Novel Image Compression Using Multiwavelets with SPECK Algorithm

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Abstract: *Compression is the process of representing information in a compact form so as to reduce the bit rate for transmission or storage while maintaining acceptable fidelity or data quality. Over the past decade, the success of wavelets in solving many different problems has contributed to its unprecedented popularity. For best performance in image compression, wavelet transforms require filters that combine a number of desirable properties, such as orthogonality and symmetry. Due to implementation constraints scalar wavelets do not possess all the properties which are needed for better performance in compression. New class of wavelets called 'Multiwavelets' which possess more than one scaling filters overcomes this problem. The objective of this paper is to develop an efficient compression scheme and to obtain better quality and higher compression ratio using Multiwavelet transform with Set Partitioned Embedded bloCK coder algorithm (SPECK). A comparison of the best known multiwavelets is made to the best known scalar wavelets. Extensive experimental results demonstrate that our techniques exhibit performance equal to, or in several cases superior to, the current wavelet filters.*

Keywords: *wavelet, multiwavelet, SPIHT, SPECK.*

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1. Introduction

It has been suggested that a "picture is worth thousand words". This is all the more true in the modern era in which information has become one of the most valued of assets. A thousand words stored on a digital computer require very little capacity, but a single picture/image can require much more. The volume of data required to describe such images greatly slow transmission and makes storage prohibitively costly. The information contained in images must, therefore, be compressed by extracting only visible elements, which are then encoded. The quantity of data involved is thus reduced substantially. Data compression algorithms are used in the standards such as 'JPEG' and 'MPEG', to reduce the number of bits required for representing an image or a video sequence, i.e., compression is necessary and essential method for creating image files with manageable and transmittable sizes. A number of methods have been presented over the years to perform image compression. They all have one common goal: to alter the representation of information contained in an image so that it can be represented sufficiently well with less information. More recently, the wavelet transform has emerged as a cutting edge technology, within the field of image compression. Wavelet-based coding [8, 9] provides substantial improvements in picture quality at higher compression ratios. For better performance in compression, filters used in wavelet transforms should have the property of orthogonality, symmetry, short support and higher approximation order. Due to implementation constraints scalar wavelets do not satisfy all these properties simultaneously. Multiwavelets [4, 5] which are wavelets generated by finite set of scaling functions, have several advantages in comparison to scalar wavelets. One of the advantages is that a multiwavelet can possess the orthogonality and symmetry simultaneously [9, 11, 12] while except for the 'Haar' (scalar wavelet) can not have these two properties simultaneously. Thus multiwavelets offer the possibility of superior performance and high degree of freedom for image processing applications, compared with scalar wavelets. Multiwavelets can achieve better level of performance than scalar wavelets with scalar wavelets with similar computational complexity.

This paper is organized as follows. Section 2 highlights some key points on multiwavelets. Section 3 provides the motivation for going into multiwavelets for image compression. Section 4 presents the iteration of decomposition in multiwavelets. Section 5 discusses the coding of multiwavelet coefficients using modified SPECK. Results and discussions are presented in section 6 and finally conclusions are drawn in section 7.

2. Multiwavelets

The wavelet transform is a type of signal transform that is commonly used in image compression. A newer alternative to wavelet transform is the multiwavelet transform. Multiwavelets are very similar to wavelets but have some important differences. In particular, whereas wavelets have an associated scaling function *Φ(t)* and wavelet function *Ψ(t)*, multiwavelets have two or more scaling and wavelet functions [5]. For notational convenience, the set of scaling functions can be written using the vector notation $\Phi(t) = [\Phi_1(t), \Phi_2(t)..., \Phi_r(t)]^T$, where *Φ(t)* is called the multiscaling function. Likewise, the multiwavelet function is defined from the set of wavelet functions as $\Psi(t) = [\Psi_1(t), \Psi_2(t)..., \Psi_r(t)]^T$. Called a scalar wavelet, or simply wavelet where $r = 1$, $\Psi(t)$. While in principle r can be arbitrarily large, the multiwavelets studied to date are primarily for $r = 2$ [2].

The multiwavelet two-scale equations resemble those for scalar wavelets

$$\phi(t) = \sqrt{2} \sum_{k=-\infty}^{\infty} H_k \phi(2t-k) \quad (1)$$

$$\psi(t) = \sqrt{2} \sum_{k=-\infty}^{\infty} G_k \phi(2t-k) \quad (2)$$

However, that $\{H_k\}$ and $\{G_k\}$ are matrix filters, i.e., H_k and G_k are rxr matrices for each integer k. The matrix elements in these filters provide more degrees of freedom than a traditional scalar wavelet [4]. These extra degrees of freedom can be used to incorporate useful properties into the multiwavelet filters, such as orthogonality, symmetry, and high order of approximation. The key idea is to figure out how to make the best use of these extra degrees of freedom. Multifilter construction methods are already being developed to exploit them. The filter bank representation is also mostly unchanged, except now the input and output of every branch in multifilter bank is a vector [4]. This can be easily understood from Figure 1 which shows the analysis (H and G multifilters) and synthesis ($\hat{H}$ and $\hat{G}$ multifilters) stages of a single level biorthogonal PR multifilter bank.

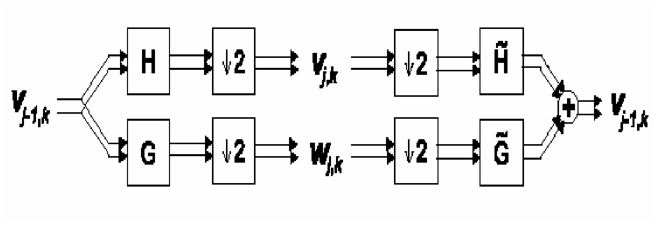


Figure.1 Biorthogonal PR multifilter bank.

The detailed structure of the H analysis multifilter is shown in Figure 2.

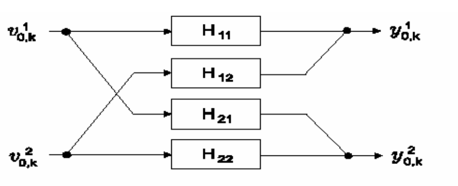


Figure 2. H Multifilter as a 2-input, 2-output system.

3. Motivation for Multiwavelets

Algorithms based on scalar wavelets have been shown to work quite well in image compression. Consequently, there must be some justification to use multiwavelets in place of scalar wavelets. Some reasons for potentially choosing multiwavelets are summarized below [4]:

- The extra degrees of freedom inherent in multiwavelets can be used to reduce the restrictions on the filter properties. For example, it is well known that a scalar wavelet cannot simultaneously have both orthogonality and symmetric property. Symmetric filters are necessary for symmetric signal extension, while orthogonality makes the transform easier to design and implement. Also, the support length and vanishing moments are directly linked to the filter length for scalar wavelets. This means longer filter lengths are required to achieve higher order of approximation at the expense of increasing the wavelet's interval of support. A higher order of approximation is desired for better coding gain, but shorter support is generally preferred to achieve a better localized approximation of the input function. In contrast to the limitations of scalar wavelets, multiwavelets are able to possess the best of all these properties simultaneously.
- One desirable feature of any transform used in image compression is the amount of energy compaction achieved. A filter with good energy compaction properties can decorrelate a fairly uniform input signal into a small number of scaling coefficients containing most of the energy and a large number of sparse wavelet coefficients. This becomes important during the quantization since the wavelet coefficients are represented with significantly fewer bits on average than the scaling coefficients. Therefore better performance is obtained when the wavelet coefficients have values clustered about zero with little variance, to avoid as much quantization noise as possible. Thus multiwavelets have the potential to offer better reconstructive quality at the same bit rate.
- Multiwavelets can achieve better level of performance than scalar wavelets with similar computational complexity.

4. Iteration of Decomposition in Multiwavelet Transform

Since multiwavelet decompositions produce two low pass subbands and two high pass subbands in each dimension, the organization and statistics of multiwavelet subbands differ from the scalar wavelet case. During a single level of decomposition using scalar wavelet transform, the 2-D image data is replaced with four blocks corresponding to the subbands representing either low pass or high pass in both dimensions. These subbands are illustrated in Figure 3-a. The data in subband '*LH*' was obtained from high pass filtering of the rows and then by low pass filtering of the columns. The multiwavelets used here have two channels, so there will be two sets of scaling coefficients and two sets of wavelet coefficients. The multiwavelet decomposition subbands are shown in Figure 3-b. For multiwavelets, the *L* and *H* labels have subscripts denoting the channel to which the data corresponds. For example, the subband labeled L_1H_2 corresponds to data from the second channel high pass filter in the horizontal direction and the first channel low pass in the vertical direction.

LL	LH
HL	HH

(a) Scalar wavelets.

L_1L_1	L_1L_2	L_1H_1	L_1H_2
L_2L_1	L_2L_2	L_2H_1	L_2H_2
H_1L_1	H_1L_2	H_1H_1	H_1H_2
H_2L_1	H_2L_2	H_2H_1	H_2H_2

(b) Multiwavelets.

Figure 3. Image subbands after single-level decomposition.

Scalar wavelet transforms give a single quarter-sized low pass subband from the original larger subband, as seen in subband *LL* in Figure 3-a. In previous multiwavelet literature, multilevel decompositions are performed in the same way. The multiwavelet decompositions iterate on the low pass coefficients from the previous decomposition. (the L_iL_j subbands in Figure 3-b), as shown in Figure 4. In the case of scalar wavelets, the low pass quarter image is a single subband. But when the multiwavelet transform is used, the quarter image of "low pass" coefficients is actually a 2x2 block of subbands – one low pass and three band pass. This is due to the use of Symmetric-Antisymmetric (SA) multifilters [4]. Due to the nature of preprocessing and symmetric extension method, data in these different subbands becomes intermixed during iteration of the multiwavelet transform.

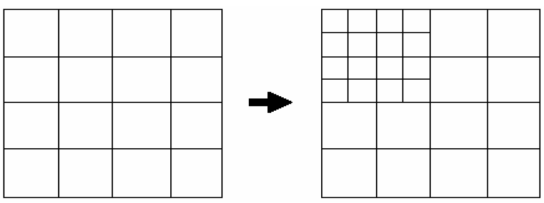


Figure 4. Conventional iteration of multiwavelet decomposition.

Since four *LL* subbands possess different statistical characteristics, mixing them together using the multiwavelet decomposition results in further subbands with mixed data characteristics. Since only the L_1L_1 subband actually has low pass characteristics, further iterations on that one subband is sufficient. Thus iterating only on the L_1L_1 subband requires one quarter of the computational complexity as iteration over the entire *LL* subband thus improving run-time performance as well.

5. SPECK Algorithm

Image coding utilizing scalar quantization [10] on hierarchical structures of transformed images has been a very effective and computationally simple technique. Shapiro was the first to introduce such a technique with his Embedded Zero tree Wavelet (EZW) algorithm [1]. Said & Pearlman successively improved the EZW algorithm based on a set-partitioning sorting algorithm called the Set-Partitioning In Hierarchical Trees (SPIHT) which provided an even better performance than the improved version of EZW [7].

The algorithm used in this paper has its roots primarily in the ideas developed in the SPIHT, EBCOT, and image coding algorithms [3]. It is different from some of the above mentioned schemes in that it does not use trees which span, and exploit the similarity, across different subbands; rather, it makes use of sets in the form of blocks. The main idea is to exploit the clustering of energy in frequency and space in hierarchical structures of transformed images [1, 6]. Thus, the image coding scheme is called *Set Partitioned Embedded block coder* (SPECK). In SPECK, the blocks are recursively and adaptively partitioned such that high energy areas are grouped together into small sets whereas low energy areas are grouped together in large sets. This algorithm makes use of the adaptive quad tree splitting to zoom into high energy areas within a region to code them with minimum significance maps [1, 6].

5.1. Pseudo Code of the Algorithm

The order in which the subsets are tested for significance is important; in a practical implementation the significance information is stored in the ordered list called (a) List of insignificant sets (LIS), (b) List of significant pixels (LSP). In SPECK algorithm we are using two lists than SPIHT which is a considerable improvement.

A. Initialization

Partition image transform X into two sets: S= root and I= X-S

Output $n = floor(log2(\max_{\forall (i,j) \in X} |C_{i,j}|))$

Add S to LIS and set LSP=Φ

B. Sorting pass

In increasing order of size C of sets

For each set S € LIS,

** Process S (S)*

Process I ( )

C. Refinement pass

For each (i,j) € LSP, except those included in the last sorting pass, output the n^th MSB of $|C_{i,j}|$.

D. Quantization step

Decrement n by 1, and go to step 2.

In the above pseudo code, process *S(S)* indicates checking the set *S* for significance. Before checking, the entire set is moved into List of Insignificant Set (LIS). If *S* is found to be significant, then the following processes take place with respect to the above pseudo code *S*, remove *S* from LIS and add *S* to List of Significant Pixels (LSP). Process *I()* indicates, checking for significance and if found significant, splitting *I* into three sets *S* and the remaining *I* and for each *S*, process *S(S)*. This splitting process of *'I'* is continued until *'I'* becomes null set.

As adding *S* to LIS and removing it from LIS if found significant for each *S* requires frequent up gradation of LIS which is quite complex and takes extra time in computation. So in this paper some alternative approach is tried such that complexity of the algorithm is much less and time required for computation is also less when compared to that of original algorithm.

5.2. Pseudo Code of the Modified SPECK Algorithm

Modified SPECK is similar to that of original SPECK algorithm with only a slight difference. Here, each set *S* is processed for its significance against the threshold value and it is moved into LIS only if found insignificant which is after the significance test. If *S* is a single pixel, then it is coded for positive or negative significance. If it is a block, then it is quad parted and further checked for significance and after checking; only insignificant blocks are moved to LIS which was not the case with original SPECK.

By proceeding with this approach, better results are obtained at much less computation time. In the Pseudo code, 'update LIS and LSP' means testing of the set for its significance and accordingly moving the set or coefficient to the LIS or LSP.

A. Initialization

Partition image transform X into two sets: S = root & I = X – S.

Output $n = floor(\log_2(\max_{\forall (i,j) \in X} |C_{i,j}|))$.

Add S to LIS & set LSP = Φ.

B. First sorting pass

Process S(S)

Process I ( )

C. Sort LIS in increasing order of set size C.

D. Further sorting passes

For each set S € LIS

Process S(S)

E. Refinement pass

For each (i,j) € LSP, except those included in the last sorting pass, output the nth MSB of $|C_{i,j}|$.

F. Quantization step

Decrement n by 1, and go to next sorting stage

6. Results and Discussion

The images taken for the experiment are 'Lena', 'Barbara', 'Peppers', 'Cameraman', 'Mandrill', 'Rice' of size (256 X 256). They are subjected to wavelet and Multiwavelet decomposition. The wavelet filters used in this experiment are "Haar", "la8", "Db_4","Bi9/7" [8]. The multiwavelet filters used in this work are "GHM" pair of multifilters, Cardinal 3-balanced orthogonal multifilter "Cardbal3", Chui-Lian orthogonal multifilter "Cl", orthogonal symmetric/Antisymmetric multifilter "Sa4" [4]. Table 1 and Table 2 represents the corresponding 'PSNR' values for different images and different levels of decomposition at 0.2bpp (CR=40) and 0.8bpp (CR=10) using multiwavelets. From these tables, it is clear that as the CR decreases, PSNR increases and as level of decomposition increases, PSNR increases.

Table 3 shows that multiwavelet decomposition gives a higher amount 'PSNR' value (better image quality) with same amount of Compression Ratio (CR) when compared to that of "Daubechies" wavelet. This is because of the multifilters available in the multiwavelets, not in the case of wavelets. Multiscaling functions and Multiwavelet functions available in multiwavelets led to better decomposition of images in each band.

SPECK algorithm is said to be an efficient algorithm than SPIHT [7]. Many comparison tables for different images are provided below from which the above said statement is made true.

Table 1. PSNR (dB) for images under various levels of decomposition at 0.2bpp (CR=40).

Multiwavelet (Cardbal3)	PSNR(dB) for Different Levels of Decomposition		
Images	2	3	4
Cameraman	18.27	23.52	24.25
Peppers	20.51	24.50	26.19
Barbara	20.67	24.59	25.73
Lena	21.86	28.80	29.69

Tables 4 and 5 indicate the comparison between SPIHT and SPECK algorithm at different levels of decomposition in case of scalar wavelets and multiwavelets for "Cameraman" image. From tables 4 and 5, it is evident that SPECK algorithm gives a higher PSNR than SPIHT at a given CR in the case of both scalar wavelets and multiwavelets.

Table 2. PSNR (dB) for images under various levels of decomposition using multiwavelet (Cardbal3) at 0.8bpp (CR=10).

Multiwavelet (Cardbal3)	PSNR(dB) for Different Levels of Decomposition		
Images	2	3	4
Cameraman	28.94	30.79	31.07
Peppers	31.09	34.15	34.36
Barbara	29.41	30.77	31.10
Lena	34.98	38.66	39.14
Rice	35.19	33.55	36.28

Multiwavelets with modified SPECK gives an increase in the PSNR value roughly 0.2 to 2dB. This is completely evident from the data available in table 5.

Table 3. PSNR (dB) for "Lena" image for 3rd level of decomposition wavelet vs. multiwavelet.

Rate (bpp)	PSNR(dB) Wavelet (Db_4)	PSNR(dB) Multiwavelet (Cardbal3)	PSNR(dB) Multiwavelet (Sa_4)
0.2	28.45	28.80	30.41
0.4	32.34	33.07	35.81
0.6	35.02	36.30	37.96
0.8	36.91	38.66	40.98
1	37.70	40.37	42.42

Table 4. Comparison between SPIHT and SPECK for PSNR (in dB) values for "Cameraman" image using scalar wavelets.

Level	Filter	SPIHT			SPECK		
	Rate (bpp)	0.2	0.6	1	0.2	0.6	1
2	Haar	12.4	16.98	20.04	18.28	26.62	31.05
	Db_4	12.53	17.19	20.29	20.40	28.32	32.51
	La8	12.6	17.2	20.73	20.72	28.60	32.58
	Bi9	12.57	17.31	20.46	20.38	26.78	28.99
3	Haar	15.83	24.31	29.87	23.24	29.19	32.51
	Db_4	16.18	24.68	30.23	23.76	30.30	34.37
	La8	16.17	24.96	30.28	24.04	30.21	33.85
	Bi9	16.38	23.53	26.52	22.82	26.33	27.50

In Table 5, 'Cardbal3' represents Cardinal 3-balanced orthogonal multifilter. Table 6 shows the comparison between the two algorithms for various images using 'Dabauchies' wavelet at various rates. Table 7 represents the comparison of PSNR values for various images using multiwavelets at a CR of 8 (bpp=1) through SPECK. From that table, it is clear that out of various multiwavelet filters, Sa_4 (Symmetric/Antisymmetric) multifilter shows a higher performance when compared to the others in all the considered images. The final conclusion from the results is that, multiwavelets with SPECK outperform wavelets with SPECK in all the observed images.

Table 5. Comparison between SPIHT and SPECK for PSNR (in dB) values for "Cameraman" image using multiwavelets.

Level	Filter	SPIHT			SPECK		
		0.2	0.6	1	0.2	0.6	1
2	Ghm	14.52	24.4	29.13	20.14	26.89	31.07
	Cl	15.96	24.8	29.75	23.39	28.90	31.62
	Sa_4	16.07	24.9	30.06	23.62	29.80	33.75
	Cdb3	17.17	25.7	30.46	18.27	26.14	29.89
3	Ghm	22.67	28.4	31.91	23.72	29.23	32.92
	Cl	22.93	29.1	32.96	23.82	28.16	30.22
	Sa_4	23.25	29.2	33.09	24.67	30.08	33.94
	Cdb3	23.62	28.9	32.42	23.52	29.45	33.33

Table 6. Comparison between SPIHT and SPECK for PSNR (in dB) values for various images using "Daubechies" wavelet at various rates.

Level	Image	PSNR(dB) using SPIHT			PSNR(dB) using SPECK		
		0.2	0.6	1	0.2	0.6	1
2	'Barbara'	11.14	17.04	20.72	20.97	28.49	31.9
	'Lena'	11	16.56	20.88	21.64	32.79	35.8
	'Peppers'	11.44	17.59	20.54	20.92	30.1	34.2
3	'Barbara'	16.15	25.42	29.91	25.41	30.04	33.5
	'Lena'	15.87	26.17	31.91	28.45	35.02	37.7
	'Peppers'	16.35	24.75	29.81	25.39	31.82	35.7

Table 7. Comparison of PSNR (in dB) values for various images using multiwavelets through SPECK at bpp=1.

Level	Filters	'Barbara'	'Peppers'	'Lena'
2	Ghm	31.79	33.32	38.05
	Cl	32.09	31.91	32.15
	Sa_4	33.91	34.38	41.35
	Cardbal2	31.70	34.31	35.89
	Cardbal3	31.04	34.10	37.00
3	Ghm	32.62	34.99	38.64
	Cl	33.02	34.94	33.94
	Sa_4	34.10	35.91	42.42
	Cardbal2	32.96	35.41	40.78
	Cardbal3	32.96	35.28	40.37

Figure 5 shows the comparison between many multiwavelets when applied for 'Peppers' image at bpp=1. From the figure, it is clear that out of all available multiwavelets, Sa_4 multifilter performs well. Figure 6 shows a comparison when SPECK compression is applied to wavelet and multiwavelets.

From the figure, it is clear that multiwavelet compression gives 3 dB improvements against wavelet compression. Figure 7 shows the comparison graph between the algorithms using 'Dabauchies' wavelet. SPECK shows 8 dB improvements over SPIHT.

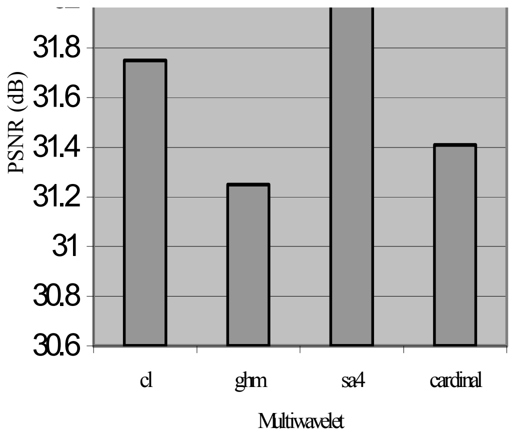


Figure 5. PSNR values for various multiwavelets at CR=13.33.

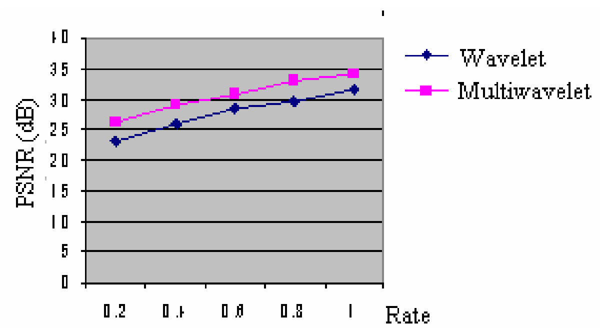


Figure 6. Comparison of wavelets vs. multiwavelets.

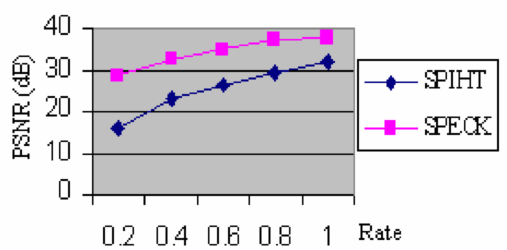
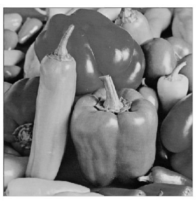


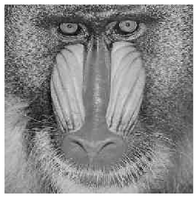
Figure 7. Comparison of SPIHT and SPECK.

(a) Original image

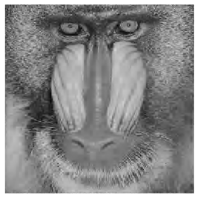


(b) 31.41dB0.6bpp(SA4multiwavelet).

Figure 8. SPECK compression of Peppers image PSNR values.



(a) Original image.



(b) 24.18 dB0.6bpp (SA4 multiwavelet).

Figure 9. SPECK compression of Mandrill image.

Figures 8 and 9 show the original and reconstructed images using SA4 multiwavelet for 'Peppers' and 'Mandrill' image with a given CR. Figure 10 shows the reconstructed images of 'Barbara' image at various CR.

(a) Original image.

(b) 0.6 bpp CR=13.33) 29.58 dB.

(c) 0.8 bpp (CR=10) 30.78 dB.

(d) 1 bpp (CR=8) 32.96 dB (SA4 tiwavelet).

Figure 10. SPECK compression of 'Barbara' image PSNR values.

7. Conclusion

The performance of multiwavelets in general depends on the image characteristics. For the images with mostly low frequency content, (ordinary still images) scalar wavelets generally give better performance. However multiwavelets appear to excel at preserving high frequency content. In particular, multiwavelets better capture the sharp edges and geometric patterns that occur in images. The SPECK algorithm has some important features which are low complexity, embeddedness, progressive coding, exploits clustering of energy to zoom into high energy areas within a region (block) to code them with minimum significance maps, better visual perception.

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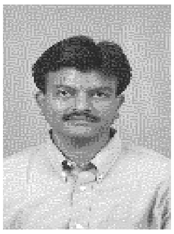

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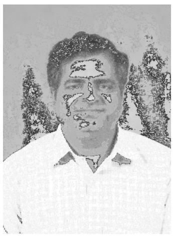

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