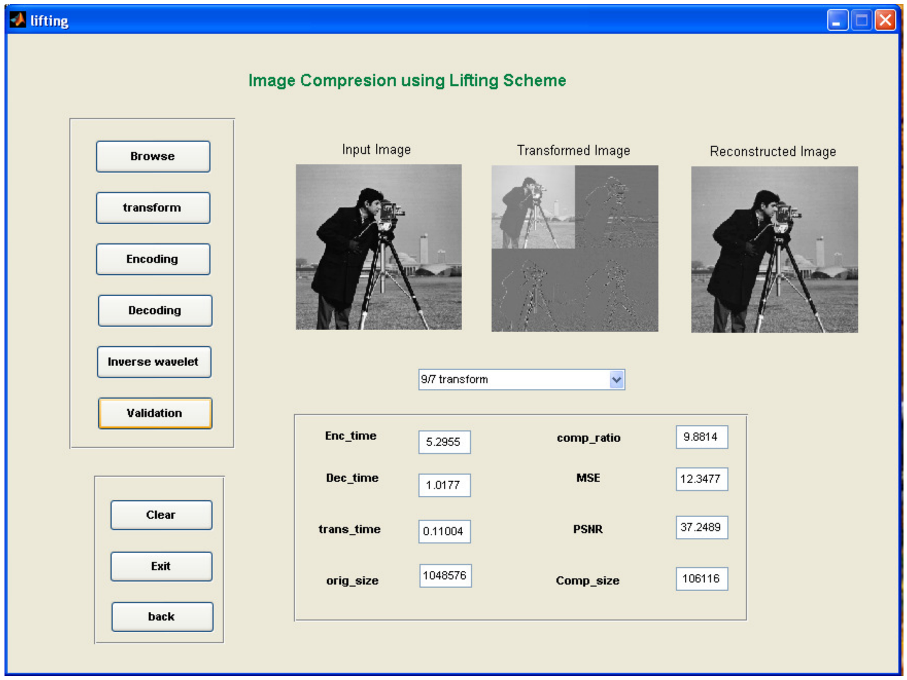

Figure 10. Sample Screen Shot of 9/7 Lifting based Wavelet transform.

Table 1. Performance comparison between Hand designed and Lifting based wavelet transforms on 'Cameraman' (Gray) image.

	HAND DESIGNED WAVELETS							LIFTING BASED WAVELET TRANSFORMS	
INPUT IMAGE	PERFORMANCE CRITERION	HAAR	DAUBECHIE	BIORTHOGONAL	DEMEYER	COIFLET	SYMLET	5/3 TRANSFORM	9/7 TRANSFORM
CAMERA MAN (Gray)	ENC_TIME (SEC)	6.0226	6.6047	6.3633	7.2604	8.1205	7.0007	6.9664	6.6507
	DEC_TIME (SEC)	0.8724	0.94074	0.90272	1.1382	1.1428	1.0361	1.1418	1.4065
	TRANS_TIME (SEC)	0.061623	0.1072	0.071691	0.27447	0.19392	0.10731	0.16648	0.20735
	ORG_SIZE (BITS)	524288	524288	524288	524288	524288	524288	1048576	1048576
	COMP_SIZE (BITS)	212994	238939.5	233163.5	437846.5	277302.5	250446.5	131427.5	106116
	COMP_RATIO	2.4615	2.1942	2.2486	1.1974	1.8907	2.0934	7.9784	9.8814
	MSE(dB)	5.91496	6.625	9.4120	7.1211	3.20903	6.90566	7.32437	12.3477
	PSNR(dB)	29.5887	30.0811	31.606	30.3947	46.9329	30.2612	39.51712	37.2489

Table 2. Performance comparison between Hand designed and Lifting based wavelet transforms on 'Lena' (Gray) image.

	HAND DESIGNED WAVELETS							LIFTING BASED WAVELET TRANSFORMS	
INPUT IMAGE	PERFORMANCE CRITERION	HAAR	DAUBECHIE	BIORTHOGONAL	DEMEYER	COIFLET	SYMLET	5/3 TRANSFORM	9/7 TRANSFORM
LENA (Gray)	ENC_TIME (sec)	5.8231	5.8567	6.0125	5.7795	6.9629	6.1638	6.7189	6.5232
	DEC_TIME (sec)	0.73565	0.55961	0.67233	0.5768	0.68106	0.6333	0.80277	1.2982
	TRANS_TIME (sec)	0.066121	0.086909	0.10446	0.27443	0.17855	0.11798	0.18788	0.24167
	ORG_SIZE (BITS)	524288	524288	524288	524288	524288	524288	1048576	1048576
	COMP_SIZE (BITS)	203487.5	201098	209046.5	356765.5	228878	209811.5	116920	102169
	COMP_RATIO	2.5765	2.6071	2.508	1.4696	2.2907	2.4989	8.9683	10.2632
	MSE(dB)	6.30228	6.80418	8.04372	6.81522	5.25666	6.77618	4.56708	5.17308
	PSNR(dB)	29.8642	30.197	30.9238	30.204	49.0763	30.179	41.5684	41.0273

Table 3. Performance comparison between Hand designed and Lifting based wavelet transforms on 'Sunflower' (color) image.

	HAND DESIGNED WAVELETS							LIFTING BASED WAVELET TRANSFORMS	
INPUT IMAGE	PERFORMANCE CRITERION	HAAR	DAUBECHIE	BIORTHOGONAL	DEMEYER	COIFLET	SYMLET	5/3 TRANSFORM	9/7 TRANSFORM
SUNFLOWER (color)	ENC_TIME (sec)	6.7218	7.3878	7.177	8.2923	8.9928	7.7673	7.2858	6.6155
	DEC_TIME (sec)	1.4615	1.3933	1.5401	1.5794	1.7247	1.4471	1.9508	1.3733
	TRANS_TIME (sec)	0.17572	0.20209	0.18348	0.30824	0.27432	0.23079	0.16963	0.22143
	ORG_SIZE (bits)	524288	524288	524288	524288	524288	524288	1048576	1048576
	COMP_SIZE (bits)	237455	260095	259495	469884.5	299713	271815	138935	15919.75
	COMP_RATIO	2.2079	2.0158	2.0204	1.1158	1.7493	1.9288	7.5472	9.0457
	MSE(dB)	5.97118	6.42763	7.39799	6.53916	2.02501	6.54834	5.24655	26.5756
	PSNR(dB)	29.6298	29.9497	30.5603	30.0244	44.9335	30.0305	4o.9661	33.92

Table 4. Performance comparison between Hand designed and Lifting based wavelet transforms on 'Lillie' (color) image.

	HAND DESIGNED WAVELETS							LIFTING BASED WAVELET TRANSFORMS	
INPUT IMAGE	PERFORMANCE CRITERION	HAAR	DAUBECHIE	BIORTHOGONAL	DEMEYER	COIFLET	SYMLET	5/3 TRANSFORM	9/7 TRANSFORM
LILLIE (color)	ENC_TIME (sec)	5.6309	5.2248	5.8246	5.0598	6.1163	5.7379	6.1691	6.1164
	DEC_TIME (sec)	0.59962	0.43903	0.6651	0.40199	0.51453	0.43718	0.63373	1.1184
	TRANS_TIME(sec)	0.61791	0.1975	0.16579	0.30806	0.27792	0.22081	0.12439	0.18936
	ORG_SIZE (BITS)	524288	524288	524288	524288	524288	524288	1048576	1048576
	COMP_SIZE (BITS)	196066.5	200910.5	217488.5	365371	231754.5	209872	118595.5	98362
	COMP_RATIO	2.674	2.6096	2.4106	1.4349	2.2623	2.4981	8.8416	10.6604
	MSE(dB)	5.9984	2.6733	7.70395	2.68621	5.0455	2.69776	3.36575	5.60411
	PSNR(dB)	29.6495	36.1397	30.7363	36.1606	48.8982	36.1792	42.894	40.6797

Table 5. Performance comparison between Hand designed and Lifting based wavelet transforms on 'Fruits' (Gray) image.

	HAND DESIGNED WAVELETS							LIFTING BASED WAVELET TRANSFORMS	
INPUT IMAGE	PERFORMANCE CRITERION	HAAR	DAUBECHIE	BIORTHOGONAL	DEMEYER	COIFLET	SYMLET	5/3 TRANSFORM	9/7 TRANSFORM
FRUITS (Gray)	ENC_TIME (sec)	6.9861	7.6709	7.4476	8.7281	9.3715	8.0347	7.3107	7.2539
	DEC_TIME (sec)	1.9407	1.6508	2.0104	2.124	2.0116	1.7352	2.1795	2.2689
	TRANS_TIME(sec)	0.16268	0.2077	0.1703	0.3134	0.29459	0.20992	0.14885	0.20697
	ORG_SIZE (BITS)	524288	524288	524288	524288	524288	524288	1048576	1048576
	COMP_SIZE (BITS)	251212.5	270295	272905.5	490304	311316	281550	143311.5	22494.25
	COMP_RATIO	2.087	1.9397	1.9211	1.0693	1.6841	1.8621	7.3168	8.5602
	MSE(dB)	5.98069	6.70372	8.52262e	6.96556	1.67402	7.03581	8.71054	27.0535
	PSNR(dB)	29.6367	30.1324	31.1749	30.2988	44.1068	30.3423	38.7643	33.8426

Table 6. Performance comparison between Hand designed and Lifting based wavelet transforms on 'Cat' (Color) image.

	HAND DESIGNED WAVELETS							LIFTING BASED WAVELET TRANSFORMS	
INPUT IMAGE	PERFORMANCE CRITERION	HAAR	DAUBECHIE	BIORTHOGONAL	DEMEYER	COIFLET	SYMLET	5/3 TRANSFORM	9/7 TRANSFORM
Cat (color)	ENC_TIME (sec)	5.8211	5.8023	6.0229	5.4969	6.8587	6.0716	6.594	6.6155
	DEC_TIME (sec)	0.79186	0.67384	0.85121	0.55731	0.73918	0.69678	0.91504	1.3733
	TRANS_TIME(sec)	0.17044	0.19319	0.18226	0.30651	0.26227	0.21288	0.17039	0.22143
	ORG_SIZE (BITS)	524288	524288	524288	524288	524288	524288	1048576	1048576
	COMP_SIZE (BITS)	206491.5	216712.5	226672.5	377265	245630.5	226170	124467	103274
	COMP_RATIO	2.539	2.4193	2.313	1.3897	2.1345	2.3181	8.4286	10.1528
	MSE(dB)	6.03144	6.73792	7.23869	6.80184	1.38312	6.81446	5.40396	5.54639
	PSNR(dB)	29.6734	30.1545	30.4658	30.1955	43.2778	30.2035	40.8377	40.7247

Table 7. Performance comparison between Hand designed and Lifting based wavelet transforms on 'Rice' (Gray) image.

	HAND DESIGNED WAVELETS							LIFTING BASED WAVELET TRANSFORMS	
INPUT IMAGE	PERFORMANCE CRITERION	HAAR	DAUBECHIE	BIORTHOGONAL	DEMEYER	COIFLET	SYMLET	5/3 TRANSFORM	9/7 TRANSFORM
RICE (Gray)	ENC_TIME (sec)	5.2331	5.4948	5.4834	5.3036	6.5248	5.5657	6.045	5.8933
	DEC_TIME (sec)	0.75507	0.45913	0.7423	0.46345	0.52074	0.45172	0.75283	0.86909
	TRANS_TIME(sec)	0.06112	0.11653	0.071976	027458	0.2022	9.11851	0.16524	0.25272
	ORG_SIZE (BITS)	524288	524288	524288	524288	524288	524288	1048576	1048576
	COMP_SIZE (BITS)	193504	204136	213764	365423	233693	212771	117693	96596.75
	COMP_RATIO	2.7094	2.5683	2.4526	1.4347	2.2435	2.4641	8.9094	10.8552
	MSE(dB)	5.61395	6.79976	7.1816	6.85833	1.00646	6.90449	4.46945	20.5165
	PSNR(dB)	29.3619	30.1941	30.4314	30.2314	41.8972	30.2605	41.6623	35.0438

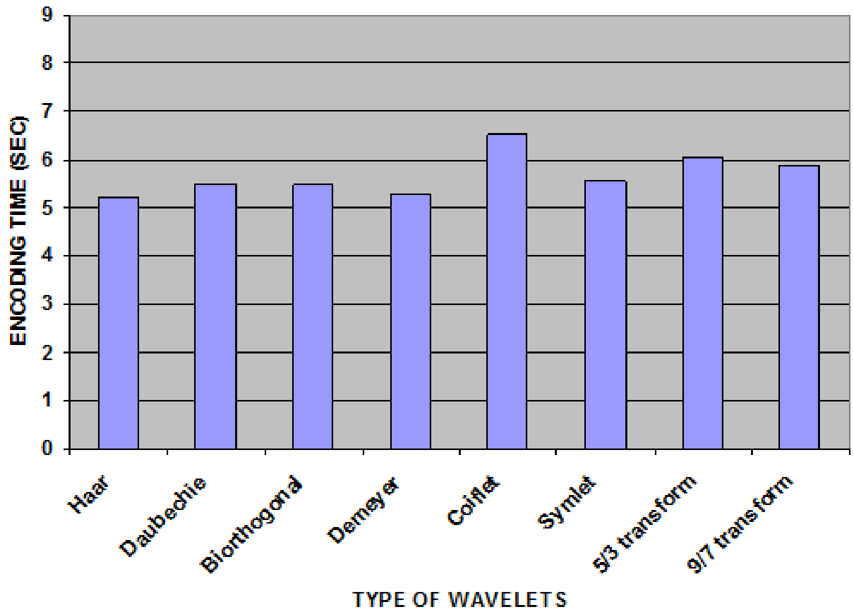

Figure 11. Encoding time values of various wavelets and non wavelets for Rice image (monochrome).

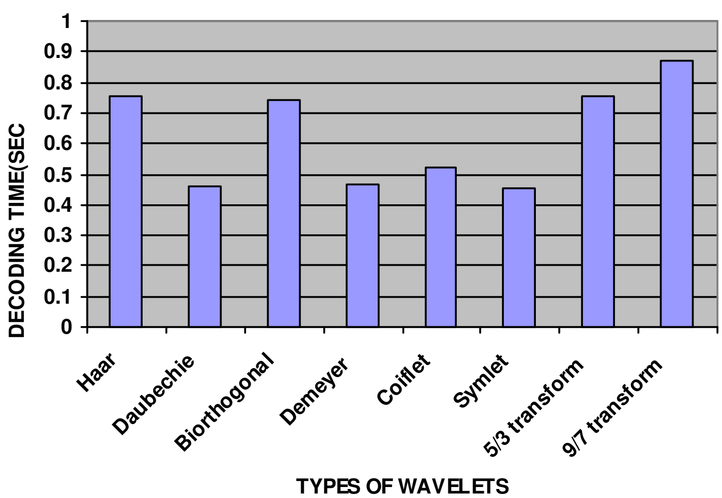

Figure 12**.** Decoding time values of various wavelets and non wavelets for Rice image (monochrome).

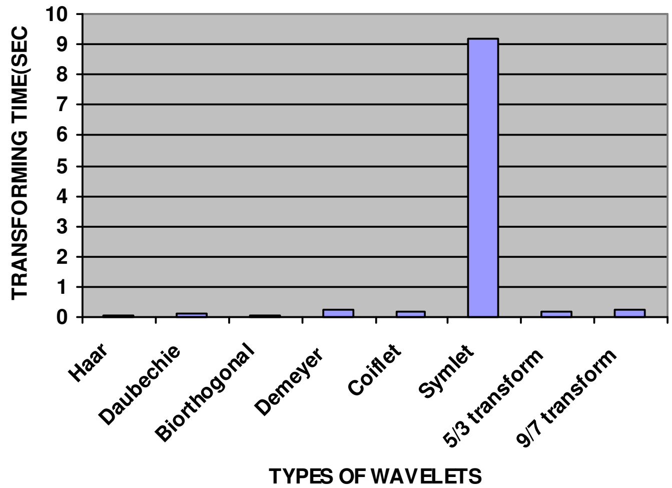

Figure 13. Transforming/Decomposition time
values of various wavelets and non wavelets for Rice image (monochrome).

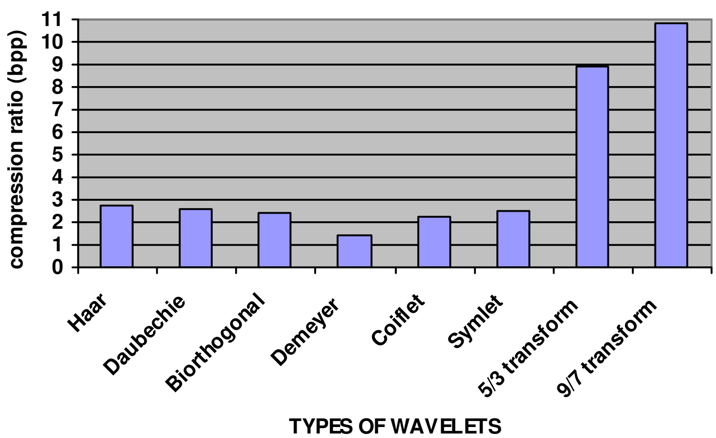

Figure 14. Compression Ratio values of various wavelets and nonwavelets
forRiceimage(monochrome).

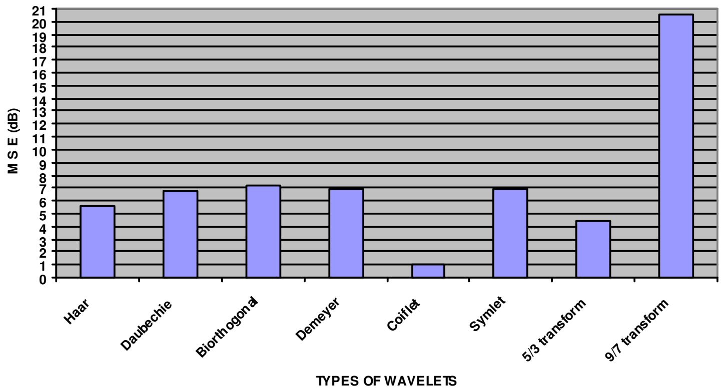

Figure 15. MSE values of various wavelets and non wavelets for Rice image (monochrome).

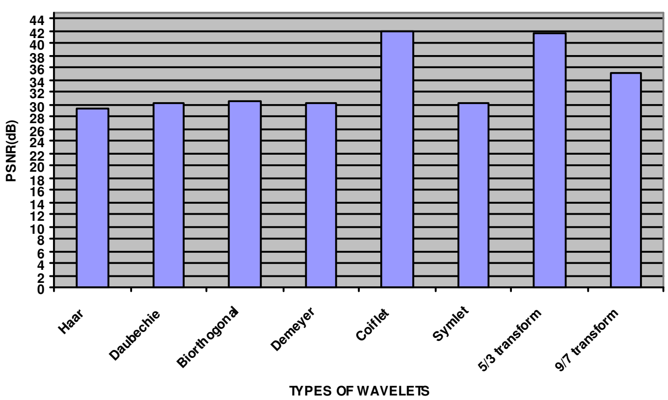

Figure 16. PSNR values of various wavelets and non wavelets for Rice image (monochrome)

Table 8. Performance comparison between Hand designed and Lifting based wavelet transforms on 'Greens' (color) image.

	HAND DESIGNED WAVELETS							LIFTING BASED WAVELET TRANSFORMS	
INPUT IMAGE	PERFORMANCE CRITERION	HAAR	DAUBECHIE	BIORTHOGONAL	DEMEYER	COIFLET	SYMLET	5/3 TRANSFORM	9/7 TRANSFORM
Greens (color)	ENC_TIME (sec)	7.1617	7.7902	7.5508	10.3992	9.4499	8.2988	7.4605	7.4213
	DEC_TIME (sec)	2.1937	2.0201	2.3267	2.4485	2.4283	2.1067	1.6689	2.5183
	TRANS_TIME(sec)	2.4525	0.19619	0.18629	0.30635	0.24622	0.21751	0.16407	0.21511
	ORG_SIZE (BITS)	524288	524288	524288	524288	524288	524288	1048576	1048576
	COMP_SIZE (BITS)	257379.5	277824	280088.5	502128	319660	289495	46394.75	25163.75
	COMP_ RATIO	2.037	1.8871	1.8719	1.0441	1.6401	1.811	7.1627	8.3776
	MSE(dB)	5.99384	6.57416	1.04467	7.68425	1.45918	7.1852	22.7319	30.9628
	PSNR(dB)	29.6462	30.0476	32.059	30.7252	43.5103	30.4336	34.5984	33.2564

Table 9. Performance comparison between Hand designed and Lifting based wavelet transforms on 'Man' (color) image.

	HAND DESIGNED WAVELETS							LIFTING BASED WAVELET TRANSFORMS	
INPUT IMAGE	PERFORMANCE CRITERION	HAAR	DAUBECHIE	BIORTHOGONAL	DEMEYER	COIFLET	SYMLET	5/3 TRANSFORM	9/7 TRANSFORM
Man (color)	ENC_TIME (sec)	5.5612	5.7885	5.8776	6.0661	7.0577	6.1337	6.6098	6.3738
	DEC_TIME (sec)	0.59915	0.61827	0.64539	0.65568	0.77493	0.64985	0.73751	1.1097
	TRANS_TIME(sec)	0.16297	1.18957	0.19389	0.34688	0.2761	0.20203	0.13	0.19878
	ORG_SIZE (BITS)	524288	524288	524288	524288	524288	524288	1048576	1048576
	COMP_SIZE (BITS)	198684.5	216922	218999	398138	250702.5	226874	122946.5	99866
	COMP_ RATIO	2.6388	2.4169	2.394	1.3168	2.0913	2.3109	8.5287	10.4998
	MSE(dB)	6.33356	6.8803	8.46805	6.91009	1.73573	7.00271	6.33426	5.24458
	PSNR(dB)	29.8857	30.2453	31.147	30.269	44.264	30.3219	40.1478	40.9677

Table 10. Performance comparison between Hand designed and Lifting based wavelet transforms on 'Rose' (color) image.

	HAND DESIGNED WAVELETS							LIFTING BASED WAVELET TRANSFORMS	
INPUT IMAGE	PERFORMANCE CRITERION	HAAR	DAUBECHIE	BIORTHOGONAL	DEMEYER	COIFLET	SYMLET	5/3 TRANSFORM	9/7 TRANSFORM
Rose (color)	ENC_TIME (sec)	5.5801	5.4288	6.0516	5.2915	6.4639	5.6384	6.4651	6.3436
	DEC_TIME (sec)	0.63338	0.57203	0.72022	0.62773	0.65737	0.57513	0.71033	1.2473
	TRANS_TIME(sec)	0.20486	0.20351	0.19314	0.30407	0.26079	0.2031	0.10883	0.24286
	ORG_SIZE (BITS)	524288	524288	524288	524288	524288	524288	1048576	1048576
	COMP_SIZE (BITS)	201581	209183.5	223100.5	352147	224825.5	203612	121133.5	100735.5
	COMP_RATIO	2.6009	2.5064	2.35	1.488	2.332	2.5749	8.6564	10.4092
	MSE(dB)	6.13288	6.84339	8.24355	6.95668	5.80183	6.88391	4.38635	6.68568
	PSNR(dB)	29.7458	30.2219	31.0303	30.2932	49.5049	30.2476	41.7438	39.9133

Table 11. Performance comparison between Hand designed and Lifting based wavelet transforms on 'Tulip' (color) image.

	HAND DESIGNED WAVELETS							LIFTING BASED WAVELET TRANSFORMS	
INPUT IMAGE	PERFORMANCE CRITERION	HAAR	DAUBECHIE	BIORTHOGONAL	DEMEYER	COIFLET	SYMLET	5/3 TRANSFORM	9/7 TRANSFORM
Tulip (color)	ENC_TIME (sec)	6.3468	5.4907	6.0952	5.6081	6.3679	6.1415	6.2897	6.6126
	DEC_TIME (sec)	0.8557	0.55009	0.69005	0.69913	0.62788	0.73797	0.70083	0.83886
	TRANS_TIME(sec)	1.0921	0.20195	1.0766	0.87822	0.23824	1.5439	0.09425	0.26108
	ORG_SIZE (BITS)	524288	524288	524288	524288	524288	524288	1048576	1048576
	COMP_SIZE (BITS)	203837.5	208043.5	210330	346688	221582.5	201187	21675.75	109171
	COMP_RATIO	2.5721	2.5207	2.4927	1.5123	2.3661	2.606	8.6178	9.6049
	MSE(dB)	6.863	6.72823	7.66203	6.92199	1.22948	6.85241	4.45399	23.3064
	PSNR(dB)	29.8166	30.1482	30.7126	30.2715	42.7664	30.2276	41.6773	34.4901

6. GENERALIZATION PROPERTIES OF EVOLVED WAVELETS

The MRA transform coefficients were evolved using a single representative sub image extracted from 'rice.jpg'. The transform was subsequently tested against several widely used images to determine whether it was capable of achieving similar error reduction for images not used during training. The evolved transform out performs the D4 wavelet for all but one of the test images. This evidence suggests that transforms trained on a representative sub image are capable of exhibiting optimized performance when tested against a broad class of images having similar visual qualities.

7. CONCLUSIONS

In this paper the results of hand designed Wavelets and lifting based wavelet transforms for photographic images compression metrics are compared. From the results the lifting based wavelet transforms/evolved wavelets gives better compression results than the hand designed wavelets/traditional wavelets/conventional wavelets presently used to compress the images.The 5/3 filters have lower computational complexity than the 9/7 s. However the performance gain of the 9/7 s over the 5/3 s is quite large for JPEG 2000.

REFERENCES

[1] Daubechies, I. 1992 "Ten Lectures on Wavelets", SIAM.

[2] Taubman, D. and M. Mercellin 2002. JPEG2000: Image compression fundamentals, standards, and practice kluwer academic publishers.

[3] A. Lewis and G.Knowles, "Image compression using the 2-D wavelet transform", IEEE rans. Image processing, Vol. 1, PP. 244-250, Apr-1992.

[4] H. Meng and Z. Wang, "Fast special combinative lifting algorithm of wavelet transform using the 9/7 filter for image block compression, Electron. Lett. , Vol.36, No.21, PP. 1766-1767, Oct-2000.

[5] Mallat, S. 1989. A theory for Multiresolution signal decomposition: The Wavelet Representation, IEEE Transactions on Pattern Recognition and machine intelligence, 11(7): 674-693.

[6] W. Sweldens, "The Lifting Scheme: A Custom-Design Construction of Biorthogonal Wavelets," *Applied and Computational Harmonic Analysis*, vol. 3, no. 15, 1996, pp. 186–200.

[7] I. Daubechies and W. Sweldens, "Factoring Wavelet Transforms into Lifting Schemes," *The J. of Fourier Analysis and Applications*, vol. 4, 1998, pp. 247–269.

[8] J. Reichel, G. Menegaz, M. Nadenau, and M. Kunt, " Integer wavelet transform for embedded lossy to lossless image compression," IEEE Trans. Image Process., Vol. 10, No. 3, PP. 383-392, Mar. 2001

[9] C.T. Huang,P,-C. Tseng, and L.-G. Chen, "Flipping structure: An efficient VLSI architecture for lifting-based discrete wavelet transform," IEEE Trans. Signal Process., Vol.52, No.4, PP. 1910-1916, April 2004.

[10] M. Grangetto, E. Magli, M. Martina, and G. Olmo, "Optimization and implementation if the integer wavelet transform for image coding," IEEE Trans. Image Process., Vol.11, No. 6, PP. 596-604, June 2002.

[11] A.Cohen, I. Daubecheies and I.C Feauveau "Biorthogonal bases of compactly supported Wavelets" Commun. On Pure and Applied mathematics 45 pp.485-560, 1992.

[12] Selesnick, I.W., "The double - density duel –tree DWT" IEEE Transactions on signal processing, May -2004.

[13] Z Wang and A.C Bovick, "A Universal Image Quality index", IEEE Signal processing letters, Vol.9, No.3, PP. 81-84, Mar-2002

[14] Standard Gray scale image http://www.icsl.ucls.edu/~ipl/psnrimages.html

[15] Bing-Fei wu, chung-Fu lin, " A high performance and memory efficient pipeline architecture for the 5/3 and 9/7 discrete wavelet transform of JPEG-2000 codec", IEEE Transactions on Circuits and Systems for video technology , Vol.15, Issue 12, Dec-2005, PP. 1615 – 1628

[16] Richard D. Forket, "Elements of Adaptive wavelet image compression", Image compression research Laboratory, IEEE 1996, PP. 435

[17] Moore, F., P. Marshal, and E. Balster 2005, Evolved Transforms for Image Reconstruction, Proceedings, 2005 IEEE Congress on Evolutionary Computation.

[18] Moore, F 2005. "A genetic Algorithm for optimized reconstruction of Quantized Signals", proceedings 2005 IEEE congress on Evolutionary computation.

[19] Babb, B., S. Becke, and F.Moore 2005. Evolving optimized matched forward and inverse transform pairs via genetic algorithms, proceedings of the 40th IEEE international Midwest symposium on circuits and systems: Cincinnati. OH, August 7-10, 2005, IEEE circuits and systems society.

Authors

G. Chenchu krishnaiah working as an Associate Professor in the Department of ECE at Gokula Krishna College of Engg. Sullurpet- 524121, Nellore (Dist) A.P, India. He is having 12 years of Experience in Teaching and in various positions. He worked as a Lecturer in SV Govt. Polytechnic College, Tirupati, as an Asst. Prof., and Head of the Dept. of ECE in AVS College of Engineering and Technology, Nellore and as an Assoc. Prof., and Head of the Dept. of ECE in Priyadarshini College of Engineering, Sullurpet. Presently he is doing Ph.D in JNT University, Anantapur, Anantapur-515002, A.P, India. His area of research is image compression using evolved wavelets. He is a life member in ISTE.

Dr.T.Jayachandra Prasad obtained his B.Tech in Electronics and Communication Engg., from JNTU College of Engineering, Anantapur, A.P, India and Master of Engineering degree in Applied Electronics from Coimbatore Institute of Technology, Coimbatore, Tamil Nadu, India. He earned his Ph.D. Degree (Complex Signal Processing) in ECE from JNT University, Hyderabad A.P, India. Presently he is working as a principal at Rajeev Gandhi memorial college of Engineering & Technology, Nandyal-528502, Kurnool (Dist) A.P, India. His areas of research interest include complex signal processing, digital image processing, compression and denoising algorithms, digital signal processing and VHDL Coding. He is a life member of ISTE (India), Fellow of Institution of Engineers (Kolkata), Fellow of IETE, Life member of NAFEN, MIEEE.

Dr. M.N. Giri Prasad received his B.Tech degree from J.N.T University College of Engineering, Anantapur, Andhra Pradesh, India, in 1982, M.Tech degree from Sri Venkateshwara University, Tirupati, Andhra Pradesh, India in 1994 and Ph.D degree from J.N.T. University, Hyderabad, Andhra Pradesh, India in 2003. Presently he is working as a Professor, Department of Electronics and Communication Engineering, at J.N.T University College of Engineering, Anantapur-515002, Andhra Pradesh, India. His research areas are Wireless Communications and Biomedical instrumentation, digital signal processing, VHDL coding and evolutionary computing. He is a member of ISTE, IE & NAFEN.