

# WAVELET BASED VIDEO COMPRESSION USING STW, 3D-SPIHT & ASWDR TECHNIQUES: A COMPARATIVE STUDY

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## ABSTRACT

*The objective of this paper is to implement and evaluate the effectiveness of wavelet based Spatial-orientated Tree Wavelet (STW), 3D-Set Partitioning in hierarchical trees (3D-SPIHT) and Adaptively Scanned Wavelet Difference Reduction (ASWDR) compression techniques using MATLAB R2010b. The performance parameters such as Peak Signal to Noise Ratio (PSNR), Mean Squared Error (MSE), Compression Ratio (CR) and Bit-Per-Pixel (BPP) ratio are evaluated based on the algorithms. Comparisons amongst the techniques are carried out on the basis of calculated performance parameters. The mentioned techniques achieved better PSNR and MSE values with respect to the Compression Ratio which makes them more efficient than the 2D-Discrete Cosine Transform (DCT). Mentioned techniques are equally compatible for video formats like .MPEG, .DAT, .3GP, .AVI, .FLV, .MOV etc making it more versatile.*

**KEYWORDS:** Video Compression, STW, 3D-SPIHT, ASWDR, Wavelet, PSNR, MSE, MATLAB.

## I. INTRODUCTION

The compression offers a means to reduce the cost of storage and increase the speed of transmission. Video compression is used to minimize the size of a video file without degrading the quality of the video. Over the past few years, a variety of powerful and sophisticated wavelet based schemes for image and video compression have been developed and implemented [1]-[7]. Some of the most promising are algorithms that minimize the amount of memory which the encoder or decoder must use [8], [9]. An algorithm which is embedded and which minimizes PSNR is described in [10] (Rate-distortion Optimized Embedding). The discrete wavelet transform (DWT) [1], [2] has gained wide popularity due to its excellent decorrelation property, many modern image and video compression systems embody the DWT as the intermediate transform stage. After DWT was introduced, several codec algorithms were proposed to compress the transform coefficients as much as possible but a compromise must be maintained between the higher compression ratio and a good perceptual quality of image. Achieving much higher compression ratio is simply not possible without discarding some perceptible information [1]-[10]. Thus, the rate of compression is application dependent. The most powerful progressive method, Embedded Zerotree Wavelet (EZW) coding algorithm introduced by Shapiro [3] combines stepwise thresholding and progressive quantization, focusing on the more efficient way to encode the image coefficients in order to minimize the compression ratio. Among these, Spatial-Orientation Tree Wavelet (STW) [4] and Set Partitioning in Hierarchical Trees (SPIHT) [5] are found to be the more advantageous because of their different approach of encoding the wavelet transform. These wavelet based image/video compression algorithms (SPIHT and STW) are considered as refined versions of the seminal EZW algorithm [3]. The 3D-Set Partitioning in hierarchical trees (3D-SPIHT) technique which is proposed by Kim and Pearlman [6] is the extended form of SPIHT coding algorithm, in which the relationship among coefficients lying in different

frequency bands is based on octal tree structure rather than quad-tree structure. The most enhanced image compression algorithm is the Adaptively Scanned Wavelet Difference Reduction (ASWDR) algorithm proposed by Walker [11], [12]. ASWDR technique adjusts the scanning order used by Wavelet Difference Reduction (WDR) algorithm [13] so as to predict locations of new significant values. The WDR method employs a fixed ordering of the positions of wavelet coefficients. Thus, ASWDR technique achieves high compression than WDR while retaining all of the important features of WDR such as low complexity, region of interest (ROI) capability and progressive SNR capability. This paper discusses the most powerful progressive compression techniques; all the three techniques offer different approaches in compression. Thus a comparative study will provide a basis for other innovative works in video compressions for superior results.

## II. LITERATURE SURVEY

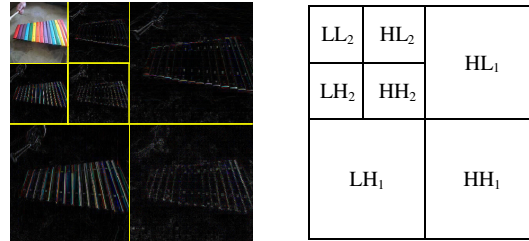
Video coding for telecommunication applications has evolved through the development of the ISO/IEC MPEG-1, MPEG-2 and ITU-T H.261, H.262, H.263 video coding standards (and later enhancements of H.263 known as H.263+ and H.263++) and H.264, [14] [15] and has diversified from ISDN and T1/E1 service to embrace PSTN, mobile wireless networks, and LAN/Internet network delivery. Throughout this evolution, continued efforts have been made to maximize coding efficiency. The performance of these coders generally degrades at low bit-rates mainly because of the underlying block-based Discrete Cosine Transform (DCT) [16] scheme. In the DCT the input image needs to be blocked. So correlation across the block boundaries is not eliminated, resulting in noticeable and annoying blocking artifacts. The wavelet transform resolved this difficulty of blocking artifacts. Research in new and better methods of image and video compression is ongoing, and recent results suggest that some newer techniques may provide much better values of performance parameters. An extension of image compression algorithms based on wavelets and making them suitable for video (as video contains sequence of still pictures) is essential.

Current compression systems use biorthogonal wavelet (bior wavelet family) instead of orthogonal wavelets (Haar, Daubechies etc) [17] despite the fact that it is not energy preserving. An orthogonal wavelet is a wavelet where the associated wavelet transform is orthogonal while in biorthogonal wavelet, the associated wavelet transform is invertible but not necessarily orthogonal. The fact that biorthogonal wavelets are not energy preserving is not a big problem since there are linear phase biorthogonal filter coefficients which are close to being orthogonal [17]. The main advantage of the biorthogonal wavelet transform is that it permits the use of a much broader class of filters, and this class includes the symmetric filters. The biorthogonal wavelet transform is advantageous because it can use linear phase filters which give symmetric outputs when presented with symmetric input. This transform solves the problems of coefficient expansion and border discontinuities [17].

Embedded Zerotree Wavelet (EZW) coding algorithm introduced by Shapiro [3] combines stepwise thresholding and progressive quantization. The Set Partitioning in Hierarchical Trees (SPIHT) [5] is the refined versions of the seminal EZW algorithm. SPIHT performs better for high bit rate but produces poor quality at low bit rates since it uses only the correlation between different subbands and doesn't consider about correlation within each subband. Set Partitioned Embedded Block Coder (SPECK) [18] performs well at low bit rates but results in poor compression because it uses only the correlation within each subband and doesn't consider about correlation between different subbands. In 3D-SPIHT algorithm [6], the relationship among coefficients lying in different frequency bands is based on octal tree structure rather than quad-tree structure.

The main property of wavelet transform in image compression is the minimum distortion in the reconstructed image even when removal transform coefficients are near zero. In the wavelet transform, there are two ways to decompose the pixel values for 2-dimensional image/frame; the standard decomposition and nonstandard decomposition [19]. Figure 1 shows the decomposition process for the Xylophone video frame at level 2.

The standard decomposition method is obtained based on applying wavelet transformation first on each row and then on each column. The process results in the form of detail coefficients and coefficient average. Nonstandard decomposition transformation is obtained by combining pairs of rows and columns alternately. In the decomposition level 1, the image will be divided into 4 sub bands; they are HH, HL, LH and LL sub bands.



**Figure 1.** Wavelet Decomposition (2 Levels)

HH sub band gives the details of diagonal, HL sub band provides horizontal details and the LH sub band provides vertical details. The LL sub band is a low-resolution residue that has low frequency components which are often referred to as the average image. LL sub band is divided again at the time of decomposition at a higher level. The process is repeated according to the desired level.

### III. SPATIAL ORIENTATION TREE WAVELET (STW)

The Spatial Orientation Tree Wavelet (STW) employs a diverse approach in coding the information of zerotree. A zerotree have insignificant wavelet transform values at each of its locations for a given threshold  $T$ . Zerotree is a tree of locations in the wavelet transform with a root say  $[j, k]$ , and its descendants (children) located at  $[2j, 2k]$ ,  $[2j+1, 2k]$ ,  $[2j, 2k+1]$ , and  $[2j+1, 2k+1]$ , and each of their children, and so on. STW is more vigilant in its organization of coding outputs than the Embedded Zerotree Wavelet (EZW) [3] and SPIHT algorithm [5]. In EZW, the root location is marked by encoding only one symbol for the output  $R$  or  $I$  as described in [3]. Consequently in EZW, the zerotrees provide narrow descriptions of the locations of insignificant values. The different approach used in STW is the use of a state transition model. The locations of transform values undertake state transitions from one threshold to the next. The number of bits required for encoding is thus reduced in STW with this representation of state transitions. The state transition model uses states  $I_R$ ,  $I_V$ ,  $S_R$  and  $S_V$  as represented in [11] to mark the locations instead of code for the outputs  $R$  and  $I$  used in [3]. The states involved are defined after knowing the significance function  $S(m)$  and the descendent indices  $D(m)$  [11].

The significance function  $S(m)$  for a given index  $m$  as symbolized in [11] is defined by

$$S(m) = \begin{cases} \max_{n \in D(m)} |w(n)|, & \text{if } D(m) \neq \phi \\ \infty, & \text{if } D(m) = \phi \end{cases} \quad (1)$$

where  $n$  is the scanning index,  $w(n)$  is the wavelet transform value at index  $n$ .

The descendant indices  $D(m)$  for a given index  $m$  is the empty set  $\phi$  when  $m$  is either at the 1<sup>st</sup> level or at the all-lowpass level. Otherwise,  $D(m)$  is the set of descendants of index  $m$  in quadtree with root  $m$  when  $m$  is at the  $j^{\text{th}}$  level for  $j > 1$ .

For a given threshold  $T$ , the states  $I_R$ ,  $I_V$ ,  $S_R$  and  $S_V$  are defined as in [11] by

$$m \in I_R \text{ if and only if } |w(m)| < T; S(m) < T \quad (2)$$

$$m \in I_V \text{ if and only if } |w(m)| < T; S(m) \geq T \quad (3)$$

$$m \in S_R \text{ if and only if } |w(m)| \geq T; S(m) < T \quad (4)$$

$$m \in S_V \text{ if and only if } |w(m)| \geq T; S(m) \geq T \quad (5)$$

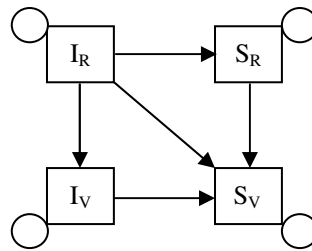


Figure 2. State transition diagram for STW

Figure 2 shows the state transition diagram for these states when a threshold is decreased from  $T$  to  $T'$  where  $T' < T$ . Now the step by step procedure of STW encoding is done as given in [4], [11].

#### IV. 3D-SET PARTITIONING IN HIERARCHICAL TREES (3D-SPIHT)

Set partitioning in hierarchical trees (SPIHT) [5] is an image compression algorithm that exploits the inherent similarities across the subbands in wavelet decomposition [20] of an image. The SPIHT algorithm is used to the multi-resolution pyramid after the sub-band/wavelet transformation is performed. The embedded coding property of SPIHT allows exact bit rate control without any penalty in performance. The same property also allows exact MSE distortion control. SPIHT codes the individual bits of the image wavelet transform coefficients following a bit-plane sequence. Thus, it is capable of recovering the image perfectly by coding all bits of the transform. The SPIHT video coding system is shown in Figure 3.

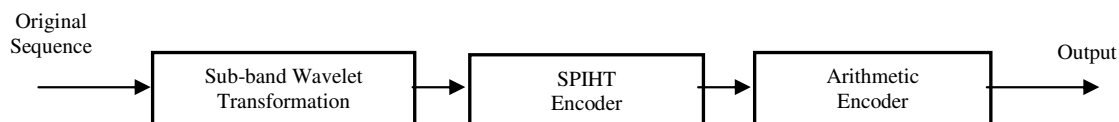


Figure 3. SPIHT Video Coding System

The 3D-Set Partitioning in hierarchical trees (3D-SPIHT) technique which is proposed by Kim et al. [6], [7] is extended from the above known SPIHT coding algorithm. It is a simple and efficient wavelet zero tree image coding algorithm which has been proved its efficiency with high performance, precise rate control and its real-time capability in compression of video. The video coder is fully embedded, so that a variety of monochrome or color video quality can thus be obtained with a single compressed bit stream. So we can stop the compression process at a desired rate [21]. The wavelet coefficients are considered as a collection of spatial orientation trees where each tree is formed of coefficients from all sub bands belonging to the same spatial location in an image [7]. The wavelet coefficients are scanned column then line, from low subbands to high subbands. After that an iterative 3D-SPIHT algorithm selects an initial threshold based on the largest wavelet coefficient [22]. When the largest coefficient magnitude in the set is greater than or equal to the selected threshold, a tree wavelet coefficient set is significant. In the 3D-SPIHT algorithm we have two important passes: sorting pass and refinement pass [7]. A recursive partitioning is realized on the tree. So the position of significant coefficient in the descendants of the considered coefficient is identified [7], [23].

In SPIHT, the relationship among coefficients lying in different frequency bands is based on quad-tree structure, while the one is based on octree structure in 3D-SPIHT. Given an image sequence to be encoded,  $7L+1$  subband image cubes are produced after  $L$ -level 3D wavelet transformation. A 2-level 3D wavelet transformation is shown in Figure 4. Where, the coefficients lying in the lowest frequency subband (LLL2) are the roots of octrees, each of which has seven child-nodes that lie respectively in the subbands (LLH2, LHL2, LHH2, HLL2, HLH2, HHL2 and HHH2) in seven directions. And each child-node has also its 8 children-nodes that lie in more refined subbands in the according directions. Thus, except the coefficients in the lowest subband (LLL2) and in the highest subbands (LLH1, LHL1, LHH1, HLL1, HLH1, HHL1 and HHH1), each coefficient has 8 children-nodes. In 3D-SPIHT encoding, in order to get higher encoding speed, image sequence is often divided into smaller sized data cubes, such as  $16 \times 16 \times 16$  or  $32 \times 32 \times 32$ . Then each data cube is wavelet transformed, quantized and encoded respectively.

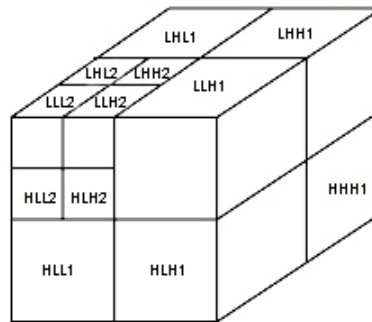


Figure 4. 3D-Wavelet decomposition

## V. ADAPTIVELY SCANNED WAVELET DIFFERENCE REDUCTION (ASWDR)

It is one of the most enhanced image compression algorithms proposed by Walker [11], [12]. The ASWDR algorithm aims to improve the subjective perceptual qualities of compressed images and improve the results of objective distortion measures. The ASWDR algorithm is a simple modification of the Wavelet Difference Reduction (WDR) algorithm [13]. The WDR algorithm employs a fixed ordering of the positions of wavelet coefficients but the ASWDR method employs a varying order which aims to adapt itself to specific image features. ASWDR adjusts the scanning order so as to predict locations of new significant values. The scanning order of ASWDR dynamically adapts to the locations of edge details in an image, and this enhances the resolution of these edges in ASWDR compressed images. Thus, ASWDR exhibits better perceptual qualities, especially at low bit rates, than WDR and SPIHT compressed images preserving all the features of WDR. The ASWDR on an image/frame is executed by a step by step procedure described below [12]:

Step 1: A wavelet transform is performed on the discrete image/frame  $f[j,k]$ , producing the transformed image/frame  $\hat{f}[j,k]$ .

Step 2: A scanning order for the transformed image is chosen,  $\hat{f}[j,k] = a(m)$ . The transform values are scanned via a linear ordering,  $m = 1, 2, 3, \dots, X$  where  $X$  is the number of pixels. In [4] and [24], row-based scanning is used in the horizontal subbands and column-based scanning is used in the vertical subbands with the zigzag scanning order through subbands from higher scale to lower scale [5].

Step 3: In this step an initial threshold  $T$  is chosen. The  $T$  is chosen in such a way that at least one transform value has magnitude less than or equal to  $T$  and all transform values have magnitudes less than  $2T$ .

Step 4: (Significance pass). The positions for new significant values are recorded as depicted in [12]. These new significant indices are then decoded using difference reduction [13], [24].

Step 5: (Refinement pass). Record the refinement bits, the next significant bits, for the old significant transform values. This generation of refinement bits is also known as standard bitplane encoding which is utilized by all embedded codecs [5], [11].

Step 6: (New scanning order). For the level containing the all-lowpass subband, the indices of the remaining insignificant values are used as the scan order at that level. The scan order at level  $k$  is used to create the new scan order at level  $k - 1$  as follows: Run through the significant values (i.e. the parent values) at level  $k$  in the wavelet transform. Each parent value induces a set of four child values for all the levels except the last. The last level induces three child values as described in the spatial-orientation tree definition in [11]. At level  $k - 1$ , the insignificant values are enclosed in the first part of the scan order lying among these child values. Now again run through the insignificant values at level  $k$  in the wavelet transform. This provides the insignificant values enclosed in the second part of the scan order lying among the child values induced by these insignificant parent values. This new scanning order for level  $k - 1$  is further used to create the new scanning order for level  $k - 2$ , until all levels are exhausted.

Step 7: Divide the present threshold by 2. Repeat Steps 4-6 until either all the levels are exhausted or a given distortion metric [12] is fulfilled.

## VI. PERFORMANCE PARAMETERS

### 6.1. Mean Squared Error (MSE) and Peak Signal to Noise Ratio (PSNR)

Two of the error metrics used to compare the various image compression techniques are the Mean Square Error (MSE) and the Peak Signal to Noise Ratio (PSNR). The MSE is the cumulative squared error between the compressed and the original image, whereas PSNR is a measure of the peak error. The phrase peak signal-to-noise ratio, often abbreviated as PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale.

The PSNR is most commonly used as a measure of quality of reconstruction of lossy compression codecs [1]-[10]. The signal in this case is the original data, and the noise is the error introduced by compression. When comparing compression codecs it is used as an approximation to human perception of reconstruction quality, therefore in some cases one reconstruction may appear to be closer to the original than another, even though it has a lower PSNR (a higher PSNR would normally indicate that the reconstruction is of higher quality). One has to be extremely careful with the range of validity of this metric; it is only conclusively valid when it is used to compare results from the same codec (or codec type) and same content. It is most easily defined via the mean squared error (MSE) which for two  $m \times n$  images  $I$  and  $K$  where one of the images is considered a noisy approximation of the other is defined as:

$$\text{MSE} = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i, j) - K(i, j)]^2 \quad (3)$$

The PSNR is defined as:

$$\text{PSNR} = 10 \cdot \log_{10} \left( \frac{\text{MAX}_I^2}{\text{MSE}} \right) \quad (4)$$

$$\text{PSNR} = 20 \cdot \log_{10} \left( \frac{\text{MAX}_I}{\sqrt{\text{MSE}}} \right) \quad (5)$$

Here,  $\text{MAX}_I$  is the maximum possible pixel value of the image. When the pixels are represented using 8 bits per sample, this is 255. More generally, when samples are represented using linear PCM with  $B$  bits per sample,  $\text{MAX}_I$  is  $2^B - 1$ . For color images with three RGB values per pixel, the definition of PSNR is the same except the MSE is the sum over all squared value differences divided by image size and by three. Alternately, for color images the image is converted to a different color space and PSNR is reported against each channel of that color space.

### 6.2. Compression Ratio (CR) and Bit-Per-Pixel (BPP)

A measure of achieved compression is given by the Compression Ratio (CR) and the Bit-Per-Pixel (BPP) ratio. CR and BPP represent equivalent information. CR indicates that the compressed image is stored using CR % of the initial storage size while BPP is the number of bits used to store one pixel of the image. For a greyscale image the initial BPP is 8. For a true color image the initial BPP is 24, because 8 bits are used to encode each of the three colors (RGB color space). The challenge of compression methods is to find the best compromise between a low compression ratio and a good perceptual result.

## VII. RESULTS AND DISCUSSION

The original video is split in the form of frames which is further subdivided into blocks to compute the 2D motion vectors per block and to perform motion compensation and estimation [25]. Each

frame is then compressed by these algorithms for various maxloop which is the number of steps for a particular compression algorithm. For any significant compression methods, the parameter 'maxloop' decides the maximum number of steps of the compression algorithm the default parameter value is '10' and the user can select any positive integer for this parameter value. The maxloop for the algorithms is selected on the basis of the preferred compression ratio (CR) and bit-per-pixel (BPP) ratio keeping the best compromise between a low compression ratio and a good perceptual result. The wavelet which is used in our experiment is biorthogonal spline wavelet 4.4 (bior 4.4) [1], [2] because of its advantages as mentioned in the literature review section. The video which we are taking is in mpeg format which is a standard Xylophone movie clip of 645 KB. The techniques are also validated for different video formats like .DAT, .3GP, .AVI, .FLV, .MOV etc by acquiring these formats for the Xylophone clip. Thus these algorithms provide compatibility for various video formats. The simulation results are nearly same for all the formats for Xylophone clip. Comparisons amongst the techniques are carried out for the mpeg format. Following general and video configurations are obtained in MATLAB R2010b for the Xylophone clip.

General Configuration:

Duration = 4.7020

Name = ABC.mpg

Tag = My reader object

Type = VideoReader

UserData = []

Video Configuration:

BitsPerPixel = 24

FrameRate = 29.9700

Height = 240

NumberOfFrames = 141

VideoFormat = RGB24

Width = 320

Total Bitrate = 1064Kbps

Data rate = 1000Kbps

The simulation results of video compression by applying the Spatial-orientation Tree Wavelet (STW), 3D-Set Partitioning in hierarchical trees (3D-SPIHT) and Adaptively Scanned Wavelet Difference Reduction (ASWDR) algorithms various comparisons are obtained on the basis of PSNR and MSE values for the particular compression ratio (CR) and bit-per-pixel (BPP) ratio.

The original frame is shown in the Figure 5 and compressed frames are shown in Figure 6, Figure 7 and Figure 8 with the number of maxloop used and the obtained values of different performance parameters:



**Figure 5.** Original Frame no.1





for maxloop 11,  
CR=1.3369, BPP =0.3209  
MSE=53.224, PSNR=30.8697 dB



for maxloop 12,  
CR= 2.6693, BPP = 0.6406  
MSE= 23.2751, PSNR = 34.46 dB

**Figure 6.** Frame no.1 compressed by using STW algorithm



for maxloop 12,  
CR=1.3983, BPP =0.3356  
MSE=29.7642, PSNR=33.394 dB



for maxloop 13,  
CR= 2.6585, BPP = 0.6380  
MSE=13.1584, PSNR = 36.939 dB

**Figure 7.** Frame no.1 compressed by using 3D-SPIHT algorithm



for maxloop 10,  
CR=1.4843, BPP =0.3562  
MSE=54.0574, PSNR=30.8023 dB



for maxloop 11,  
CR= 2.9729, BPP = 0.7135  
MSE=24.1368, PSNR=34.304 dB

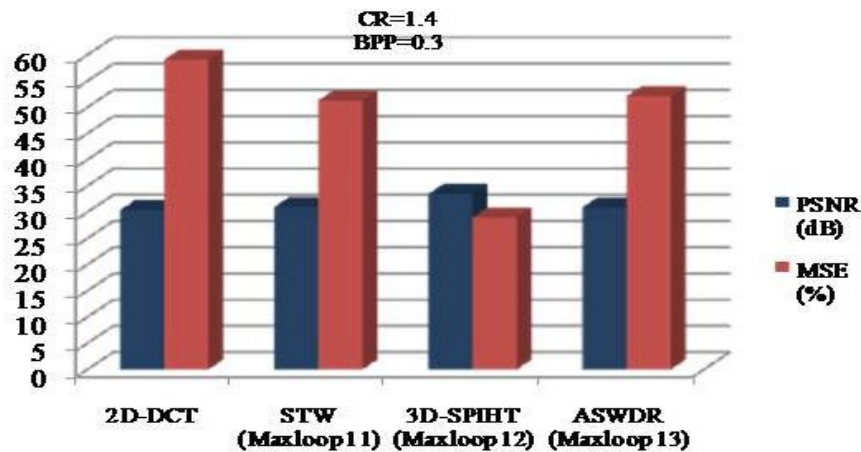
**Figure 8.** Frame no.1 compressed by using ASWDR algorithm

Table 1 shows the average value of PSNR and MSE for the different algorithms considered in this paper when CR and BPP is approximately 1.4 and 0.3 respectively.

**Table 1:** The Average value of PSNR and MSE

Algorithm	PSNR (dB)	MSE (%)
Conventional 2D-DCT	30.414	59.12
STW (Maxloop 11)	31.0297	51.3305
3D-SPIHT (Maxloop 12)	33.5094	29.0107
ASWDR (Maxloop 10)	30.96	52.1607



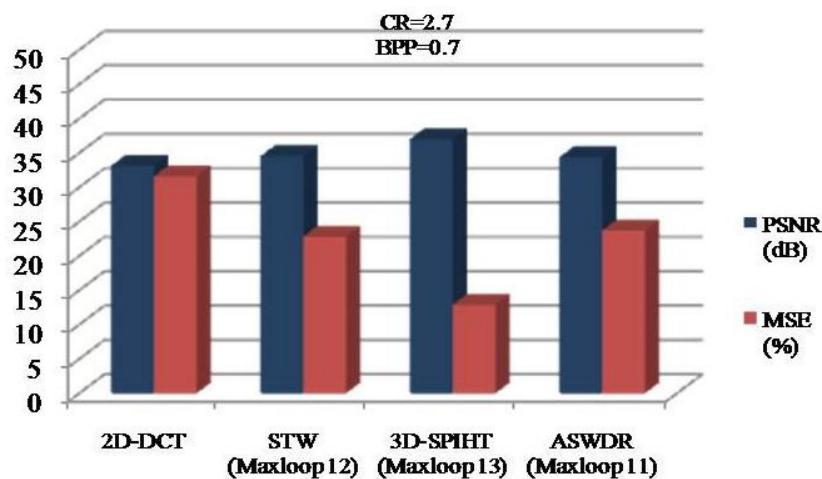


**Figure 9.** Average value of PSNR and MSE when the CR and the BPP is approximately 1.4 and 0.3 respectively.

Table 2 shows the average value of PSNR and MSE for the different algorithms considered in this paper when CR and BPP is approximately 2.7 and 0.7 respectively.

**Table 2:** The Average value of PSNR and MSE

Algorithm	PSNR (dB)	MSE (%)
Conventional 2D-DCT	33.135	31.59
STW (Maxloop 12)	34.5548	22.8116
3D-SPIHT (Maxloop 13)	37.0335	12.8926
ASWDR (Maxloop 11)	34.3888	23.701



**Figure 10.** Average value of PSNR and MSE when the CR and the BPP is approximately 2.7 and 0.7 respectively.

The algorithm with highest PSNR and Lowest MSE values for the given CR and BPP are in the order:

- (1) 3D-SPIHT
- (2) STW
- (3) ASWDR

The order of algorithms is just reverse with less number of maxloop for the given CR and BPP.

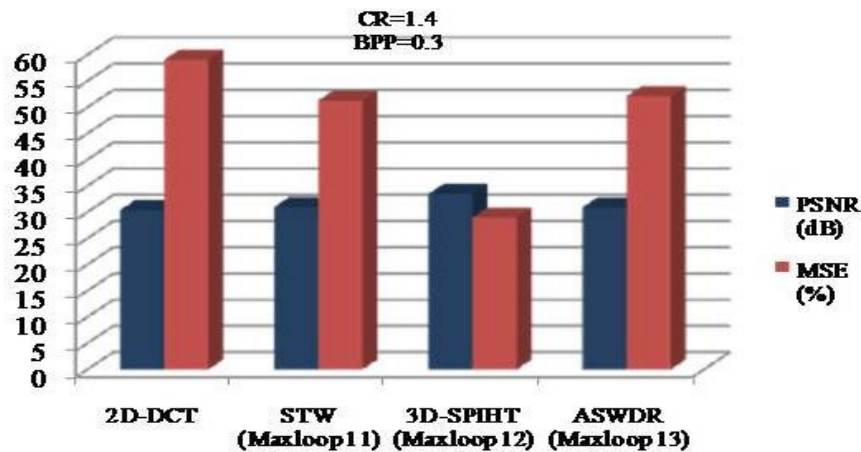
## VIII. CONCLUSION

Spatial-orientation Tree Wavelet (STW), 3D-Set Partitioning in hierarchical trees (3D-SPIHT) and Adaptively Scanned Wavelet Difference Reduction (ASWDR) algorithms are implemented for video compression and the results are compared. The original video is split in the form of frames which is further subdivided into blocks via block matching algorithm [26]. Each frame is then compressed and decompressed by these algorithms. The average MSE and PSNR values are considered as a quality parameter for the video quality. On the basis of the preferred compression ratio (CR) and bit-per-pixel (BPP) ratio, maxloop for the compression algorithm is selected. The selection of maxloop is done keeping the best compromise between a low compression ratio and a good perceptual result. Less number of maxloop provide smaller compression time because of less number of steps.

Comparisons amongst the techniques are carried out on the basis of calculated performance parameters. The results show that the PSNR and MSE value are 8% better in 3D-SPIHT as compared to STW and ASWDR methods. So 3D-SPIHT can be used for the video compression, where lower BPP is vital. In context to minimum number of maxloop, ASWDR is better than the other two algorithms which can be used where higher perceptual quality is essential rather than the lower BPP. These algorithms sustain faithful compression and reproduction of the video, preserving the picture quality. In future, many methodological aspects like choice of the mother wavelet, scale parameters, threshold values etc of the wavelet technique will always require further investigations and can lead for enhanced outcome.

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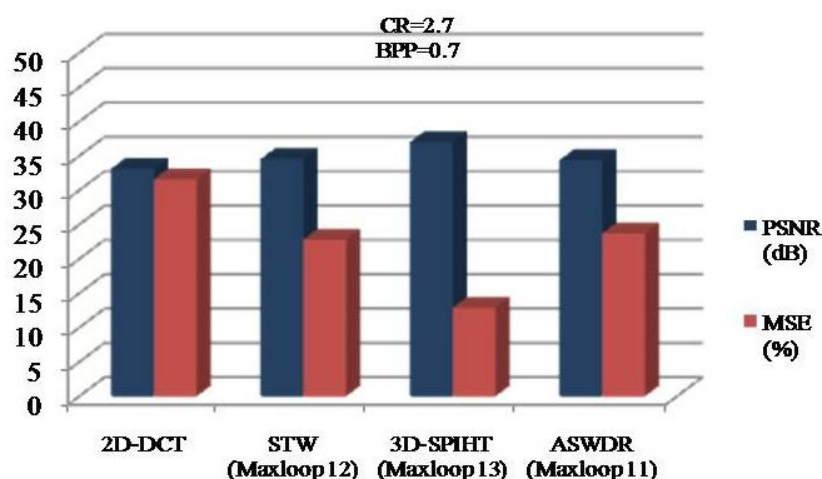


**Figure 9.** Average value of PSNR and MSE when the CR and the BPP is approximately 1.4 and 0.3 respectively.

Table 2 shows the average value of PSNR and MSE for the different algorithms considered in this paper when CR and BPP is approximately 2.7 and 0.7 respectively.

**Table 2:** The Average value of PSNR and MSE

Algorithm	PSNR (dB)	MSE (%)
Conventional 2D-DCT	33.135	31.59
STW (Maxloop 12)	34.5548	22.8116
3D-SPIHT (Maxloop 13)	37.0335	12.8926
ASWDR (Maxloop 11)	34.3888	23.701



**Figure 10.** Average value of PSNR and MSE when the CR and the BPP is approximately 2.7 and 0.7 respectively.

The algorithm with highest PSNR and Lowest MSE values for the given CR and BPP are in the order:

- (1) 3D-SPIHT
- (2) STW
- (3) ASWDR

The order of algorithms is just reverse with less number of maxloop for the given CR and BPP.

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