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Performance analysis of modified wavelet difference reduction methods in image compression and transmission

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ABSTRACT

The wavelet difference reduction (WDR) method, a variant of run-length coding, finds its significance in data transmission applications. Over time, numerous enhanced iterations of WDR methods have emerged. Notably, the Adaptive Scalable WDR method exhibits superior coding gains, as evidenced by the peak signal-to-noise ratio (PSNR) and structural similarity index metric (SSIM), when compared to its predecessors. This paper conducts an exhaustive examination, encompassing both coding performance and time complexity, of various WDR methods vis-à-vis the conventional image compression algorithm SPIHT. Furthermore, it delves into the performance assessment of diverse coding techniques in the realm of encoding arbitrary-shaped objects. The analysis underscores that modified WDR variants demonstrate remarkable prowess in compression, rendering them invaluable for rapid transmission in bandwidth-constrained networks. To substantiate these findings, coding results (measured in terms of PSNR) are derived from the application of these algorithms to standard test images, MRI images, and video still images. The results reveal coding gains ranging from 0.5 dB to 1 dB for regular resolution images and a substantial 2 dB to 12 dB for scalable resolution scenarios, in comparison to traditional coding approaches. Consequently, this analysis underscores the convenience and superiority of modified WDR methods, not only for still images but also for encoding and transmitting arbitrary-shaped objects.

1. Introduction

Image coding algorithms have an important role in multimedia image transmission scenarios. Among them, wavelet-based image coding algorithms (Thomas et al., 2023; Khandelwal and Sharma, 2023; Bovik, 2005; Garg and Kumar, 2022; Vetterli and Kovacevic, 1995) are the most popular. To achieve cost-effective transmission (Danyali and Mertins, 2004), the coding algorithms are focused on the region of interest area (ROI) (Salomon, 2004; Manpreet and Wasson, 2015) based concepts. The ROI part of images may be considered as arbitrary shapes (Caguazzo et al., 2005) that are more general than rectangular frames. The coding of these objects become an important issue in multimedia communications.

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Arbitrary-shaped objects are identified by the process of segmentation applied to an image considering different characteristics. Adaptive coding schemes are applied to these objects and separately encoded to increase the compression performance. These approaches are different from coding schemes such as JPEG (Christopoulos et al., 2000) with cosine transformation and JPEG2000 coding standards (Christopoulos et al. 2000) with wavelet transformation. The other approach has been developed to decompose arbitrary-shaped objects which uses FIR wavelet filter and it can be either in bi-orthogonal or orthogonal form. The approach proceeds by decomposing the individual 1-D image segments inside the object. First, the row of the object is considered, and then the same process is repeated on each column. Moreover, this approach (Li and Li, 2000; Xu and Zhu, 2005) maintains the overall number of pixels inside the objects and the overall number of wavelet coefficients inside the transformed domain are equal.

The video coding standard MPEG-4 has been implemented by using shape-adaptive discrete wavelet transform with zero tree coding algorithms (Martin et al., 2006; Mehrotra et al., 2004). The coding scheme which is used to code texture in video objects, generally avoids generated transform coefficients present in the outside of arbitrary-shaped objects. Due to the limited performance of these algorithms, different coding algorithms were considered and analyzed. Among them, the run length coding method is the most famous. In this paper, the performance of a modified version of run length coding called the wavelet difference reduction method (WDR) method (Tian and Wells, 1998) is presented. A lot of modified versions of WDR methods were developed such as the adaptively scanned WDR (ASWDR) scheme (Walker, 2000) and context-modeling with the WDR (CMWDR) method (Yuan and Mandal, 2004; Yuan and Mandal, 2005; Law et al., 2004; Lamsrichan and Sanguankotchakorn, 2006; Berghorn, 2001a). These methods offer better coding performance in different compression ratios than the zero-tree coding methods such as the SPIHT method (Said and Pearlman, 1996).

The paper presents a novel method called the adaptive scalable WDR method (Bindulal and Kaimal, 2007). This is a hybrid method that uses the layered approach of the WDR coding method with a selected region growing (WDR-SRG) approach (Bindulal and Kaimal, 2006) in association with shape-adaptive wavelet transform (Mehrotra et al., 2004). This helps to competently code random molded objects to preserve adaptive scalability properties. The coding performance of the new versions of the WDR algorithm is compared to traditional methods in terms of distortion metrics like PSNR values and structural similarity index (SSIM) metric (Wang et al, 2004). The calculated values in PSNR and SSIM show that the coding performance of scalable WDR schemes is much better than the traditional coding methods like SPIHT (Said and Pearlman,1996) and its scalable version (Martin et al, 2006). Complexity analysis of different WDR methods is also performed and compared with spatial orientation tree-based coding techniques like SPIHT. Obtained time complexity shows that different WDR methods based on run length coding have less time required than that of the SPIHT method. Moreover, it is better in the situation of high-speed networks with limited bandwidths (Marinov et al., 2005, Manpreet et al., 2015).

2. Shape-adaptive discrete wavelet transform

The shape-adaptive discrete wavelet transform is a modified method used to generate transform coefficients (Li and Li, 2000; Mehrotra et al., 2004) of arbitrary-length image segments. The arbitrary-shaped image segments are identified using subsampling methods and applied wavelet transform. The transform can use odd symmetric or even symmetric bi-orthogonal wavelet filters. Here, the odd symmetric bi-orthogonal wavelet filters were used which have much better rate-distortion performance than even symmetric filters.

2.1. 2D shape-adaptive DWT

The discrete wavelet transform with sub-sampling method is applied on the random shaped regions. The approach called shape-adaptive transform is progressed through the following steps:

- The first row of pixels inside the identified shape information is considered for transformation. One-dimensional wavelet transform is applied on this line of segment. The transformed coefficients are placed into the low pass band and the high pass band of corresponding rows.
- The same operation moves forward through the section of successive pixels in each row downwards and then is applied to the respective columns of the low-pass and high-pass objects.
- Similar transformation is done on the low-pass object to get different heights of wavelet subbands.

Thus, the two-dimensional transformation of random span objects (Fig. 1) produces a multiresolution pyramid form of objects which effectively preserves the spatial correlation properties.

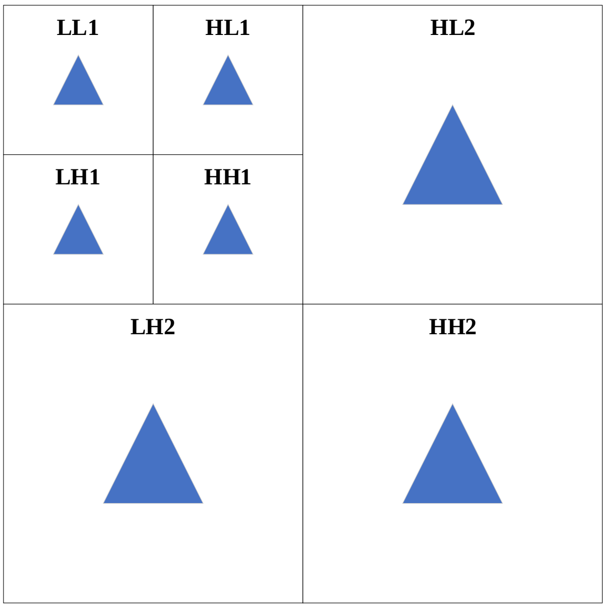

Fig. 1: Subband structure of arbitrary length object in wavelet domain

3. Complexity analysis of WDR methods

Visual image coding is most important in the current image transmission scenario. The digital data can be coded using a simple method called run length coding (Berghorn, 2001b). The coding procedure digitally represents the run between the neighboring pixels of a given image that have similar properties.

Modified run length coding is called index coding (Tian and Wells, 1996) and it is used in different coding methods. Among them, the WDR method (Tian and Wells, 1998) is a significant one. Here, the run length coding is modified as a differential coding procedure to generate bit streams. Here, the coding is based on the calculation of run between the significant coefficients identified using threshold value checking concepts. Thus, the method acts as an embedded image coder. The run length coding uses a linear data structure whereas the pyramidal structure-based coding scheme like EZW (Shapiro, 1993) and SPIHT (Said and Pearlman, 1996) uses a non-linear data structure. The time complexity for searching an element in a data set arranged in a nonlinear fashion which has *n* number of elements, is *O(nlogn).* But, for a linearly arranged data set, it is *O(n)*. The upper edge in the time estimation value is considered in the WDR method. Because the way of selection of significant coefficients using linear data structures took less time than that of non-linear data structures. WDR method is simple as compared to SPIHT and has no more computational complexity. Because the WDR method maps the 2D image coefficients into 1D scanning order. Thus, it avoids complex searching processes as compared to the hierarchical tree-based SPIHT algorithm. Bit-plane image encoding similar to SPIHT is also performed in WDR methods. Positions of significant coefficients are arranged using (Kamata et al., 1996) a predefined scanning process. A difference reduction method is used to digitally encode the distance between the significant positions. After analyzing the performance of WDR methods, it is concluded that the method has improved identifiable and quantitative results during the encoding of images which have both intra-scale correlation and inter-scale correlation amongst subbands.

3.1. Complexity analysis of SPHIT algorithm

Identified significant coefficients are arranged in different sets and list in the spatial orientation tree-based SPIHT algorithm (Said and Pearlman, 1996), and the method is called set partitioning. The time required to process the ordered lists is compared to *O(n)* for the respective list. Moreover, SPIHT uses the concept of the pyramidal structure of coefficients as sets. Hence, the time complexity for processing and checking the significance of these sets is proportional to *O(logn)*. Because the SPIHT uses a binary search tree algorithm to traverse this pyramidal structure of coefficients. This process progresses in a recursive manner and increases the time considering the height of the tree.

After analyzing the processing time, the complexity is generally represented as *C*O (nlogn).* Here, 'n' represents the number of wavelet coefficients and C represents the constant for any other operations related to the above. Hence, it is concluded that the overall complexity of the SPIHT method is *O(nlogn).* Any other operations are negligible here.

3.2. Estimation of time complexity in WDR

A linear data structure-based WDR method maintains a set used to store the index positions of wavelet coefficients. The significance of coefficients is checked by a linear search algorithm and stores the amount of run between these coefficients in a linear fashion. So, the time complexity is *O(n)*, where *n* is the space of data.

Total time expenditure is calculated as follows:

$$\text{Time} = \sum_{i=0}^{T} N_i \times (\, \text{O (n-i)}\,) \tag{1}$$

where, *T* is the estimated iteration count. That is, the overall cost is calculated as follows:

$$Time = C\times O\ (n). \tag{2}$$

where, C is a constant. The time for bit-plane representation and coding is not considered here. According to the complexity estimation, the results show that the WDR method is (Bindulal and Kaimal, 2009) one faster method than tree-based coding methods.

3.3. Complexity analysis of modified versions of WDR methods

The modified version WDR method called adaptive scanned WDR also uses the linear probing algorithm (Walker, 2000; Yuan and Mandal, 2005). But, during the process, one level of tree searching corresponding to each significant coefficient is also done to identify more significant coefficients. So, the cost function is *O (nlogn)*. Assume that the index list consists of K_1 number significant elements. Then, for each parent significant element K_1, there must be a present *M* number of child elements at the next level of pyramidal structure. For processing each parent significant element, the estimated time will be as follows:

$$K_1 \times O(\log M). \tag{3}$$

Assume that, there will be N number of elements. The significant element *K* is identified in each level *L* and represented as K_i where *i* varies from 1 to(N/K_L). The time count is estimated as follows:

$$K \times \sum_{i=1}^{L} (N/K_i) \times O(\log(M)) \tag{4}$$

where, *M* is $\quad M << N$

$$\text{Time} = N \times O(\log(M)). \tag{5}$$

$$\text{Time} = O(n \log(M)) \tag{6}$$

Thus, we can prove that $\log(M) << \log(n)$. Here, *M* is the quantity of child elements and *n* is the overall quantity of elements. Thus, as per the estimated total complexity, it is concluded that $O(n \log(M)) << O(n \log(n))$ compared to SPIHT. All other operations above are neglected here. One another modified version called context-modeled WDR considers the combination of parent-child relation with neighborhood property. Due to the increase in child coefficients, even if it increases the time complexity, it is better than that of the SPIHT method.

3.4. Time-saving of scalable WDR methods

Let P is the number of child coefficients collected on each level L and N is the whole quantity of elements. The estimated time will be as follows:

$$\text{Time} = N \times O\,(\log (N / L)) \tag{7}$$

where, $P = (N / L))$

$$\text{Time} = N \times (O\,(\log (N) - (\log (L))) \tag{8}$$
$$\text{Time} = O\,(n \times \log (n) - O\,(n \times \log (L))) \tag{9}$$

It is concluded that improved versions of WDR methods like ASWDR (Walker, 2000), CMWDR (Yuan and Mandal, 2005), and a novel version of layered WDR called scalable WDR (Bindulal and Kaimal, 2009) have better performance in terms of time complexity estimated. This may be at least O ($n \log L$) where n will be the size of data and L will be the depth of identified pyramidal structure. Hence, it is proved that both the basic WDR method and its modified versions are superior to the non-linear data structure-based coding algorithms.

4. Layered WDR method for arbitrary-shaped visual objects

The layered structure of the WDR (Bindulal and Kaimal, 2007) method called scalable WDR is applied to pre-processed visual objects considered the region of interest area. The simulations are done on the objects identified as the region of interest area extracted using the shape mask. The lossy or lossless encoding process is done considering the nature of images. According to these properties, an appropriate wavelet transform is applied.

The encoding process (Fig. 2) is progressed in each bit plane. The significant information is evaluated using test function $\sigma(w_{ij}, t_n)$ at bit plane n. The sign info is projected by means of $Sign(w_{ij})$. Function $mask(i, j)$ to check the positions of wavelet coefficients and whether it is an exclusive object area or not.

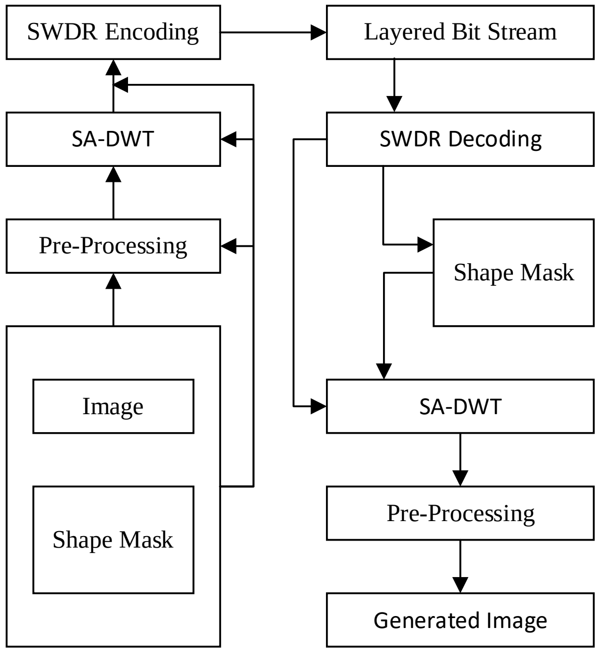

Fig. 2: Shape-adaptive object coding using scalable WDR method

Experiments are performed on sample test images like MRI medical images (Fig. 3) and video visual images like announcer (Fig. 4). The representation of arbitrary-shaped objects of the sample test image announcer in the transform domain shows the multiresolution pyramid form of objects (Fig. 5) which effectively preserve the spatial correlation properties.

(a) (b) (c)

Fig. 3: (a) Test image - MRI medical image (b) Object mask for object extraction (c) Extracted object

(a) (b) (c)

Fig. 4: Test image - Announcer (a) Video image (b) Object mask for object extraction (c) Extracted object

Fig. 5: Representation of one level arbitrary-shaped object in transform domain of test image announcer

4.1. Adaptive scalable WDR method

The adaptive scalable WDR (SWDR) is compared with traditional methods like SPIHT and also with its scalable version. The new method adopts an adaptive scan path technique with a region-growing procedure which increases the coding efficiency. The algorithm produces the bit streams and can be used to generate different resolution images as per the user's needs.

Adaptive scalable properties are maintained in the WDR method through multiple resolution-dependent lists. Different data structures are used and listed below:

- RGC - Collection of coefficients in a region
- SNS - Collection of significant coefficients with neighborhood property.
- SPS - Collection of significant coefficients with parent-child property
- LIC - Collection of insignificant coefficients
- SCS - Collection of significant coefficients
- TSC - Collection of significant coefficients arranged for intermediate use.

The collections of coefficients are arranged as a set of $\{RGC_L, SNS_L, SPS_L, LIC_L\}$ for respective subband group λ_L, where L is the depth of spatial resolution. The transform coefficients in the subband level L are processed and arranged as

$\lambda_L = \{LL_{(L-1)}, LH_{(L)}, HL_{(L)}, HH_{(L)}\}$.

The algorithm Adaptive Scalable WDR (Fig. 6) can produce a bit stream in a reordered manner which supports multiple resolution properties at any chosen bit rate.

The algorithm was restructured as a layered model to produce flexible bit streams. For that, different sets, symbols, and functions were used. The significance test is done using a function $\sigma(w_{ij}, t_n)$ at bit level plane n. The function $Sign(w_{ij})$ is used to check the sign of significant coefficients. The encoding process is based on a masking function $mask(i,j)$ to check the presence of wavelet coefficients inside the object area.

Using a recognized scan path, the significant coefficients are collected. The function $cluster\ (w_{ij}, t_n)$ is used for collecting clustering coefficients with neighboring property in connection with the substantial coefficient w_{ij} and the $child(w_{ij}, t_n)$ for child coefficients of substantial coefficient w_{ij}.

The symbols, sets, and functions used in the algorithm are listed below.

4.1.1. Notations and functions

- (i,j)= index position of coefficients.
- w_{ij}= coefficient at pixel location (i,j)
- $n = \left\lfloor log_2\left(\max_{(i,j)\in I}|w_{ij}|\right)\right\rfloor$, represents the depth of bit planes.
- t_n= Threshold value at bit level plane n
- (m,n) = index position obtained from (i,j)
- Lmax= Level of spatial resolution scalability generated from the bit stream.
- i.e., (1<= Lmax <=N+1), where N is the level of decomposition
- $\lambda_L = \begin{cases} LL_{L-1} & : \ if\ L = N+1 \\ \{HL_L, LH_L, HH_L\} & : \ 1 \le L \le N \end{cases}$, collective set of subbands at L

4.1.2. Significance checking functions

- $\sigma(w_{ij}, t_n) = \begin{cases} 1 - significant\ data & :|w_{ij}| \ge t_n \\ 0 - insignificant\ data & :|w_{ij}| < t_n \end{cases}$
- $Sign(w_{ij}) = \begin{cases} + & : \ w_{ij} \ge 0 \\ - & : \ w_{ij} < 0 \end{cases}$
- $Mask(i,j) = \begin{cases} 1 & if (i,j) inside\ the\ object\ area \\ 0 & if (i,j) outside\ the\ object\ area \end{cases}$

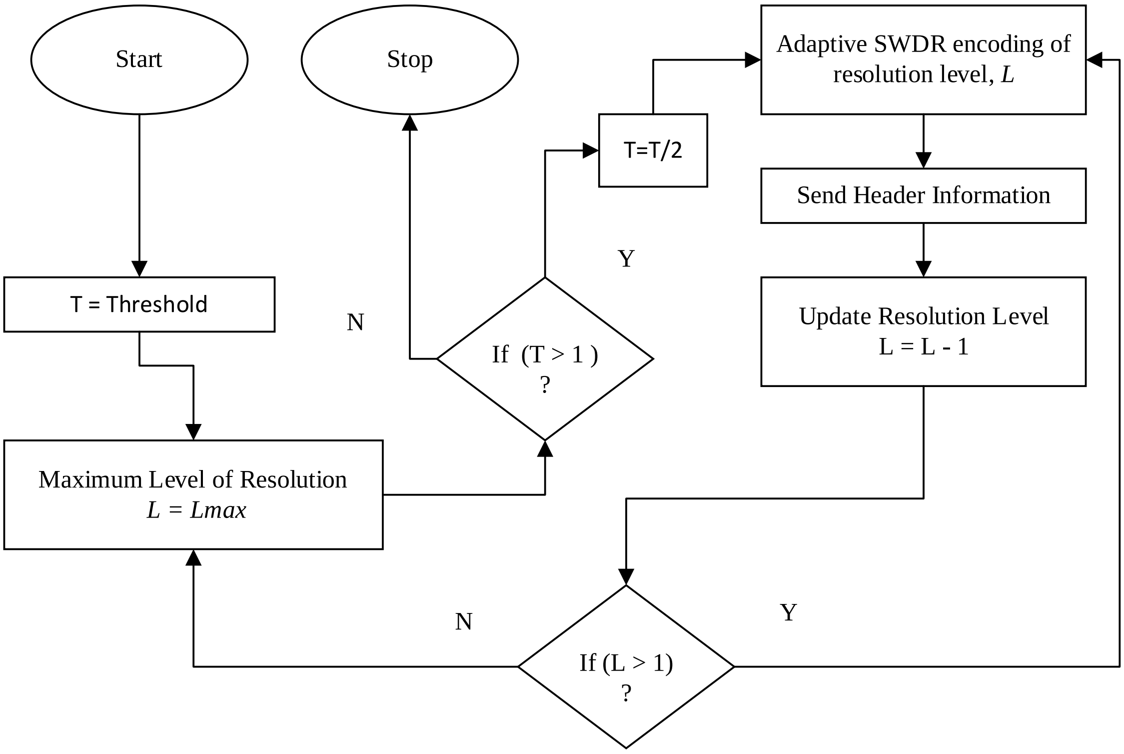

Fig. 6: Adaptive salable WDR method with layered structure

4.1.3. Neighborhood functions

- $cluster\ (w_{ij}, t_n) = \{(m,n)\}$ *, when*
    1. $(i-1) \le m \le (i+1), (j-1) \le n \le (j+1)$
    2. $(m,n) \in \lambda_L and (i,j) \in \lambda_L$
- $child(w_{ij}, t_n) = \{(m,n)\}$ *, when*
    1. $(m,n) \in \begin{Bmatrix} and(2i,2j),(2i,2j+1) \\ and(2i+1,2j),(2i+1,2j+1) \end{Bmatrix}$
    2. $(m,n) \in \lambda_{L-1} and (i,j) \in \lambda_L$

4.1.4. Encoding procedure

Step 1. Initialization

- $LSC_L = \varphi \quad , TSC_L = \varphi \quad \forall L \quad ,1 \le L \le L_{max}$
- $LIC_L = \begin{Bmatrix} \varphi \quad , \quad \forall L \quad ,1 \le L \le L_{max} \\ RGC_L = \varphi, SNS_L = \varphi, SPS_L = \varphi \end{Bmatrix}$
- $n \quad = \quad \left\lfloor log_2 \left(\max_{(i,j)\in I} |w_{ij}| \right) \right\rfloor$
- $t_{n-1} = 2^{n+1}$
- $t_n = t_{n-1}/2$
- *L=Lmax;*

Step 2. Sorting pass

If mask (i, j) = 1{
If $LIC_L(\sigma(w_{ij}, t_{n-1}) = 0)${
{*If* $LIC_L(\sigma(w_{ij}, t_n) = 1)$
{coding (w_{ij}*,L);}}}*
If mask (i, j) = 1{
If ($\lambda_L \neq \varphi$*){*
{*If (*$\sigma(w_{ij}, t_{n-1}) = 0$*) {*
If ($\sigma(w_{ij}, t_n)$ *=1){*
coding (w_{ij}*, L);*
$RGC_L = cluster(w_{ij}, t_n)$*;*
Do {
If ($RGC_L \neq \varphi$*){*
If ($RGC_L(\sigma(w_{ij}, t_{n-1})) = 0$*){*
If($RGC_L(\sigma(w_{ij}, t_n))$ *=1) {*
coding (w_{ij}*, L);*
$RGC_L = cluster(w_{ij}, t_n)$*}}}*
} while (End (RGEL)!=True) ;}}}}
Function coding (w_{ij}*, L)*
{
Generate Binary (run) between significant coefficients and send without leading MSB '1' with sign information of w_{ij}*.*
Add w_{ij} *into TSCL.*
}

Step 3. Index updating pass

If $TSC_L \neq \varphi$ {
$SNS_L = cluster(w_{ij}, t_n) \quad ; \forall (i,j) \in TSC_L$
$SPS_{L-1} = child(w_{ij}, t_n) \quad ; \quad \forall (i,j) \in TSC_L\}$
LICL=RGEL+SNSL + SPSL;

Step 4. Refinement Pass

If $SCS_L \neq \varphi$ *{ If (*$SCS_L(\sigma(w_{ij}, t_{n-1}) = 1)$*)*
{Add nth MSB of $SCS_L(w_{ij})$*}}*
SCSL=SCSL+TSCL.;
TSCL=∅;

Step 5. Scalability updation

Send Scalability depth information;
If (L > 1){
L=L-1;
Go to step 2.}
Else
L=Lmax;

Step 6. Threshold update

If (tn >1){
$t_{n-1} = t_n$

$t_n = t_n/2$;
Go to step 2.}

The proposed algorithm generated four symbols {+, -, 1, 0} and these are represented using 2 bits such as 11 for +, 10 for -, 01 for 1, and 00 for 0. The novel scheme follows this method and avoids arithmetic coding.

5. Simulation results

Analysis of the various WDR methods is performed using a predefined scan path named Hilbert Scan (Kamata et al. 1996). The modified version of the WDR method called WDR with Selected Region Growing (WDR-SRG) (Bindulal and Kaimal, 2006) is compared with the traditional coding method SPIHT. The quality of images at any bit rate is calculated as the peak signal-to-noise ratio (PSNR). It is defined as,

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

where, MSE is the mean squared error obtained by comparing the original and the recreated image; *max* is the extreme value of a pixel inside the image. Simulations are done on standard test image Barbara and the results (Table 1) are well compared (Fig. 7). The analysis of generated symbols by various WDR methods is also done (Fig. 8) compared with other methods.

The Scalable WDR (Bindulal and Kaimal, 2007) is a hybrid method that is a combination of WDR-SRG (Bindulal and Kaimal, 2006) with scalability properties. The experimental results are compared with original SPIHT (Said and Pearlman, 1996) and scalable SPIHT (Martin et al, 2006). The simulations are done on test image Barbara, medical images with resolution size 512×512, and video objects like announcer with resolution size 480×512, etc. The sixth level of transformation is done using bi-orthogonal 9/7 wavelet filters for announcer objects for lossy coding. For MRI image coding, use 5/3 tap wavelet filters. Each transformation uses symmetric extension at the image boundary. Then, the encoder sets to encode the coefficients from the maximum level of bitplane to the lowest level bitplane to support spatial scalability.

Table 1: PSNR Values of test image Barbara using Hilbert scene

Methods	Normal wavelet decomposition			
	1 bpp	0.5 bpp	0.25 bpp	0.125 bpp
WDR-SRG	37.39	32.16	28.29	25.39
CMWDR	37.29	32.09	28.22	25.16
ASWDR	36.84	31.70	27.65	25.05
WDR	36.51	31.53	27.48	25.05
SPIHT	36.80	31.63	27.64	24.89

Values in dB

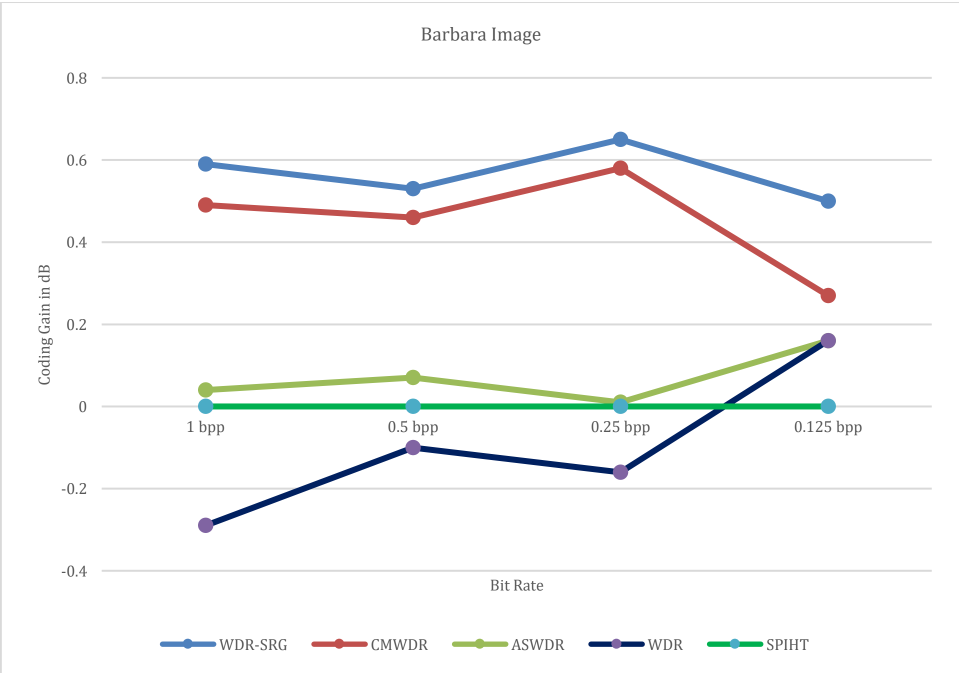

Fig. 7: Coding gain in PSNR values – test image Barbara

The performance comparison is done in terms of PSNR values. Considering the test image Barbara, the coding gain for full-resolution reconstruction is between 0.2 dB and 0.5 dB at any bpp rate (Table 2). At the lowest level of resolution, gain is from 2 dB to 12 dB. The values are compared with normal SPIHT and scalable version (Table 3). The coding gain for test image MRI varies from 0.3 dB to 5 dB for various bpp rates (Table 4 and Table 5) at different resolution levels.

The video still objects in YUV format are used in the simulation and the luminance plane (Y) is used to calculate the similarity index. The comparison shows that the visual quality of reconstructed images is improved and obtained coding gain is from 0.7 dB to 1.4 dB for desired bpp for full resolution (Table 6) and from 3 dB to 12 dB for half resolution (Table 7).

The structural similarity index (SSIM) metric (Zhou et al, 2004) is another distortion rate estimation method. The SSIM of test image Barbara and the MRI image shows (Table 8) that the proposed coding method is a novel one that has much better performance and can be one considerable method in all senses. The structural similarity index (SSIM) metric is defined in the following equations.

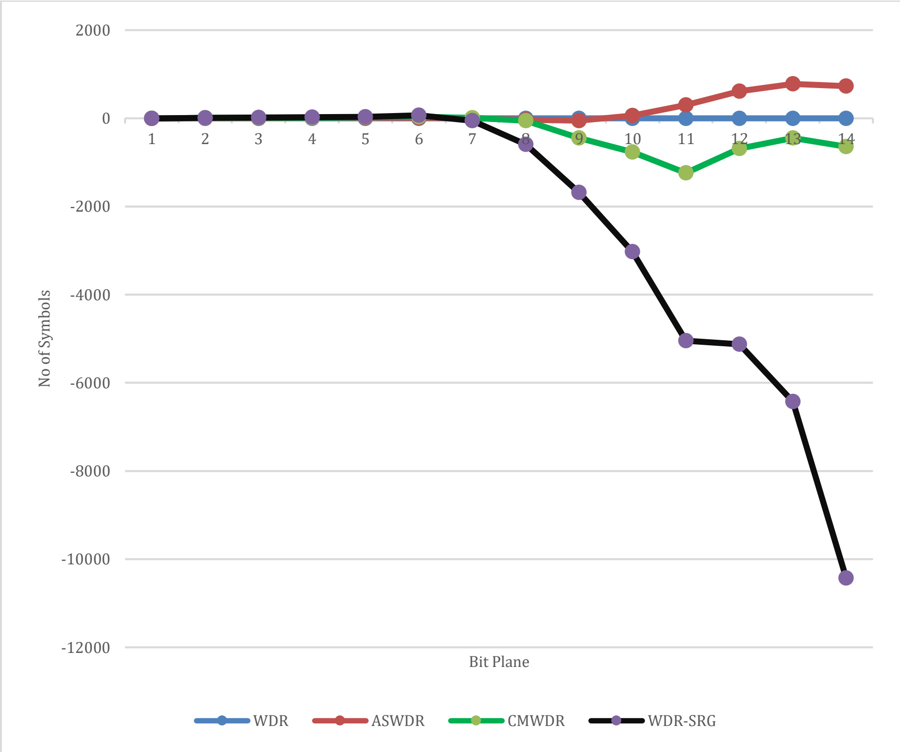

Fig. 8: Analysis of symbols produced by various WDR methods using scan path Hilbert curve – test image Barbara

Table 2: PSNR values – test image Barbara (512×512) image

Image	Bit rate (bpp)	Full resolution (512×512)	
		SPIHT	SWDR
Barbara	0.125	24.89	25.21
	0.25	27.64	28.20
	0.5	31.62	32.09
	0.75	34.50	34.92
	1	36.84	37.23

Values in dB

Table 3: PSNR values – test image Barbara (512×512) image

Image	Bit rate (bpp)	Half resolution (256×256)		
		SPIHT	Scalable SPIHT	SWDR
Barbara	0.125	28.56	30.11	30.30
	0.25	31.46	34.64	34.95
	0.5	36.02	41.39	41.82
	0.75	38.82	46.87	47.11
	1	41.68	51.57	51.69

Values in dB

Table 4: PSNR values – test image - MRI (512×512) image

Coding scheme	Full resolution			
	0.125 bpp	0.25 bpp	0.5 bpp	1.0 bpp
SPIHT	-	-	-	-
Scalable SPIHT	31.21	35.84	40.35	47.11
SWDR	31.92	36.43	40.93	47.45

Values in dB

Table 5: PSNR values – test image - MRI (512×512) Image

Coding scheme	Half resolution (256×256)			
	0.0625 bpp	0.125 bpp	0.25 bpp	0.5 bpp
SPIHT	27.55	31.21	36.50	43.60
Scalable SPIHT	27.75	31.50	37.00	47.70
SWDR	28.55	32.02	38.01	48.79

Values in dB

Table 6: PSNR values – test image - announcer (480×512) image

Coding scheme	Full resolution			
	0.125 bpp	0.25 bpp	0.5 bpp	1.0 bpp
SPIHT	-	-	-	-
S-SPIHT	36.49	40.77	45.46	51.51
SWDR	37.83	41.66	46.25	52.60

Values in dB

Table 7: PSNR values – test image - announcer (480×512) image

Coding scheme	Half resolution (240×256)			
	0.0625 bpp	0.125 bpp	0.25 bpp	0.5 bpp
SPIHT	33.60	38.11	43.85	50.51
S-SPIHT	34.20	39.72	46.45	58.80
SWDR	36.61	41.50	48.55	62.65

Values in dB

$$\mu_x = \bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i \quad (11)$$

$$\mu_y = \bar{y} = \frac{1}{N}\sum_{i=1}^{N} y_i \quad (12)$$

$$\sigma_x^2 = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})^2 \quad (13)$$

$$\sigma_y^2 = \frac{1}{N-1}\sum_{i=1}^{N}(y_i - \bar{y})^2 \quad (14)$$

$$\sigma_{xy} = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})\,(y_i - \bar{y}) \quad (15)$$

where, μ_x is mean of x, μ_y is mean of y, ${\sigma^2}_x$ is variance of x, ${\sigma^2}_y$ is the variance of y and σ_{xy} is the covariance of x and y. The Structural Similarity (SSIM) index between signals x and y is calculated using the following equations:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (16)$$

where, C_1 and C_2 are constants, i.e., $C_1 = (K_1L)^2$ and $C_2 = (K_2L)^2$ where L is the dynamic range of the pixel values, and K_1 and K_2 are two constants.

The overall quality value called the average of the quality map or the *Mean SSIM* (*MSSIM*) index is defined as,

$$MSSIM(X,Y) = \frac{1}{M}\sum_{j=1}^{M} SSIM(x_j, y_j) \quad (17)$$

where, X is the reference image and Y is the distorted image. x_j and y_j are the image contents at the j^{th} local window and M is the number of local windows of the image.

Table 8: Structural similarity index values – test image - Barbara (512×512) image and MRI image (512×512)

Test image	Bit rate (bpp)	Full resolution (512×512)	
		SPIHT	SWDR
Barbara	0.125	0.83037	0.84586
	0.25	0.89146	0.90146
	0.5	0.95027	0.95382
	0.75	0.97289	0.97563
	1	0.98475	0.98538
MRI	0.125	0.91672	0.91946
	0.25	0.95834	0.96079
	0.5	0.98360	0.98604
	0.75	0.99225	0.99297
	1	0.99605	0.99648

6. Conclusion

Analysis and complexity estimation of various wavelet different reduction methods are discussed in this paper. The paper also describes the performance of wavelet based scalable encoder called scalable WDR method. After analyzing the methods, identified point is that the hierarchical coding schemes is much more time consuming which uses hierarchical tree structure. Moreover, even if it is better to encode small-size images, but need more time to encode large-size images. So, for avoiding tree-based data structure, an alternative method which is WDR is considered. In addition, the simpler RLC method is used here. Thus, it can be used in networks with different capabilities to achieve the fastest data transmission.

In this paper, a number of modified versions of different WDR methods have been analyzed. The coding performance of these algorithms is much better in terms of PSNR values than that of traditional methods such as SPIHT, even without using arithmetic coding or Huffman coding. The coding gain in PSNR value is from 0.2 dB to 12 dB in different situations. The time complexity analysis of different WDR methods is also done. After analysis, it is concluded that the projected method is sound and has better coding speed with 10% gain than that of traditional SPIHT method.

A hybrid method using video object coding with shape-adaptive coding is presented here. At any point of bit rate, the novel method has better performance which has least time complexity than that of pyramidal structure coding technique. The method also supported the scalability features that have interesting prospects for frequent visual data communication over different networks. This facility will fulfill the initial goal of resolving network heterogeneity. This feature will provide the facility to each receiver to select the data packets of any number of data layers. i.e., the decision can be made by considering the visualization capacity to limit their bandwidth usage. It is concluded that the novel method is able to encode high-quality arbitrarily shaped visual object streams in real-time with an average compression ratio of 10 times than any other coding method, with high visual quality.

Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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