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Selective Coding for Multilevel Wavelet Image Compression

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Abstract

Objectives: The basic aim of this paper is to develop a coding method which will give effective compression by retaining image accuracy with lower computational overhead in image coding. The objective for obtaining such a coding technique is made by the development of an improvised preprocessing approach followed by a modified planar coding with the transformation made from wavelet to multi-wavelet. **Methods/Statistical Analysis**: This paper analyzes the performance of existing wavelet based compression techniques. Also develops a coding approach so as to obtain effective compression by retaining image accuracy with lower computational overhead in image coding. The overall implementation consists of improvised preprocessing followed by a modified planar coding with the transformation made from wavelet to multi-wavelet approach. The main problems focused in this research work are 1. Preprocessing (Filtering), 2. Representing image coding coefficients and 3. Coding schemes for multi-Bit rate compatibility with minimum representation. For noise removal a modified weighted filtration approach is proposed. With the proposed approach an improvement in coding efficiency is achieved. The simulation observation evaluates the proposed approach and the comparative analysis of the proposed approach presents the improvements achieved. The performance of proposed selective MWVLT (S-MWLT) is compared with the conventional Multi Wavelet coding (MWVLT) and DWT based coding. The assessment is carried out by observations on various test samples. **Findings:** To test the operation performance for developed system the PSNR, RMSE for the system is evaluated under different medium distortion level. The observation illustrates that the obtained visualization of the filtered result using weighted filtration is comparatively more accurate than the conventional filtration approach while RMSE value for the proposed approach is decreased to about 40 units as comparative to the conventional approach. It is observed that the obtained filtration is improved with the block size increment. At N=4 the obtained filtration is comparatively accurate. Analysis of different wavelet transformations at variable bits per pixel is carried out. From analysis it is clear that Mean Square Error (MSE) and computational time is less in symplet transformation as well as high PSNR is obtained for symplet transformation. Analysis of DWT, MWVLT, S-MWVLT at different noise variance is carried out. The MSE value is observed minimum for the proposed S-MWLT coding than DWT and MWLT. This is due to minimal correlative band selection, the MSE of recovered sample is observed to be lower. While the compression achieved for the proposed S-MWVLT coding, is comparatively higher than the DWT based coding. The overhead is lower in case of DWT based, however in comparison to MWVLT coding; proposed S-MWVLT coding has lower overhead. The PSNR for the proposed approach is observed to be improved by a factor of 7 dB in comparison to MWVLT coding and about 10 dB in comparison to DWT based coding. Also at higher coding rate proposed S-MWVLT coding performs better than DWT, MWVLT. **Application/Improvements:** The image compression using selective Multiwavelet coding can be extended for video compression and can be applied in multimedia communication. It can also be extended for other image processing applications (may be face recognition, passport size image compression, etc.) for better results. This technique can also be combined with image security.

Keywords: Adaptive Filtering, Compression Ratio (CR), DWT, Hybrid Hierarchical Coding, Image Compression, Multi-wavelet Transformation, MWLT, Peak Signal to Noise Ratio (PSNR), Root Mean Square Error (RMSE), Selective Coding

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1. Introduction

In today's scenario, there is rapid improvement in image processing based applications and services. The applications based on medical image processing and video processing suffers from several limitations. The conventional multi bit rate transformations doesn't work effectively in diverse conditions. Mostly, complete reconstruction of original image is not possible with multi bit stream coding as we change resolution levels. Various coding algorithms have been proposed and developed by recognized international organizations and recommended as international standards. But these standards are designed for specific applications and cannot be applicable for some another purpose. Thus main issue of conventional multi bit stream approaches is its inefficiency and practical implementation difficulty due to extensive requirement from customers.

Currently, wavelet based image compression is popular as a cutting edge technology as these coding[1,2] schemes provide better picture quality even at high compression ratios. This is possible because of symmetry, orthogonality higher approximation etc. properties of the wavelet transform. Scalar wavelet does not possess all these characteristics. Multiwavelets[3,4] have several advantages and can be generated by only a finite set of functions. They have symmetry and orthogonality simultaneously[2,5] which is not possible with the scalar wavelet. Because of this multi-wavelet perform better than scalar wavelets and can be used extensively in various image processing based applications especially in image compression. In spite of these advantages, decomposition of multi-wavelet bands results in large number of coefficients which increases the coding complexity as well as computations. From decomposed bands it is clear that there are certain bands exhibiting same properties. From this inspection, a band selection and coding procedure for selected bands is proposed to reduce computational complexity. In signal processing band selection and coding process called Adaptive Band Filters (ABF)[6] is proposed where from k decomposed bands, 'k-n' bands are selected as useful bands for processing. These selected bands are then coded using new hybrid hierarchical coding to improve coding efficiency. This coding approach is a combination of the zero block[7] and context coding[8]. This paper is organized in five sections. Section two describes the multi-wavelet transform while section three explains the adaptive coding. Hierarchical band coding is outlined in section four. The results obtained after implementation of proposed coding as well as its comparison with existing methods is given in section five. Lastly paper is concluded from observations obtained in previous section.

2. Multi-wavelet Transform

The wavelet transform is one of the commonly used techniques in image compression, after development of JPEG 2000 standard. Multi-wavelet transform is modified version of wavelet transform and some additional features are available with it. Wavelets consists of two basic functions named wavelet function $\Psi(t)$ and scaling function $\Phi(t)$. While multi-wavelet consists of multi scaling and multi wavelet set of functions[4]. In multi-wavelet scaling function set ($\Phi(t)$) can be written as, $\Phi(t) = [\Phi_1(t), \Phi_2(t) \ldots, \Phi_r(t)]^T$. Similarly, the multi-wavelet function set $\Psi(t)$ for multi-wavelet coding can be written as $\Psi(t) = [\Psi_1(t), \Psi_2(t) \ldots, \Psi_r(t)]^T$. In above equation 'r' can have any value, but from literature it is clear that for multi wavelets r takes value equal to two[7]. The scale equations for multi-wavelet can be written as,

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

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

Where, $\{H_k\}$ and $\{G_k\}$ are matrices of wavelet filters of 'r x r'dimensions for specified integer k. The coefficients of these filters offer more degree of freedom as compared to scalar wavelets[3]. Filter coefficients are also responsible to integrate important properties such as orthogonality, symmetry and higher order approximation into the multi-wavelet filters. For each and every multi filter bank the input and output is a vector[3]. Figure 1 represents the analysis filters (H and G multi filters) and synthesis filters (Ĥ and Ĝ multi filters for a single level bi-orthogonal multi filter bank.

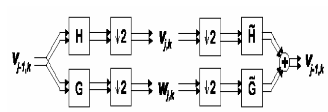


Figure 1. Single level Biorthogonal multifilter bank.

The basic properties of a Multiwavelet transform are illustrated as;

- The inherent property, extra degree of freedom in multi-wavelets is the main property, which is useful to remove deficiency of scalar filter. As an example, scalar wavelet cannot possess symmetry and orthogonality simultaneously. Orthogonality provides the easier design and implementation process while symmetry is necessary for symmetric filters for signal extension. Also, the scalar wavelets are directly linked with the vanishing moments and support length. i.e., to achieve higher order approximation, longer length filters are necessary. Better localized approximation prefers shorter support of the respective input function, but higher approximation is necessary to achieve the higher coding gain.

- For any transform to be useful in image compression, necessary feature required is the amount of energy compaction. So, a filter which consists of most of energy concentrated in less number of scaling coefficients can exhibit good energy compaction. This becomes significant during the quantization since the number of bits required to represent the wavelet coefficients will be less compared to scaling coefficients. The quantization noise can be avoided as well as better performance can be achieved by clustering the wavelet coefficient values about to zero with a little variance. Thus, multi-wavelets can provide the better reconstruction.
- Compared to scalar wavelets, multi-wavelets can provide better level of performance with same computational complexity. Multi-wavelets produce two high pass bands and two low pass bands in each level of decomposition. One level of decomposition of an image results into four sub bands corresponding to low pass and high pass in both dimensions. Figure 2 (a) and (b) shows the single level of decomposition for scalar wavelets and multi-wavelets respectively. The sub-band 'LH' corresponds to high pass filtering of rows followed by low pass filtering of columns. The multi-wavelets having two channels, so there will be two sets of wavelet coefficients and also two sets of scaling coefficients.

In multi-wavelet transform single level of decomposition results in sixteen subbands, which will be further decomposed during next level of decomposition and formulate quad-tree representation. So during each iteration count of subband go on increasing tremendously. Number of calculations required during processing of these subbands also becomes very large. Each subband is represented into four lower bands. So, similarity exists among these bands. This similarity among bands can be utilized to reduce the count of processing coefficients in selective band coding which is described below.

LL	LH
HL	HH

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

(a) Scalar wavelets. (b) Multiwavelets.

Figure 2. First level of decomposition for (a) Scalar wavelets (b) Multiwavelets.

3. Selective-Multiwavelet Coding

In any image processing application, first step carried is the preprocessing which helps to improve accuracy. During each level of decomposition number of bands goes on increasing, but it is observed that all bands do not contain useful information. So, with increase in level of decomposition probability of redundant data goes on increasing. Also, it is clear that most of the important information is available in finer details than coarse details. Hence idea of adaptive band selection i.e. extracting bands which are carrying important information is proposed. A adaptive band selection process was utilized in signal processing[6] but such approach is not observed in image coding. So, this section highlights the adaptive band selection for multi-wavelet coefficients. Multi-wavelet transformation results in multi band decomposition which is shown in Figure 3.

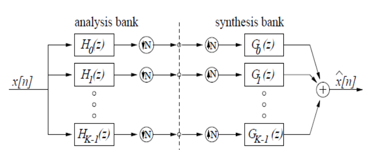


Figure 3. Filter bank for channel of order N[6].

Each filter is composed of analysis and synthesis filters. Analysis filters are responsible for decomposition of the image while synthesis filters works during reconstruction phase. During decomposition, input image is passed through analysis filter ($H_k(z)$) and decimated by factor N. This stage results in decomposition of image into k subbands. While, during reconstruction initially expansion by factor of N takes place and then filtering with synthesis filters $G_k(z)$ followed by summation takes place. Analysis filters are real low pass FIR filters of even length. The cost optimization approach is used to estimate the signal from filtered output. The subbands are processed adaptively known as Subband Adaptive Filter (SAF)[6]. The basic principle of SAF is same as Least Mean Square (LMS) adaptive filter. Optimization of LMS function and weight function is used for convergence of filter and mean error respectively. A Normalized SAF (NSAF) was proposed to increase the speed of convergence[9,10]. In this approach the convergence speed is increased by increasing the number of subband filters while maintaining the same level of steady-state error. However, it suffers from huge complexity when used in adapting an extremely long unknown system such as acoustic echo cancellation application. This drawback is overcome in[11] a Dynamic Selection based NSAF (DS-NSAF) approach. DS-NSAF first sort out the subband filters which are involved in convergence and then adaptive filter weight is updated according to contributing filter coefficients. The successive Mean Square Deviations (MSDs) are decreased at every iteration because of dynamic sub band selection. This method decreases the computational complexity of the conventional SAF with critical sampling while band selection performance is maintained same. The conventional DS-SAF[9] is explained below.

The desired band d(n) is defined by,

$$d(n) = u(n)W^o + v(n) \tag{3}$$

Where, W^o is an unknown column vector, $v(i)$ corresponds to a variance σ_v^2 for each band, and $u(n)$ denotes a input vector of length M given as;

$$u(n) = [u(n)u(n-1) \ \dots \ u(n-M+1)] \tag{4}$$

The block diagram of Normalized Subband Adaptive Filter (NSAF) [11] is as shown below in Figure 4.

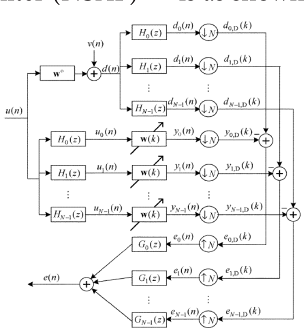


Fig. 1. Structure of the NSAF.

Figure 4. Block diagram of NSAF filter[8].

In NSAF analysis filters first partitions image samples into N subbands viz. $H_0(z)$, … $H_{n-1}(z)$. Which are then decimated as per required bandwidth to lower sampling rate.

The decimated filter output at each subband is given as;

$$y_{i,D}(k) = u_i(k)w(k), \tag{5}$$

Where, dimensions of $u_i(k)$ is a 1 x M,

$$u_i(k) = [u_i(kN), u_i(kN-1), \dots\dots, u_i(kN-M+1)] \tag{6}$$

The estimated weight is given as,

$$w(k) = [w_0(k), \quad w_1(k), \dots\dots, w_{M-1}(k)]^T \tag{7}$$

The error in each band is then defined by,

$$e_{i,D}(k) = d_{i,D}(k) - y_{i,D}(k) = d_{i,D}(k) - u_i(k)w(k) \tag{8}$$

Where $d_{i,D}(k) = d_i(kN)$ is the reference information at each band. The weight optimization is calculated as,

$$w(k+1) = w(k) + \mu \sum_{i=0}^{N-1} \frac{u_i^T(k)}{\|u_i(k)\|^2} e_{i,D}(k) \tag{9}$$

Where μ is the step size.

The optimization of convergence based on weight requires more number of calculations. This problem is solved in DS-NSAF which utilizes MSD based weight optimization[9].

Hence the weight error vector can be calculated as

$$\tilde{w}(k) = w^o - w(k) \ . \tag{10}$$

The weight optimization is then defined as,

$$\tilde{w}(k+1) = \tilde{w}(k) - \ \mu \sum_{i=0}^{N-1} \frac{u_i^T(k)}{\|u_i(k)\|^2} e_{i,D}(k) \tag{11}$$

Expectation of weight vector is used to compute MSD as given below,

$$E\|\tilde{w}(k+1)\|^2 \ = E\|\tilde{w}(k)\|^2 \ + \mu^2 E\left[\sum_{i=0}^{N-1} \frac{e_{i,d}^2(k)}{\|u_i(k)\|^2}\right] - 2\mu E\left[\sum_{i=0}^{N-1} \frac{u_i(k)\tilde{w}(k)e_{i,D}(k)}{\|u_i(k)\|^2}\right] \tag{12}$$

$$\triangleq \ \mathrm{E}\|\tilde{w}(k)\|^2$$

Where

$$\Delta = \mu \sum_{i=0}^{N-1} \left(2E\left[\frac{u_i(k)\tilde{w}(k)e_{i,D}(k)}{\|u_i(k)\|^2}\right] - \mu E\left[\frac{e_{i,d}^2(k)}{\|u_i(k)\|^2}\right]\right) \tag{13}$$

Δ is the difference of MSDs between two successive bands.

The bands having minimum MSD are selected for processing. This procedure reduces the number of coefficients to be processed. These bands are then encoded using modified encoding algorithm as presented below.

4. Hybrid Hierarchical Coding

Different encoding techniques were developed to improve image compression. After wavelet decomposition inter band relation is used to develop hierarchical coding. Embedded Zero Tree Wavelet (EZW)[12], Set Partitioning in Hierarchical Tree (SPIHT)[13] and Embeded Block Coding with Optimum Truncation (EBCOT)[14] are the some examples of hierarchical coding. Shapiro has introduced EZW algorithm fist[12] which has been improved by Said and Pearlman as SPIHT algorithm[13]. All these algorithms use relationship between sub band coefficients.

In these algorithms, initially threshold value is selected and coefficients having value greater than threshold are considered significant while others become insignificant which can be coded into one symbol.

In such coder the coding is performed using the property that, images in general have a low pass spectrum. When an image is wavelet transformed the energy in the subbands decreases as the scale decreases. Thus wavelet coefficients become smaller in higher sub bands than in lower sub bands[15-17]. This shows that progressive encoding was a significant way for compressing wavelet transformed images. Again one more feature can be noticed that the higher sub-bands only add detail and large wavelet coefficients are more significant than small wavelet coefficients. These features are taken into account by encoding algorithm and wavelet coefficients are encoded in decreasing order. During each pass a threshold value is selected and all coefficients are compared against specified threshold. If coefficient is larger than threshold it is encoded, otherwise processed in the next pass. In this way procedure is repeated until all coefficients are processed and encoded. These encoding algorithms explicitly use relationships between wavelet coefficients. The parts of image below specified threshold formulate a zero tree. Naturally, if root pixel is smaller than threshold, probability of other coefficients in a quad tree being small increases.

To derive a zero tree coefficient the upper band coefficients are recursively traced with lower band in a scan order (such as, raster mode) to obtain significant and non-significant coefficient. In each scale the threshold is decreased by a factor two, and the tracing process is recursively carried out. These repetitive iterations results in more computation, resulting in overhead, and such approach of scanning are validated for wavelet decomposition, but the lower band decomposition in multiwavelet approach is not applicable, due to two level of detail band decomposition. For such a case, an up-down coding of bands is presented. In such coding, the obtained multi-bands are coded from bottom to top and a selection status of '1' or '0' is made for selecting coefficient to process. This decreases the tracing overhead in coding. The Multiwavelet decomposition proposed encoding for a multi wavelet band is as illustrated in Figure 5 and 6 respectively.

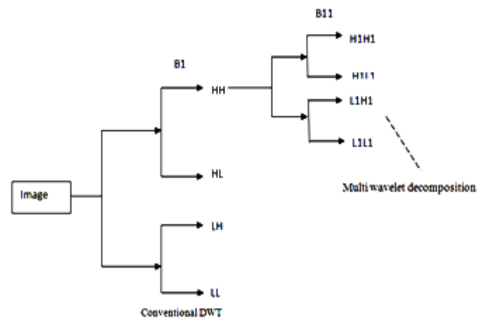


Figure 5. Multi wavelet decomposition.

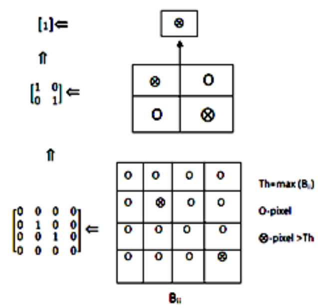


Figure 6. Proposed coding approach for coefficient selection.

For the selected band a coefficient selection process is carried out in prior to performing significant coding. To code the selection process, for selected band 'B_{ii}' a threshold, th_{ii} is computed as made in the conventional approach, defined as;

$th_{ii}= max(B_{ii})$.

A coefficient selection algorithm is defined as,

Algorithm:

Initialization;

Compute threshold,

$th_{ii}= max(B_{ii})$.

process;

For coefficient $C_{ii} € B_{ii}$

If $C_{ii}>= th_{ii}$

$Coeff_{ii}=1$;

Else

$Coeff_{ii}$=0;
End
If $coeff_{ii}$= 1
$Coeff_{ii-1}$ = 1;
End
End

Retaining the selected coefficients which are coded as '1' and making all other coefficients to zero, the selective coefficients are considered. This selection process reduces the selected coefficients to a very low count before passing for processing for hierarchical coding. As the selection are made based on the process of thresholding and carried out on a relational wise for a selected band, the selected coefficients reflects the significant coefficient for selection as made in other hierarchical coding such as EZW and SPHIT Coding[18-20]. The hierarchical refinement is carried out processing for, List of Insignificant Sets (LIS), and List of Significant Pixels (LSP).

Algorithm:

A. Band coefficients (X) are divided into two groups.
As R= root and I= X-R,
n = floor($\log_2$(max $|C_{i,j}|$))\ C(i,j) € X,
If C(i,j) ~= 0
If C(i,j) >= n
Add R to LIS ,
End
End
For each set R € LIS,
If Rand its descendent are significant
Remove R from LIS
Add Rto LSP
For each (i,j) € LSP,
Output the n^{th} MSB of $|C_{i,j}|$.
Decrement n by 1, and repeat the process
Until stopping criterion reach.

The adaptive band selection procedure is carried out after multi-wavelet transformation. These band coefficients are then encoded using modified hierarchical encoding which reduces the computational complexity as well as number of computations. Next section represents the simulation results for developed methods.

5. Simulation Results

The performance of proposed selective multi-wavelet coding is analyzed in terms of different parameters such as Compression Ratio (CR), PSNR, MSE and computation time. As well as it is analyzed with respect to conventional multi-wavelet and Discrete Wavelet coding (DWT).

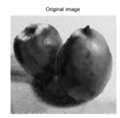


Figure 7. Original image.

Initially, input image is resized to 256 x 256 which is shown in Figure 7.

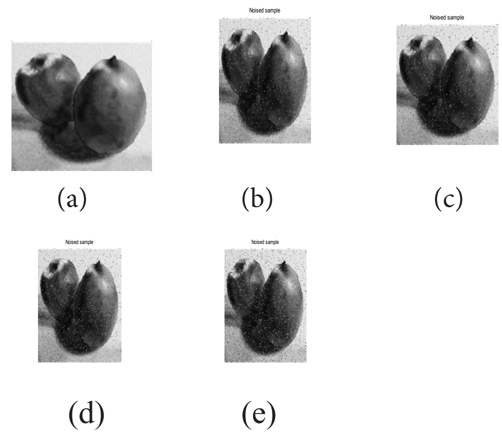


Figure 8. Noise added image with variance (a) σ=0, (b) σ=0.01, (c) σ=0.02, (d) σ=0.03, (e) σ=0.04.

The pepper and salt noise with a variance 0.01 to 0.04 is added in original image. These noisy samples are then processed with the help of adaptive filter as shown in Figure 8.

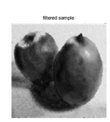


Figure 9. Filtered sample.

Figure 9. illustrates one of the filtered result obtained after the application of filtration operation. An adaptive filtration process is applied to achieve the objective of noise filtration.

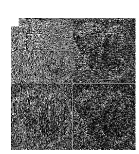
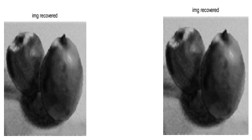


Figure 10. Decomposition by DWT.

Figure 10 shows the decomposition of original image due to DWT. DWT consists of combination of low pass and high pass filters. So, when image is passed through these filter banks it gets separated in high and low resolution spectrums. Increase in decomposition level increases number of decomposition bands.

(a) **(b)** **(c)**



(d) (e)

Figure 11. Recovered samples for DWT at, (a) σ=0, (b) σ=0.01, (c) σ=0.02, (d) σ=0.03, (e) σ=0.04.

The obtained image samples after the DWT based coding is presented in Figure 11. The obtained results ate different noise variances are shown in Figure 11 (a)-(e).

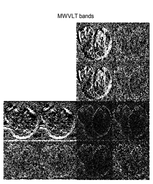
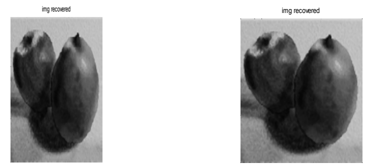


Figure 12. Multi-wavelet decomposition.

Similar to DWT, Multiwavelet transformation decomposes the image in sub bands as shown in Figure 12. From Figure it is clear that each resolution band is further decomposed into next four sub bands. In this way one level of decomposition produces sixteen sub bands.

Decomposition is followed by reconstruction phase where original image is reconstructed from decomposed image as illustrated in Figure 13.

In the process of selective MWVLT coding the process of LMSE computation and estimation is carried out among each inter bands in a resolution band and a band selection process is executed to achieve the band selection process in multi wavelet bands. The selective band for the multi wavelet band sown in Figure 12 is illustrated in Figure 14. The process of encoding is carries over these selected bands, which reduces the overhead and as well provide higher PSNR due to the selection approach.



(a) (b)

(c) (d) (e)

Figure 13. Recovered samples for MWT at, (a) σ=0, (b) σ=0.01, (c) σ=0.02, (d) σ=0.03, (e) σ=0.04.

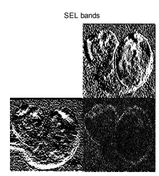


Figure 14. Selected Bands using S-MWT.

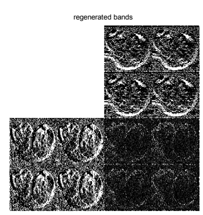
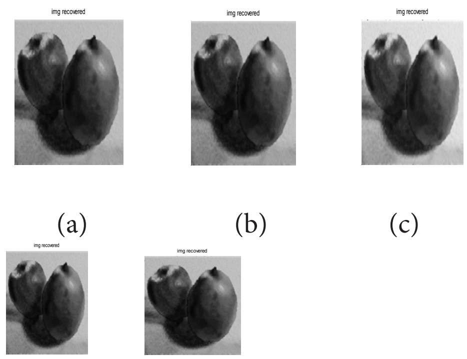


Figure 15. Band reconstruction for multi-wavet.

The processed sub bands are regenerated at the decoder side by the repetition of the decoded selective bands. A regenerated multi wavelet band for the given query sample is shown in Figure 15.

The recovered images after the image coding based on selective band coding at different noise variance is demonstrated in Figure 16.

The MSE for the developed method at different level of noise variance is shown in Figure 17. The MSE value is observed to be minimum for the proposed S-MWLT coding. The approach shows a lower MSE due to the selective nature of band selection. Due to minimal correlative band selection, the MSE of recovered sample is observed to be lower. Wherein this value is higher in the case of DWT approach due to single level of spectral decomposition. In the case of MWVLT coding this is lower than the DWT approach due to finer band decompositions. The recovered MSE level is observed to about linear with increase in variance due to initial adaptive filtration and spectral level band selection process.



(a) (b) (c) (d) (e)

Figure 16. Recovered samples for MWT at, (a) σ=0, (b) σ=0.01, (c) σ=0.02, (d) σ=0.03, (e) σ=0.04.

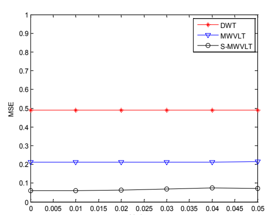


Figure 17. MSE with increase in noise variance.

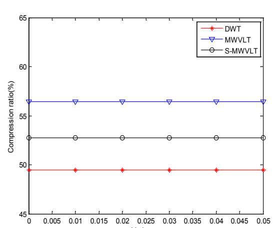


Figure 18. Compression ratio with increase in noise variance.

The achieved compression level for the developed three methods is presented in Figure 18. The compression achieved for the proposed S-MWVLT coding, is comparatively higher than the DWT based coding. Due to higher spectral band decomposition the number of coefficient processing increases. This result in higher number of coefficients hence reducing the compression factor in multi spectral based coding. However the issue of lower compression is improved in the proposed approach of S-MWVLT by introducing the selective coding approach.

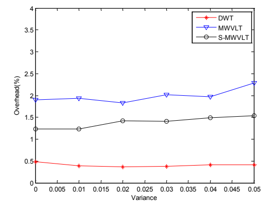


Figure 19. Overhead with increase in noise variance.

The overhead is defined as a ratio of number of processing coefficient over the processing time taken. In this analysis the overhead for the three methods are evaluated as shown in Figure 19. The overhead is lower in case of DWT based, however in comparison to MWVLT coding; proposed S-MWVLT coding has lower overhead.

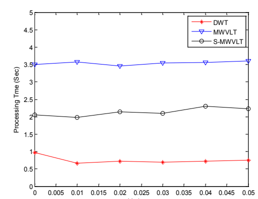


Figure 20. Effect of noise variance on computation Time.

The computation time is measured for the three methods with respect to increase in the variance level is illustrated in Figure 20. The time taken for the proposed method is observed to be lowered due to selective coding in comparison to MWVLT coding.

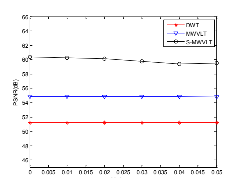


Figure 21. PSNR with increase in noise variance.

From Figure 21 it is clear that the PSNR for the proposed approach has improved by a factor of 7dB in comparison to MWVLT coding and about 10dB in comparison to DWT based coding.

To evaluate the effect of coding rate on the reconstruction accuracy, the test sample is tested at different targeted coding rate of 0.2, 0.5 and 0.8. The obtained results are as illustrated in Figure 22 (a)-(c) respectively.

(a) (b) (c)

Figure 22. Recovered sample at, (a) coding rate (r) =0.2, (b) r =0.5, (c) r =0.8.

The recovered samples processed at a variance of 0.04 at different data rates are shown in Figure 22 (a)-(c). The measured quality metrics for the developed approaches are illustrated below.

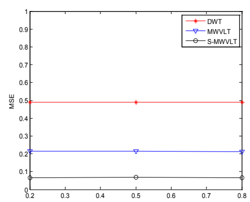


Figure 23. MSE with variation in coding rate.

The MSE for the S-MWVLT coding is observed to be lower and it is maintained constant over increase in coding rate in Figure 23. As the coding rate increases, the selective coding in accordance selects the bands, which maintains the MSE over different coding rate.

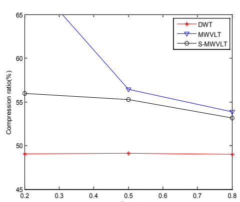


Figure 24. Analysis of Compression ratio with respect to coding rate.

Figure 24 gives the performance analysis of DWT, MWVLT and S-MWVLT considering compression ratio as performance parameter. Form Figure it is noticed that multi-wavelet performs better at lower coding rate but as coding rate increases its performance is degraded. But at higher coding rate performance of selective multi-wavelet coding has improved. The appropriate band selection procedure number of coding coefficients and hence number of bits to be processed decreases.

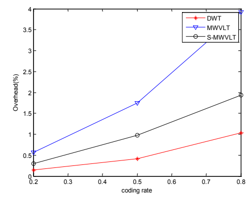


Figure 25. Overhead with variation in coding rate

From Figure 25 the overhead is observed to be increasing with increase in coding rate. This is comparatively higher in case of MWVLT coding, wherein lower in S-MWVLT coding and minimum in DWT based coding.

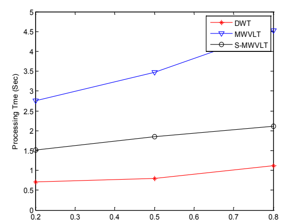


Figure 26. Processing Time with respect to coding rate.

The processing time is the time required to process coefficients obtained from image. Figure 26 illustrates that processing time for S-MWVLT is smaller than multi-wavelet.

Table 1. Observation for compression ratio over different noise variance

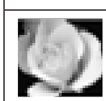
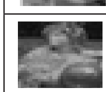
Sample	CR@⍰=0.1			CR@⍰=0.3			CR@⍰=0.5		
	DWT	MWT	SEL-MWT	DWT	MWT	SEL-MWT	DWT	MWT	SEL-MWT
	49.01	58.749	55.60	49.01	58.76	50.60	49.01	58.74	50.62
	52.34	59.23	56.46	52.47	59.1	56.16	52.77	51.86	56.01
	50.12	58.77	55.44	50.33	58.04	56.32	50.32	56.22	56.1
	49.64	60.02	56.54	49.44	59.74	58.98	49.22	57.21	59.1

Table 2. Observation for MSE over different noise variance

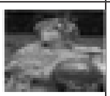
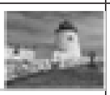
Sample	MSE@□=0.1			MSE@□=0.3			MSE@□=0.5		
	DWT	MWT	SEL-MWT	DWT	MWT	SEL-MWT	DWT	MWT	SEL-MWT
	0.60	0.24	0.13	0.60	0.24	0.13	0.60	0.24	0.124
	0.54	0.32	0.15	0.56	0.22	0.14	0.44	0.25	0.136
	0.56	0.48	0.15	0.53	0.23	0.136	0.32	0.33	0.14
	0.61	0.53	0.18	0.56	0.21	0.15	0.11	0.24	0.145

Table 3. Processing time over different noise variance

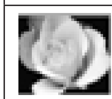
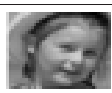
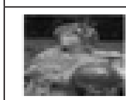
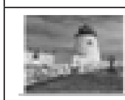
Sample	CT@□=0.1			CT@□=0.3			CT@□=0.5		
	DWT	MWT	SEL-MWT	DWT	MWT	SEL-MWT	DWT	MWT	SEL-MWT
	0.95	3.98	2.45	0.75	3.75	2.32	0.71	3.81	2.64
	0.94	3.63	2.1	0.71	3.55	2.18	0.69	3.66	2.1
	0.99	3.12	2.8	0.66	3.1	2.7	0.4	3.87	2.78
	0.12	4.22	2.33	0.9	3.8	2.05	0.8	3.4	2.3

Table 4. Observation for PSNR over different noise variance

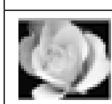
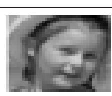
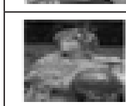
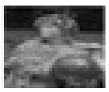
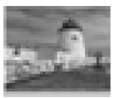
Sample	PSNR@□=0.1			PSNR@□=0.3			PSNR@□=0.5		
	DWT	MWT	SEL-MWT	DWT	MWT	SEL-MWT	DWT	MWT	SEL-MWT
	50.31	54.21	56.89	49.22	54.21	56.89	51.26	53.4	55.2
	49.65	53.97	56.1	50.1	54.56	56.1	50.41	54.1	56.1
	50.11	54.1	56.65	50.55	54.3	56.44	50.86	53.51	56.35
	51.54	56.75	56.89	51.04	53.51	55.94	51.66	54.03	56.03

Table 5. Observation for overhead over different noise variance

Sample	OVR@□=0.1			OVR@□=0.3			OVR@□=0.5		
	DWT	MWT	SEL-MWT	DWT	MWT	SEL-MWT	DWT	MWT	SEL-MWT
	0.47	1.99	1.31	0.37	1.87	1.90	0.35	1.16	1.8
	0.43	1.76	1.2	0.36	1.44	1.52	0.31	1.3	1.4
	0.35	1.45	1.4	0.27	1.2	1.66	0.38	1.27	1.73
	0.44	1.3	1.36	0.3	1.55	1.22	0.364	1.8	1.44

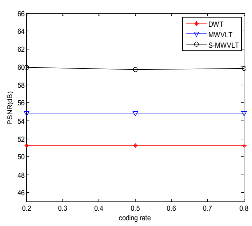


Figure 27. PSNR with respect to coding rate.

The performance of S-MWVLT coding is analyzed in terms of Peak Signal to Noise Ratio at different coding rates and compared with multi-wavelet and DWT as shown in Figure 27. It indicates that S-MWVLT provides higher PSNR than other methods.

A comparative analysis is carried out for different test sample and the observations made are presented in Table 1-5 illustrated below.

6. Conclusion

A new selective approach to multi wavelet decomposition following inter-band hierarchical coding is developed. Adaptive band selection is developed for multi wavelet coefficients. Bands having minimum Mean Square Deviation (MSD) are then chosen as a selective band for processing rather than all decomposed bands. This band selection process reduces the processing coefficient with minimum deviation due to the selecting criterion of minimum MSD value. These selected bands are then encoded using modified encoding algorithm to achieve higher level of compression.

The proposed approach provides better performance in terms of Compression ratio, Peak Signal to Noise ratio, processing time etc. than conventional methods. In Future this technique may be combined with artificial intelligence so as to further reduce computational complexity and processing time.

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