Video Compression by using new Wavelet Bi-Orthogonal Filter Coefficients

[1]Manimozhi. D, [2]Dr. T. K. Shanthi
[1]PG Scholar, Department of Electronics and Communication Engineering, Thanthai Periyar Government Institute of Technology, Vellore, Tamil Nadu, India;
[2]Assistant Professor, Department of Electronics and Communication Engineering, Thanthai Periyar Government Institute of Technology, Vellore, Tamil Nadu, India.

***Abstract*— In this paper new wavelet bi-orthogonal filter coefficients for wavelet decomposition and reconstruction of Video are introduced for better Video compression, when the Video is compressed by using these filter coefficient in DWT-SPIHT schema then it perform better than DWT-SPIHT schema with wavelet 9/7 filter and wavelet 5/3 filter. The compression result by using these filter coefficient show that the reconstructed Video has higher PSNR and low MSE than wavelet 9/7 filter and wavelet 5/3 filter.**

Keywords*— *Video Compression, wavelet Transform, Video texture, wavelet 9/7 filter, wavelet 5/3 filter

I. INTRODUCTION

Digital video techniques have been used for a number of years, for example in the television broadcasting industry. IMAGE sequence coding has been an active research area for a long time. Video conferencing image sequence coding is becoming even more important now with the widespread use of networks and the affordability of video capturing equipments. Video compression plays an important role in many digital video applications, such as digital libraries, video on demand and high definition television.

However, until recently a number of factors have prevented the widespread use of digital video. When an ordinary analog video sequence is digitized according to the standard CCIR 601, it can consume as much as 165 Mbps, which is 165 million bits every second. With most surveillance applications infrequently having to share the network with other data intensive applications, this is very rarely the bandwidth available.

To circumvent this problem, a series of techniques – called picture and video compression techniques – have been derived to reduce this high bit-rate. Their ability to perform this task is quantified by the compression ratio. The higher the compression ratio is, the smaller is the bandwidth consumption. However, there is a price to pay for this compression: increasing compression causes an increasing degradation of the video.

Since last two decade the discrete wavelet transform (DWT) has witnessed great success for Video compression. All those DWT based method whether they are conventional and directional, use wavelet 9/7 filter or wavelet 5/3 for better compression. This paper introduces new wavelet based bi-orthogonal filter coefficient that can give better result in case PSNR and MSE comparison to wavelet 9/7 filter and wavelet 5/3 filter.

II. COMPRESSION ALGORITHM AND VIDEO CODING

A. The Rgb And Yuv Representation Of Video Signals

A color can be synthesized by combining the three primary colors red, blue, and green (RGB). The RGB color system is one means of representing color images. Alternatively, the luminance (brightness) and chrominance (color) information can be represented separately. By calculating a weighted sum of the three colors R, G, and B, we can obtain the luminance signal Y which represents the "brightness" of the color.

Of the three color difference signals, only two of them are linearly independent, the third one can always be expressed as a linear combination of the other two. Therefore, we only need the luminance Y and any two of the color difference signals to represent the original color. The three major standards for analog color television in current use are PAL, SECAM, and NTSC. All three systems use three components: luminance Y, blue color difference U (equivalent to Cb above) and red color difference V (equivalent to Cr above) to represent a color. We call this the YUV system.

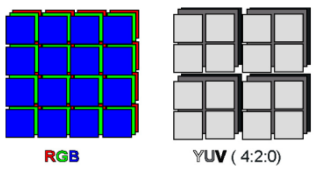

Fig.1 RGB to YUV representation

Computer graphics community to convert RGB to YUV mostly uses the following formulas,

$$Y = (0.257 * R) + (0.504 * G) + (0.098 * B) +16$$
$$U = (0.439 * R) + (0.368 * G) – (0.071 * B) +128$$
$$V = -(0.148 * R) - (0.291 * G) + (0.439 * B) +128$$

ffpThis YUV representation system has certain advantages over the RGB system. Since the human visual system (HVS) is less sensitive to chrominance than to brightness, the chrominance signals can therefore be represented with a lower resolution than the luminance without significantly affecting the visual quality. This by itself achieves some degree of data compression.

B. Motion Estimation

An MPEG video can be understood as a sequence of frames. Because two successive frames of a video sequence often have small differences (except in scene changes), the MPEG-standard offers a way of reducing this temporal redundancy. It uses three types of frames:

I-frames (intra)
P-frames (predicted) and
B-frames (bidirectional).

The I-frames are “key-frames”, which have no reference to other frames and their compression is not that high. The P-frames can be predicted from an earlier I-frame or P-frame. P-frames cannot be reconstructed without their referencing frame, but they need less space than the I-frames, because only the differences are stored. The B-frames are a two directional version of the P-frame, referring to both directions (one forward frame and one backward frame). B-frames cannot be referenced by other P- or Bframes, because they are interpolated from forward and backward frames. P-frames and B-frames are called *inter coded frames*, whereas I-frames are known as *intra coded frames.*

The references between the different types of frames are realised by a process called *motion estimation or motion compensation*. The correlation between two frames in terms of motion is represented by a *motion vector*. The resulting frame correlation, and therefore the pixel arithmetic difference, strongly depends on how good the motion estimation algorithm is implemented

C. Wavelet Video Coding

Wavelet transforms involve representing a general function in terms of simple, fixed building blocks at different scales and positions. The discrete wavelet transform (DWT) has gained wide popularity due to its excellent de correlation property, many modern image and video compression systems embody the DWT as the transform stage .After DWT was introduced, several codec algorithms were proposed to compress the transform coefficients as much as possible. Among them, stationary Wavelet Transform (SWT) and Set Partitioning in Hierarchical Trees (SPIHT) are the most famous ones. The DWT and IDWT are the most computationally intensive and time critical portions of the algorithm. The DWT uses 7-tap and 9-tap FIR filters. Motion estimation and compensation on spatial domain is used in wavelet video coding in order to exploit the spatial correlation present in the video sequences. A discrete wavelet transform (DWT) is applied to generate a set of wavelet coefficients for each subband which is generally coded separately.

We denote the relationship between DWT and subbands and focus on low frequency subbands:

DWT(Fsource(i, j)) = LL(Fsource(i,j)) + LH(Fsource(i, j))+ HL(Fsource(i, j)) + HH(Fsource(i,j))

where L denotes a low pass filter function, H denotes a high pass filter function, Fsource represents an original input frame, and (i, j) is the block location on a frame.

Still images are considered as 2-D signals. Applying the subband/wavelet transform to such signals is most commonly done by using the 1-D transform version and applying it to the still image in both row-order and column-order. This is because implementation of the single dimension transform is more efficient than an equivalent 2-D transform, and was shown [10] to be an effective solution. Video images can be considered as a 3-D signal, the three dimensions being the horizontal, the vertical, and the temporal dimension. In this section, we will summarize the implementation of the 1-D wavelet transform which is also representative of the subband transform in this context.

The wavelet transform, as a data decorrelating tool, has won acceptance because of its multiresolution analysis capabilities in which the signal being transformed is analyzed at many different scales to give a transformation whose coefficients can efficiently describe fine details as well as global details in a systematic way. This, in addition to the locality of the wavelet basis functions as opposed to the Fourier transform, for example, which uses infinite width basis functions. Wavelets also unify the many other techniques that are of local type, such as the Gabor transform and the short time Fourier transform. The wavelet/subband transform is implemented using a pair of filters: a highpass filter and a lowpass filter , which split a signal’s bandwidth in two halves. The frequency responses of and are mirror images. To reconstruct the original signal an inverse transform is implemented, using the inverse transform filters , which are also mirror images.

The bi-orthogonal 9/7 filter coefficient and the new proposed filter coefficient are shown in table:-

TABLE 1. NEW FILTER COEFFICIENTS

9/7 FILTER COEFFICIENT		PROPOSED FILTER COEFFICIENT	
LPF	HPF	LPF	HPF
0	0	-0.0015	0.0015
0.0378	-0.0645	0.0027	0.0027
-0.0238	0.0407	0.0049	-0.0049
-0.1106	0.4181	-0.0128	-0.0128
0.3774	-0.7885	-0.0025	0.0025
0.8527	0.4181	0.0264	0.0264
0.3774	0.0407	-0.0050	0.0050
-0.1106	-0.0645	-0.0455	-0.0455
-0.0238	0	0.0211	-0.0211
0.0378	0	0.0756	0.0756
		-0.0568	0.0568
		-0.1404	-0.1404
		0.1817	-0.1817
		0.6594	0.6594
		0.6594	-0.6594
		0.1817	0.1817
		-0.1404	0.1404
		-0.0568	-0.0568
		0.0756	-0.0756
		0.0211	0.0211
		-0.0455	0.0455
		-0.0050	-0.0050
		0.0264	-0.0264
		-0.0025	-0.0025
		-0.0128	-0.0128
		0.0049	0.0049
		0.0027	-0.0027
		-0.0015	-0.0015

The computation of the wavelet transform used recursive averaging and differencing coefficients. It behaves like a filter bank. Recursive application of a two-band filter bank to the lowpass band of the previous stage.

Figure 2 shows the synthesis filter bank that reverses the process just described. As would be expected, the reconstruction algorithm is similar to the one-dimensional case. At each iteration, four scale j approximation and detail sub Video frames are up sampled and convolved with two one - dimensional approximation and the process is repeated until the original Video is reconstructed.

D. *Set Partitioning In Hierarchical Trees (SPIHT) :*

This compression schemes is based on wavelet coding technique. The image is transformed using a discrete wavelet transform. In the beginning, the image is decomposed into four sub-bands by cascading horizontal and vertical two-channel critically sampled filter-banks. This process of decomposition continues until some final scale is reached. In each scale there are three sub-bands and one lowest frequency sub-band. Then successive-approximation quantization (SAQ) is used toper form embedding coding. This particular configuration is also called QMF pyramid.

The SPIHT algorithm is used to the multi-resolution pyramid after the subband/wavelet transformation is performed . The SPIHT video coding system is shown in the figure.

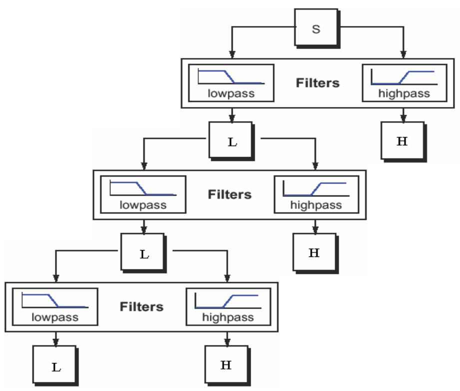

Fig.2 Synthesis filter Bank

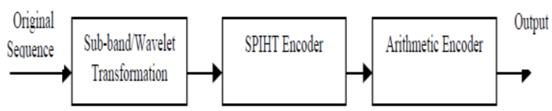

Fig.3. SPIHT Video Coding System

These are the steps involved in Compressing the video frames. The decoder does exactly opposite, that is it performs arithmetic decoding on the input bit stream, then SPHIT decoding, finally sub-band/wavelet transform. Those steps are summarized below.

E. *Decompression*

1. Read the coded Video.
2. Decode the coded Video by using SPIHT encoder.
3. Pass the decoded Video through inverse DWT with proposed filter coefficient.
4. Convert the video from YCbCr to RGB Format.
5. Measure MSE and PSNR for the Video.
6. Repeat compression and decompression process by using wavelet 9/7 filter coefficient.

filters—one operating on the sub Video frame columns and the other on its rows. Addition of the results yields the scale j + 1

7. Compare the result for both the cases

After reconstruction of Video parameters are measured as follows:-

III. PEAK SIGNAL TO NOISE RATIO (PSNR)

The phrase peak signal-to-noise ratio, often abbreviated 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 codec's (e.g., for image and video compression). The signal in this case is the original data, and the noise is the error introduced by compression. When comparing compression codec's 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

$$\text{MSE} = 1/k \sum_{i=1}^{k} (\text{P}_\text{i} - \text{Q}_\text{i})^2$$

And root mean square error is given by:-

$$\text{RMSE}= \sqrt{MSE}$$

Here

Pi=Original data

Qi= Reconstructed Data

K= Size of video

The peak signal to noise ratio for reconstructed image is given by:-

$$\text{PSNR}=20 \log_{10}\left(\frac{\max(Pi)}{RMSE}\right)$$

IV. CONCLUSION

Our Approach is based on new filter coefficients for bi-orthogonal 9/7 filter. In this method we explain how new filter coefficients increase the PSNR and reduces the MSE. We examine that the PSNR value and MSE value is better in the proposed method. It also supports faithful reproduction of the image, keeping the picture quality of the image/video. In future other evolutionary computing techniques also can be tried for the better results. Future research efforts focus on better PSNR and MSE value. There are many other methods for compression technique, like fuzzy logic, neural network. In compression technique we can try to implement techniques like neural network and fuzzy logic will further better PSNR and MSE.

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