Adaptive Scalable Wavelet Difference Reduction Method for Efficient Image Transmission

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Abstract. This paper presents a scalable image transmission scheme based on the wavelet-based coding technique supporting region of interest properties. The proposed scheme scalable WDR (SWDR), is based on the wavelet difference reduction scheme, progresses adaptively to get different resolution images at any bit rate required and is supported with the spatial and SNR scalability. The method is developed for the limited bandwidth network where the image quality and data compression are mopst important. Simulations are performed on the medical images, satellite images and Standard test images like Barbara, fingerprint images. The simulation results show that the proposed scheme is up to 20-40% better than other famous scalable schemes like scalable SPIHT coding schemes in terms of signal to noise ratio values (dB) and reduces execution time around 40% in various resolutions. Thus, the proposed scalable coding scheme becomes increasingly important.

1 Introduction

The multimedia images are coded efficiently using the wavelet transform based traditional coding techniques. Due to the popularity of multimedia applications, the scalable image compression and transmissions are necessary through the heterogeneous networks with different processing capabilities and network access bandwidths. The images like medical images and satellite images are focussed on efficient use of compressed data without causing the quality of outputted data. Hence, the code scheme should be controlled adaptively to provide flexible bit streams so as to support the scalable image processing [1].

Compression of different types of images with various imaging models like real time transmission, image library archival, limited buffer and bandwidth resources etc are designed using image compression standard JPEG2000. Now a days, the object based coding scheme have much attention due to the ROI based functionalities of JPEG2000 [7]. JPEG2000 utilizes two types of wavelet filter. Daubechies 9/7 floating point wavelet filter provides lossy compression. Biorthogonal 5/3 integer wavelet filter supports lossless compression at the cost of higher compression bit rate. Here, the reverse integer filter is used to produce a scalable bit stream for medical images and biorthogonal 9/7 filter for satellite images and standard test images like Barbara, fingerprint images etc. which builds up scalable quality image representation.

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The multi-resolution signal representation using wavelet transform is used in most famous embedded coding algorithms like EZW [10] and SPIHT [2] algorithms. Danyali and Mertins proposed a SPIHT [6] algorithm which supports the spatial resolution scalability in spite of its SNR scalability. But some times, the zero tree coding methods are computationally very complex. The wavelet difference reduction method of Tian and Well [3] is one of the major alternatives of the SPIHT algorithm which is quite useful for fast reconstruction using the idea of run-length coding technique for coding images. The WDR algorithm has been improved by various authors. Among them, ASWDR of Walker and Nguan [4] and context-modeling with WDR (CMWDR) method by Yuan and Mandal [5] offer better performances than SPIHT algorithm even without entropy coding.

The proposed scalable coding scheme is based on the wavelet difference reduction method and incorporates the scalability property. Compression of multimedia images like medical images, satellite images etc. and its transmission offers better utilization of available bit rate such that high fidelity is maintained for relatively small regions rather than for the entire image. The wavelet coefficients of regions of interest are rearranged using the zero tree concepts in accordance with a priority so that the run length coding performance can be increased.

The paper is organized as follows: the extraction of region and the scalability concept is presented in the section 2, the proposed scalable WDR algorithm is presented in section 3, the experimental results are discussed in section 4 and conclusion in section 5.

2 Region Extraction and Scalability Concepts

The traditional coding techniques follow the multi-resolution form of the image. The wavelet transform is one mathematical tool for viewing or processing the image at multiple resolutions. In addition to being an efficient, highly intuitively framework for the representation and storage of multi-resolution images, the DWT provides powerful insight into the spatial and frequency characteristics of the images. Even if the wavelet transform is applied to the image, each and every subband maintains not only its frequency domain characteristics but its time domain characteristics also. So, here we are considering both time and frequency characteristics for locating the wavelet coefficients inside the textured regions and edges accurately and remove the back ground noise part.

Consider the multiresolution form of the image, I as

$$I = \begin{bmatrix} LL_i & HL_i \\ LH_i & HH_i \end{bmatrix} \quad (1)$$

The most significant coefficients are clustered in some areas of each subband. The corners and textures are to be re-arranged for coding efficiently with proper priority assigned to each component. So we applied eigen value analysis to the subbands to get the textured regions. Consider the subband B, any one from set $\{HL_i, LH_i, HH_i\}$ at level 'i', for eigen value analysis. Apply linear transformation to the subband B to get subband L_B which has spatial resolution dependency with the subband LL_i. The linearly transformed subband L_B is divided into fixed size window w for labelling content feature inside the subband B. Before starting the eigenspace analysis, the subband gradient calculations are carried out, so that the most textured regions can be seperated in terms of edges and corners more accurately. $L_B(i)$ is the linearly transformed wavelet coefficient value in 2-D window w which has the spatial domain dependency with the LL_i. $\nabla L_B(i)$ is the gradient at each point i in w.

$$\nabla L_B(i) = \left(L_{Bx}(i), L_{By}(i)\right)^T , \tag{2}$$

where $L_{Bx}(i) = \partial L_B / \partial x$ and $L_{By}(i) = \partial L_B / \partial y$ and the autocorrelation matrix is formed as,

$$C = \begin{bmatrix} \sum L^2{}_{Bx}(i) & \sum L_{Bx}(i) L_{By}(i) \\ \sum L_{Bx}(i) L_{By}(i) & \sum L^2{}_{By}(i) \end{bmatrix} \tag{3}$$

The singular value decomposition is performed on the 2x2 symmetric autocorrelation matrix C in equation (3) , so that we get the normal equation $\mathrm{C} = \mathrm{UDU}^{\mathrm{T}}$, where U is the orthonormal column vector and D is the diagonal matrix $diag\,(e_1, e_2)$, $e_1 \geq e_2$, where e_i are the eigen values of the autocorrelation matrix C.

Based on the meaning of Us and e 's , there are three different cases regarding the visual content of the images.

1. If e_1 is small, $L_B(i)$ in w corresponds to smooth regions in w.
2. If e_1 is of predominant magnitude, or equivalently e_2 is of extremely small magnitude, then there will be edge(s) in w.
3. If e_2 is significant, there remains considerable frequency gradients and regular patterns and textures in the window w.

Considering these three typoes of conditions, we can apply particular threshold value on eigen values (e_1 , e_2) of L_B so that edges and textures area of B are located and extracted [9]. Examples of such extracted texture area of Barbara image, MRI head image and satellite image are shown in figure 1 Meaningful extracted areas can be obtained by selecting appropriate values for the eigen values above. After the region extraction process, we consider the processed subband B for applying the zero tree concept. Each textured block in B has four child blocks in the next level of subband decomposition and all such child blocks are collected from parent node to lowest level child blocks. Moreover, the processed subband block B has the mirror image on all other subbands of the same level. Hence, we get the texture regions on the wavelet coefficients in all subbands in a single eigen value analysis and this can be encoded as fast as possible from lowest frequency to highest frequency.

The scalable coding technique codes different resolution subbands independently one by one in each bit plane. The resolution level of the image is identified from the number of wavelet decompositions performed. Let the image be decomposed into N levels, the image has the (N+1) levels of spatial resolution subbands [6]. We can also represent the spatial resolution with original resolution as $(1/2^{L-1})$, where L is the level of resolution. Each level of the subband consists of three parts HL_L, LH_L and HH_L. The scalable algorithm considers each subband level as coded separately allowing the decoder or encoder to reconstruct different spatial resolution images.

Consider the subband level L, the subbands are grouped as $\lambda_L = [HL_L, LH_L, HH_L]$. The algorithm progresses through each level of suband groups from $(N+1) \le L \le 1$ so that a flexible stream of bits will be generated. The general structure of scalable encoder bit stream is shown in figure 2.

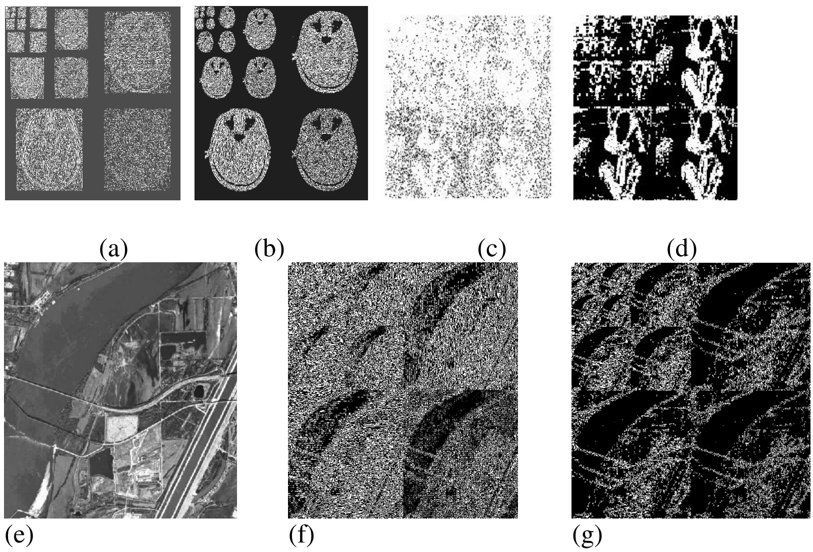


Fig. 1. (a) Multi resolution form of MRI images. (b) Region extraction of MRI images. (c) Multi resolution form of Barbara image. (d) Region extraction of Barbara image. (e) Satellite image (f) multi resolution form of satellite image (g) Region extraction of satellite image.

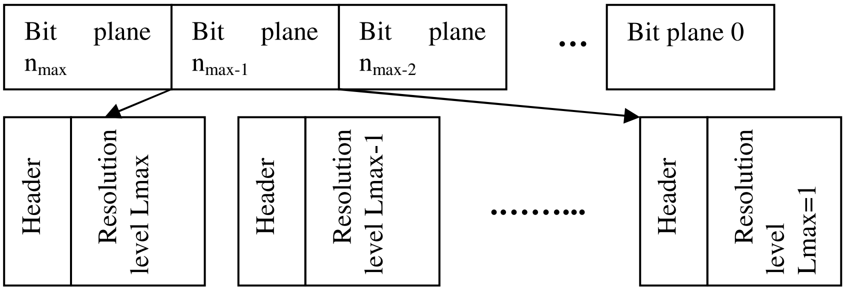


Fig. 2. Scalable bit stream structure with progressive quality

3 Scalable Wavelet Difference Reduction Method

The proposed algorithm is a modification of wavelet difference reduction method (WDR) [5, 6] incorporating the scalability property. The scalability properties are incorporated through multiple resolution dependent lists. The scalable WDR (SWDR) coding scheme uses the data structures *RGE* (coefficients that are collected during the adaptive scanning process in Region Growing manner)*, SNS* (Significant Neighbour Sub-array*, SPS* (Significant Parent Sub-array)*, LIP* (List of Insignificant Pixels), *LSP* (List of Significant Pixels), *TPS* (Temporary Set of Significant coefficients) to divide the wavelet coefficients and code efficiently and get good compression results.

For each spatial subband group λ_L , the lists are ordered as RGE_L, SNS_L, SPS_L, LIP_L so that L will be L_{max}, *L-1,----1* where L_{max} is the maximum number of spatial resolution level supported by the encoder or decoder. During the processing of wavelet coefficients from the subband level λ_L , coefficients from outside the subband will be included in the next level of list at *(L-1)* level. Scalable WDR bit stream can easily be reordered for multi resolution decoding at any desired bit rate. The total number of bits belonging to a particular bit plane is the same for original scheme and its scalable version, but they are re-arranged in accordance with their spatial resolution dependency. The definitions of sets, symbols and functions are listed below.

(i, j) = Pixel coordinates.

w_{ij} = Wavelet coefficient at pixel location (i, j)

$n = \left\lfloor \log_2\left(\max_{(i,j)\in I}|w_{ij}|\right)\right\rfloor$, maximum number of bit planes.

t_n = Threshold value at bit-plane n

(m, n) = Pixel coordinate generated from (i, j)

L_{max} = maximum level of spatial scalability to be supported by the bit stream *(1<=* L_{max} *<=N+1),* where *N* is he number of wavelet decomposition levels applied to the image.

$$\lambda_L = \begin{cases} \{LL_{L-1}\} & if L = N+1 \\ \{HL_L, LH_L, HH_L\} & 1 <= L <= N \end{cases}$$

$$\sigma(w_{ij}, t_n) = \begin{cases} 1 : & |w_{ij}| \geq t_n \\ 0 : & |w_{ij}| < t \end{cases} \quad \text{Significant test of a coordinates } (i,j) \text{ at bitplane } n_n$$

$$Sign(w_{ij}) = \begin{cases} + & : w_{ij} \geq 0 \\ - & : w_{ij} < 0 \end{cases}$$

Neighborhood functions

1. $cluster\ (w_{ij}, t_n) = \{(m,n)\}$, when
   1. $(i-1) \leq m \leq (i+1), (j-1) \leq n \leq (j+1)$
   2. $(m,n) \in \lambda_L \ \& \ (i,j) \in \lambda_L$
2. $child\ (w_{ij}, t_n) = \{(m,n)\}$, when

1. $(m,n)\in\begin{Bmatrix}(2i,2j),(2i,2j+1)\\(2i+1,2j),(2i+1,2j+1)\end{Bmatrix}$
2. $(m,n)\in\lambda_{L-1}$ & $(i,j)\in\lambda_L$

Encoding Procedure is outlined below.

1. *Initialization*

   $LSP_L=\phi \quad ,TSP_L=\phi \quad \forall L \quad ,1\le L\le L_{\max}$

   $LIP_L=\begin{cases}\phi \quad , \quad \forall L \quad ,1\le L\le L_{\max} \quad such \quad that\\ \quad RGE_L=\phi, SNS_L=\phi, SPS_L=\phi\end{cases}$

   $t_{n-1}=2^{n+1}$, $t_n=t_{n-1}/2$

   L=Lmax;

2. *Sorting pass*

```
 If  LIP_L(σ(w_ij, t_{n-1}) = 0)
     {If LIP_L(σ(w_ij, t_n) = 1){Coding (w_ij ,L) ;}}
 If  λ_L ≠ φ
     {If σ(w_ij, t_{n-1}) = 0{If σ(w_ij, t_n) =1
        {Coding (w_ij , L); RGE_L = cluster(w_ij, t_n);
        Do {If RGE_L ≠ φ
           {If RGE_L(σ(w_ij, t_{n-1})) = 0{{If RGE_L(σ(w_ij, t_n)) =1
                Coding (w_ij , L); RGE_L = cluster(w_ij, t_n)}}
                 } while (End (RGE_L)! =True) ;}}}
```

Function coding $(w_{ij}$ *,L)*

{ Output distance ‘d’ from previous significant
Send binary representation of ‘d’ without leading
MSB ‘1’.Send sign information of w_{ij} , $Sign(w_{ij})$

Add w_{ij} into TPS_L.

}

3 *Index updating pass*:

 If $TPS_L\neq\phi$ {

   $SNS_L=cluster\left(w_{ij},t_n\right) \quad ; \quad \forall(i,j)\in TPS_L$

   $SPS_{L-1}=child\left(w_{ij},t_n\right) \quad ; \quad \forall(i,j)\in TPS_L$ }

 $LIP_L=RGE_L+SNS_L+SPS_L$

4 *Refinement Pass:*

   If $LSP_L\neq\phi$ **{** If $LSP_L(\sigma(w_{ij},t_{n-1})=1)$

     {Add nth MSB of $LSP_L(w_{ij})$ **.}}**

   $LSP_L=LSP_L+TPS_L$.;$TPS_L=\phi$;

5 *Resolution scale updates:*

   Send Header Information;

```
    If (L > 1) L=L-1; Goto step 2.
    Else L=Lmax;
6 Threshold update:
    I f tn >1 t_{n-1} = t_n   &   t_n = t_n / 2
       Goto step 2.
    End
```

The above encoder steps are recapitulated in the decoder side for producing a quantization output. The algorithm produces four symbols: +, -, 1, 0. These symbols are coded as in CM-WDR [5] algorithm using 2 bits as 11 for +, 10 for -, 01 for 1 and 00 for 0. The proposed algorithm Scalable WDR coding scheme also avoids the arithmetic coding.

4 Experimental Results

The proposed scheme is compared with original SPIHT and its scalable version. The simulations were done on 8-bit images like Barbara, Fingerprint etc with size 512x512, satellite images and 8-bit MRI images of 512x512. 10 classes of medical images with 100 frames in each class are also considered for the simulation. The original resolutions of these images were (512x512) pixels. The wavelet decomposition is based on the bi-orthogonal 5/3 integer wavelet filter and 9/7-tap bi-orthogonal Daubechies filter with symmetric extension at the image boundary [8]. Six levels of wavelet decomposition were first applied to each test image, then the scalable WDR encoder was set to encode the coefficients from $\text{bitplane}_{\max}$ to bitpane_0 supporting maximum spatial scalability levels as 7.

The bit stream for each spatial resolution at different rates and the fidelity was measured by the peak signal to noise ratio defined as,

$$PSNR = 10 \log_{10}\left(\frac{\max^2}{MSE}\right) dB, \tag{4}$$

where MSE is mean squared error between the original and the reconstructed image; ***max*** is the maximum possible magnitude of a pixel inside the image. The integer wavelet decomposition produced the ***max*** value is 255. and the ***max*** value for biorthogoanl 9/7 wavelet filter is 255 for an 8 bits/pixel original image (level-1) and $255*2^{L-1}$ for resolution level L This is done by considering the fact that the resolution level L is obtained from the original image after applying (L-1) levels of 2-D wavelet decomposition with filters having a DC amplification of $\sqrt{2}$. The bit rates for all levels were calculated according to the number of pixels in the original full size image [6].

All the results for SPIHT, scalable SPIHT and scalable WDR were obtained by decoding the binary bit streams without considering the arithmetic coding. The simulation results obtained using bi-orthogonal 5/3 integer wavelet filter performed on medical images are given in Table 1 and the results obtained using bi-orthogonal 9/7 wavelet filter performed on standard test images and satellite images are given in

Table 2. The reconstructed images at different resolution level are shown in figure 3. The simulation results show that the proposed coding scheme is much better than the existing SPIHT and its scalable version. The performance gain for full resolution is meaningless, because both encoders, original and its scalable version, produce almost the same number of bit streams. For full resolution MRI image reconstruction, the performance gain is from 0.30 dB to 0.40 dB for various bit rates using bi-orthogonal 5/3 integer wavelet filter. For full resolution reconstruction, the standard test images Barbara, fingerprint images and satellite images have from 0.35 to 0.50 db coding gain in various bit rates.

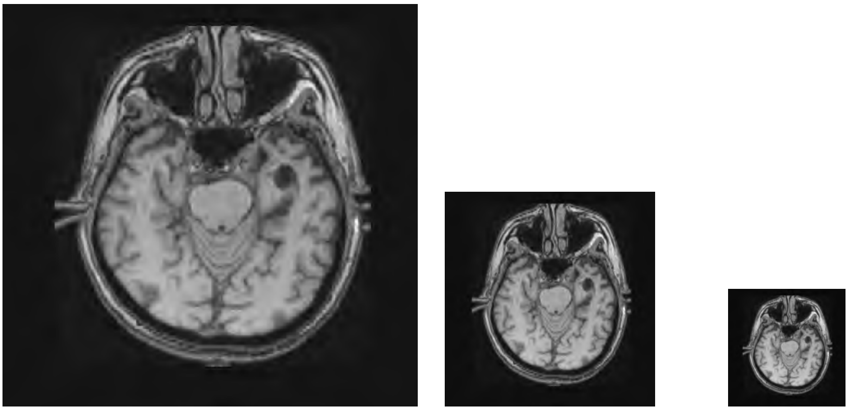
Table 1. Scalable coding results of MRI using biorthogonal 5/3 tap Integer wavelet transform

Test Image	Bit rate	Full Resolution (512x512)		(1/2 Resolution) 256x256		
		SPIHT	SWDR	SPIHT	SSPIHT	SWDR
MRI	0.0313	23.47	23.99	23.29	23.30	23.79
	0.0625	27.41	27.54	27.16	27.36	27.43
	0.125	29.10	29.52	28.99	29.28	30.97
	0.25	33.77	34.13	33.85	37.16	38.29
	0.5	39.08	39.35	39.36	45.84	46.20
	1	43.99	44.40	-	-	-

Table 2. Scalable coding results of standard test images and satellite image using biorthogonal 9/7 tap wavelet transform

Image	Bit rate	Full Resolution (512x512)		(1/2 Resolution) 256x256		
		SPIHT	SWDR	SPIHT	SSPIHT	SWDR
Finger-print	0.125	21.92	22.27	22.67	22.68	23.04
	0.25	24.65	25.14	25.67	25.90	26.26
	0.5	28.12	28.74	30.18	30.90	31.33
	0.75	30.48	30.91	34.24	36.07	36.41
	1	32.04	32.56	35.88	41.80	41.95
Barbara	0.125	24.89	25.21	28.56	30.11	30.30
	0.25	27.64	28.20	31.46	34.64	34.95
	0.5	31.62	32.09	36.02	41.39	41.82
	0.75	34.49	34.92	38.82	46.87	47.11
	1	36.80	37.23	41.68	51.57	51.69
Satellite Image	0.125	23.49	23.71	25.61	25.71	25.91
	0.25	25.69	25.89	28.68	29.54	29.85
	0.5	28.55	28.98	31.86	35.93	36.26
	0.75	30.97	31.29	35.54	42.05	42.21
	1	32.96	33.42	37.09	47.88	47.95

But, the performance of coding in PSNR value (in dB) increases when the resolution scale decreases. For resolution level 2 of medical images MRI, i.e. 256x256, the performance gains of SWDR are from 0.26dB to 6.84 dB compared to the normal SPIHT and from 0.36 dB to 1.68 dB compared to the scalable SPIHT for various bit rates using 5/3 integer wavelet filter shown in table 1. Similar experimental results are obtained for the various resolutions for satellite images and standard test images like Barbara, Fingerprint images etc. Moreover, around 40% of time is saved for proposed scheme as compared to the zero tree coding scheme.



(a) Full resolution -1 (b) (½) (c) (¼)

(d) Full resolution -1 (e) (½) (f) (¼)

Fig. 3. Scalable image reconstruction at bit rate 0.0625 (a, b, c) MRI image, (d, e, f) satellite image

The original decoder decodes the whole image at each bit rate and then the requested spatial resolutions are reconstructed. The scalable decoder obtained the proper bit streams tailored by the parser for each resolution level. All bits in the reordered scalable bit stream for a particular resolution belong only to that resolution; while in the original coding scheme stream bits that belong to different resolution levels are interwoven. The performance expected is much better than the existing methods for resolution level greater than one. The difference between scalable and non scalable methods becomes more and more significant, when the resolution levels increases.

5 Conclusion

We propose a scalable WDR coding method which supports spatial and SNR scalability. The flexible bit stream generated by the encoder can be decoded adaptively to get any level of spatial resolution images. The scalable WDR is 20 - 40 % better than the scalable SPIHT and original SPIHT at any bit rate in scalable properties and is of low complexity than the zero tree coding techniques. The proposed coding scheme is applied to the medical images, satellite images and standard test images like Barbara, Fingerprint images. The scalability features of proposed method have interesting perspectives for numerous visual communications applications. Extensions of this work to video coding, and particularly to efficient frame-rate adaptive methods, are worth investigating for potential solutions to adaptive video delivery scenarios.

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