ORIGINAL RESEARCH PAPER

Engineering

HIGH DYNAMIC RANGE VIDEO COMPRESSION EXPLOITING WAVELET TRANSFORM

KEY WORDS: Range of luminance level,DWT method,video reconstruction using IDWT algorithm.

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ABSTRACT

The Human visual system model (HVS) is used by image processing, video processing and comport vision experts to deal with biological and psychological processes that are not yet fully understood. The human visual system can adapt to a broad range of luminance levels ranging from scotopic (10–5–10 cd/m2) to photopic (10–106 cd/m2) condition. This project proposes a novel wavelet transform based video compression algorithm, and then it apply in the video transmission. Firstly, introduce a general video coding framework and Basic coding process in the video compression. Secondly, I design an improved wavelet transform in the video compression problem. The proposed modified wavelet transform is executed by a luminance. Video compression reduces the amount of data required to represent an image/frame by removing redundant information. There are several methods of image compression available today. Although Video looks like continuous motion, it is actually a series of still images. In this project Discrete Wavelet transform method applied for image and video compression. We also calculated the compression ratio(CR) and Peak Signal to Noise Ratio(PSNR) values after video reconstruction using Inverse Discrete Wavelet transform(IDWT) algorithm.

I. INTRODUCTION

The human visual system (HVS) exhibits nonlinear sensitivity to the distortions introduced by lossy image and video coding. Conventional capture and display devices, which typically employ a 24-bit per pixel encoding format, can cover only a limited dynamic range and colour gamut, known as standard dynamic range (SDR) or low dynamic range (LDR). In the real world, luminance levels and colour gamut can vary a lot more than what is captured by SDR imaging. Humans are able to visible frequencies in the range approximately from 430 to 770 Thz.

However, this does not mean that all frequencies are visible in the same way. One could make the assumption that a human would see frequencies that make up visibility better than others, and that is in fact a good guess. Furthermore, one could also hypothesize that seeing a tone becomes more difficult close to the extremes frequencies (i.e. close to 430 and 770 Thz).

State-of-the-art high dynamic range (HDR) imaging technologies (capture and display) are capable of providing high levels of immersion through the use of a dynamic range that meets or exceeds that of the HVS. With extended dynamic range and wide colour gamut display devices becoming affordable to consumers, sending a signal in a legacy encoding space that is oblivious to the capabilities of the display undermines progress. For example, increasing the dynamic range of the display for the same compressed input image will increase the contrast of any signal as well as any distortion, and thus increase the visibility of distortions caused by compression.

In this paper, Video compression is important for webmasters who want to create faster loading web pages which in turn will save a lot of bandwidth. Video compression is important for people who attach photos/video to emails which will send the email more quickly and not make the recipient of the email angry. Therefore, compression is necessary and essential method for creating video files with manageable and transmittable sizes. Video is a series of still images which are called frames. The consumers using digital video increasing day by day, so video compression is necessary to reduce the size. Video compression has two important benefits. First, it makes it possible to use digital video in transmission and storage environments that would not support uncompressed video for example current Internet throughput rates are insufficient to handle uncompressed video in real time. A DVD can only store a few seconds of uncompressed video so video storage would not be practical without video and audio compression. Second video compression enables more efficient use of transmission and storage resources. If a high bit rate transmission channel is available, then it is more attractive proposition to send a high resolution compressed video or multiple compressed video channels than send a single, low resolution, uncompressed stream.

Experimental result in this method shows that, our method gives the better result than the other existing compression method in terms of PSNR and compression ratio. The greater the compression ratio means the better the wavelet function. PSNR is one of the parameters that can be used to quantify image quality..

II. PROPOSED METHOD

Here, Wavelet video coding schemes can provide flexible spatial, temporal, SNR and complexity scalability with fine granularity over a large range of bit-rates, while maintaining a very high coding efficiency. The wavelet representation provides multi-resolution, multi-frequency expression of signal with localization in both time and frequency. This multi-resolution frame also provides representation of global motion structures of the video signals at different scales. The motion activities for a particular sub-frame at different resolutions are different but highly correlated since they actually specify the same motion structure at different scales. The spatial redundancy which is present between the image pixels can be reduced by taking transforms which decorrelates the similarities among the pixels.

The choice of the transforms depends upon a number of factors, in particular, computational complexity and coding gain. Coding gain is a measure of how well the transformation compacts the energy into a small number of coefficients. The wavelet representation provides multi-resolution, multi-frequency expression of signal with localization in both time and frequency. This property is very desirable in image and video coding applications

- Real-world images and video signals are non-stationary in nature. The wavelet transform decomposes a non-stationary signal into a set of multi-scale wavelets where each component becomes relatively more stationary and hence easier to code.
- The wavelet representation matches the spatially tuned frequency modulated properties experienced in early human vision as indicated by the research results in psychophysics and physiology.
- It avoids inherent blocky effects found in the DCT based encoder/decoder.

Image is two dimensional signal which is denoted by X (m,n) here m is number of rows and n is number of columns. So for image compression, firstly apply DWT algorithm to rows followed by columns. then inter change the order of rows and columns means, first apply DWT algorithms to column first followed by rows next. Similarly, IDWT algorithm also applied to columns followed by rows completes the reconstruction of video frame. The following figure shows the level one DWT and IDWT architecture for video frame

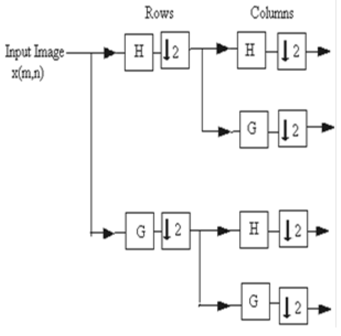

Fig 1. Level One DWT for images

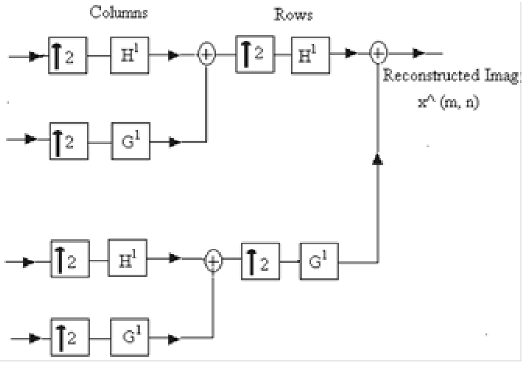

Fig 2. Level One IDWT for images

The following approach was used to compress an video file. First, the data is divided into frames. For each frame, a wavelet representation is used to minimize the number of bits required to represent the frame while keeping any distortion inaudible. This scheme is highly successful because it reduces the number of non-zero wavelet coefficients. In addition, these coefficients may be encoded using a small number of bits. The capabilities of MATLAB's Wavelet Toolbox were utilized. The Wavelet Toolbox incorporates many different wavelet families and their coef ficients. From the analysis, it was decided to use the Daubechies family of wavelets for coding video signals. The Wavelet Toolbox's built-in functions *dwt, wavedec, waverec* and *idwt,* were used to compute the forward and inverse wavelet transforms. *Wavedec* computes the multi-level decomposition of a signal and *waverec* reconstructs the signal from their coefficients. Multi-resolution nature of wavelet decomposition is ideal for providing spatially scalable video.

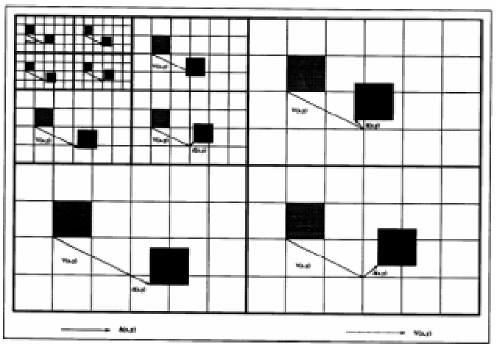

Fig 3. Multi-Resolution Motion Compensation

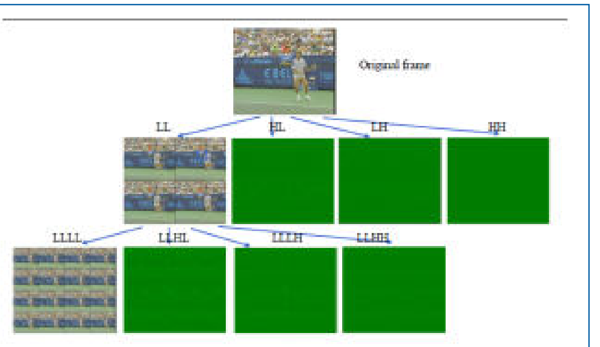

Fig 4. Over complete Wavelet Transform by Low-Band Shift

I am trying to simulate an video codec that utilizes the wavelet transformation to perform compression of high quality video whilst maintaining transparent quality at low bit rates. The diagram below illustrates the MATLAB implementation used. It consists of the following features:

(a) Signal division and processing using small frames
(b) Discrete wavelet decomposition of each frame
(c) Compression in the wavelet domain
(d) Encoding the video file by using encoder
(e)Decoding the video file by using decoder
(f) Signal reconstruction
(g) Main output: video files.

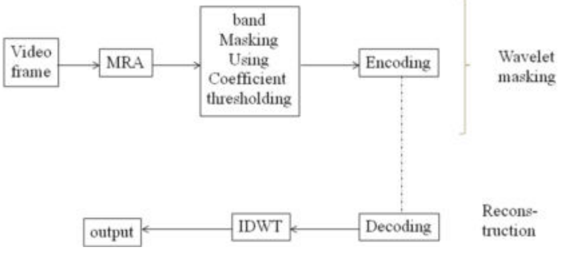

Fig 5 : Block diagram

III. EXPERIMENTAL CRITERIA

Video Quality is a characteristic of a video that measures the perceived video degradation Peak signal to noise ratio (PSNR) and compression ratio were used to measure the efficiency of the proposed method.

1) Peak Signal To Noise Ratio

PSNR is the peak signal to noise ratio in decibels (DB).The PSNR is measured in terms of bits per sample or bits per pixel. The frame with 8 bits per pixel contains from 0 to 255.
Peak signal to ratio can be calculated as

$$PSNR = 10X\log_{10}\left(\frac{peak^2}{MSE}\right)$$

MSE is the mean square error. That, can be calculated as,

$$MSE = \frac{1}{M*N}\sum_{i=0}^{1-N}\sum_{j=0}^{1-M}(A(i,j) - B(i,j))^2$$

Here A - Perfect image
B - Denoised image
i – Pixel row index
j – Pixel column index

2) Compresssion ratio

The compression ratio is used to measure the ability of data compression by comparing the size of the image being compressed to the size of the original image. The greater the compression ratio means the better the wavelet function. PSNR is one of the parameters that can be used to quantify image quality.

$$compression\ ratio = \frac{size\ of\ compressed\ video\ file}{size\ of\ original\ video\ file}$$

I. RESULTS AND DISCUSSIONS

Experiments are conducted MATLAB 2009 as simulation software. Test video used in experiment are shaky_car (503Kb), staples (130Kb), viplane(300Kb) and vipsnowydays(296Kb). Applying wavelet transform in each frames. PSNR and Compression Ratio calculated in this paper. PSNR value is decreasing as the compression ratio increasing, means the reconstructed image quality is decreasing.

In this experiment, here, choose PSNR and compression ratio as evaluated standard. The greater the compression ratio indicate the better the wavelet function. PSNR is one of the parameters that can be used to quantify image quality.

Below tables evaluates the performance of different test videos with proposed and existing method. PSNR and compression ratio are tabulated for existing method shown in Table 1: . PSNR and compression ratio are tabulated for proposed method shown in Table 2:

Name of Video file	Input video Size	CR	PSNR
viplane.avi	300 kb	0.5456	87.5365
vipsnowydays.avi	296 kb	0.2842	85.6292
shakycar.avi	503 kb	0.2264	98.8261
staples.avi	130 kb	0.0425	83.9912

Table 1: PSNR and compression ratio for existing method .

Name of Video file	Input video Size	CR	PSNR
viplane.avi	300 kb	0.5866	84.6969
vipsnowydays.avi	296 kb	0.3040	77.4250
shakycar.avi	503 kb	0.2345	104.8445
staples.avi	130 kb	0.0384	88.8928

Table 2: PSNR and compression ratio for proposed method .

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From these tables, we can show that, PSNR and compression ratio values of proposed method successfully performed better result than compared to existing method. The greater the compression ratio means the better the wavelet function.

Figure illustrated the result of proposed method is given to this paper are shown below.fig 1 shows frames of video file.fig 2 shows level one discrete wavelet transform for video frames.fig 3 shows level two discrete wavelet transform for video frames. Fig 4 shows compressed video frames. Fig 5 shows Reconstructed video frames.

Fig 1: frames in Video Traffic

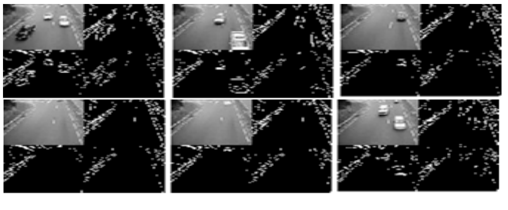

Fig 2: one DWT for frames

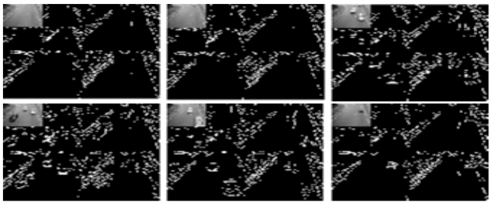

Fig 3: Two DWT for video frames

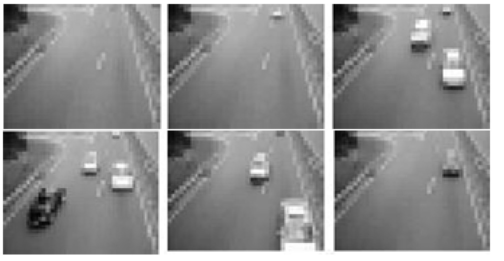

Fig 4: compressed video frames

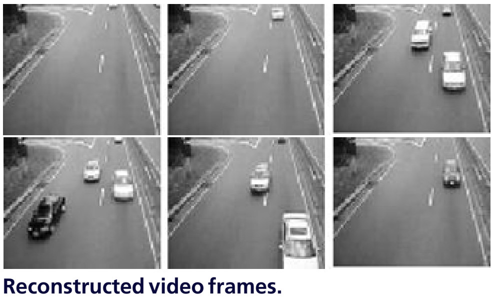

Fig 5: Reconstructed video frames.

V. CONCLUSION

In this paper, I have proposed a new wavelet tool for perception-based HDR video compression, which supports frame-level content adaptation. Digital video compression techniques have played an important role in the world of telecommunication and multimedia systems where bandwidth is still a valuable commodity. Hence, video compression techniques are of prime importance for reducing the amount of information needed for picture sequence without losing much of its quality, judged by human viewers. Here I have used Discrete Wavelet Transform (DWT) to achieve the compression for video and it extended to series of images which is nothing but a video. PSNR and Compression Ratio calculated in this paper. PSNR value is decreasing as the compression ratio increasing, means the reconstructed image quality is decreasing.

VI. REFERENCES

[1] M. Johnstone and B.W. Silverman, "Wavelet threshold estimators for data with correlated noise," J. Roy. Statist. Soc. B, vol. 59, pp. 319–351, 1997.

[2] Iain E. G. Richardson, "H.264 and MPEG Video Compression", Wiley Publication,2003

[3] D.G.Sampson, E.A.B. de Silva, and M. Ghanbari, "Low bit-rate video coding using Wavelet quantization", Proc. Inst. Elect. Eng., 1995, vol 142, Page:141-148.

[4] Lazar, D.; Averbuch, A., "Wavelet-based video coder via bit allocation," IEEE Transactions on Circuits and Systems for Video Technology, Volume: 11 Issue: 7, July 2001, Page(s): 815 –832.

[5] S.G. Mallat. "A Wavelet Tour of Signal Processing." 2nd Edition. Academic Press, 1999. ISBN 0-12-466606-X

[6] Symes, P., 2001. Digital Video Compression. New York: McGraw-Hill.

[7] Burrus, C.S., Gopinath, R.A., Guo, H., 1998. Introduction to Wavelets and Wavelet Transforms. New Jersey: Prentice-Hall.

[8] G. Davis, S. G. Mallat, and Z. Zhang, "Adaptive time-frequency decompositions," Optical Engineering, vol. 33, pp. 2183–2191, July 1994.

[9] Seigneurbieux, P. and Zixiang Xiong, "3-D wavelet video coding with rate-distortion optimization," Proc. International Conference on Information Technology: Coding and Computing, 2001. pp. 322 – 326, April 2001, Las Vegas, NV, USA

[10] S. Miller, M. Nezamabadi, and S. Daly, "Perceptual signal coding for more efficient usage of bit codes," SMPTE Motion Imag. J., vol. 122, no. 4, pp. 52–59, 2013.

[11] Y. Zhang, D. Agrafiotis, and D. R. Bull, "High dynamic range image & video compression a review," in Proc. IEEE 18th Int. Conf. Digit. Signal Process. (DSP), Jul. 2013, pp. 1–7.

[12] J.-L. Starck, E. J. Cand´es, and D. L. Donoho. Very high quality image restoration by combining wavelets and curvelets. In Proceedings of SPIE, volume 4478 (Wavelet Applications in Signal and Image Processing IX), 2001.

[13] J. Portilla, V. Strela, M.Wainwright, and E. P. Simoncelli. Image denoising using scale mixtures of Gaussians in the wavelet domain. IEEE Trans. on Image

Processing, 12(11):1338–1351, November 2003
[14] B.-B. Hao, M. Li, and X.-C. Feng. Wavelet iterative regularization for image restoration with varying scale parameter. Signal Processing: Image Comm unication, 23(6):433–441, 2008.
[15] M. A. T. Figueiredo, R. D. Nowak, and S. J. Wright. Gradient projection for sparse reconstruction: Application to compressed sensing and other inverse problems. IEEE J. Sel. Top. Signal Process., 1(4):586–598, December 2007..