Low Performance Based Video Compression

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Abstract: The image processing is very essential aspect for image and video processing application. One of application Video compression is an essential part of recording and saving security camera footage, for the reason that it compresses the raw files into a lesser format. This allows you to store more videos on our computer device. video compression an important part of our surveillance is the ability to compress files - this maximizes your hard drive space so you can store more videos for longer periods of time before your hard drive is full. Large video files become a problem when we record extremely long videos, or high quality HD videos. In this paper, Low Performance Based Video Compression approach which tends to hard exploit the pertinent temporal redundancy in the video frames to improve compression efficiency with less processing complexity. Generally, video signal has high temporal redundancies due to the high correlation between successive frames. Actually, this redundancy has not been exposed enough by current video compression techniques. It consists on 3D to 2D transformation of the video frames that allows exploring the temporal redundancy of the video using 2D transforms and avoiding the computationally challenging motion compensation step. This transformation turns the spatial temporal correlation of the video into high spatial correlation. In this paper transforms each group of pictures (GOP) to one picture (Accordion Representation) eventually with high spatial correlation. Thus, the decorrelation of the resulting pictures by the DCT makes efficient energy compaction, and therefore produces a high video compression ratio. Many experimental tests had been conducted to prove the method efficiency especially in high bit rate and with slow motion video. The proposed method seems to be well suitable for video surveillance applications and for embedded video compression systems.

***Keywords*— DCT, Group Of Pictures (GOP), Decorrelation, Slow Motion Video, 3D to 2D transformation , High Video Compression Ratio, Image, Accordion Representation.**

I. INTRODUCTION

Video compression as a subject matter may seem really dull, but the real-world benefits of using the latest technology can radically increase the flexibility. Put simply, better compression means greater flexibility the more efficiently data is handled, the more choices you have with your existing resources. An existing network can support more cameras, better audio-video quality or both. The main objective of video compression in most video applications is to reduce the amount of video data for storing or transmission purposes without affecting the visual quality. The desired video performances depend on applications requirements, in terms of quality, disks capacity and bandwidth. For portable digital video applications, highly integrated real-time video compression and decompression solutions are more and more required.

1.1 Video Compression: JPEG and MPEG are recently the most used image and video compression methods. These methods are not lossless. With growing compression ratio (CR) the quality of the output image or video sequence decreases as a result of removing redundant data which is allowed by using the human eye imperfection. Both methods use Two-Dimensional Discrete Cosine Transform (2D DCT) to produce a kind of spatial frequency spectrum. The magnitudes of low frequency components can be stored with lower accuracy accordingly to different sensitivity of human vision to colour or brightness changes in large areas than to the high frequency brightness variations.

Considering that MPEG is based on compression of the sequence of single images, there could be a possibility to reach good compression ratio using the Three-Dimensional Discrete Cosine Transform (3D DCT). This idea differs by using "video cube" which is a cube of N × N × N video elements. The 3D DCT can make the account of the neighboring pictures correlation in the video cube the same as the 2D DCT uses the correlation of the neighboring pixels in 2D matrix. The aim of my dissertation thesis is to verify the possibility of implementing the 3D DCT compression algorithm into Digital Signal Processor (DSP). This article describes some necessary basics for introducing into this field.

1.1.1 Compression Process: The compression process can be divided into three main parts (Figure). The video sequence is on the input, compressed video sequence on the output.

Figure 1: Compression process

The input video sequence can be divided into so-called video cubes. The principle of a video cube composition from video sequence frames is shown in the Figure 2, each video cube contains 512 video elements. If the monochromatic video sequence is on the input, the first part of the compression process is the 3D DCT block which is the most time consuming. Most of today's established compression standards like MPEG-2/4 and H263 (+) rely on the so called motion-estimation/compensation approach to exploit inter frame correlation. This is a highly complex process, which requires a large number of operations per pixel and is therefore less appropriate for the implementation as real-time compression in a portable recording or communication device.

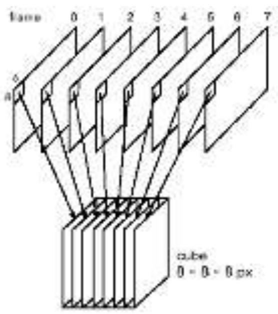

Figure 2: Video cube of 8 × 8 × 8 pixels

The 3d transform based video compression methods treat the redundancies in the 3D video signal in the same way, which can reduce the efficiency of these methods as pixel's values variation in spatial or temporal dimensions is not uniform and so, redundancy has not the same pertinence. Often the temporal redundancies are more relevant than spatial one. It is possible to achieve more efficient compression by exploiting more and more the redundancies in the temporal domain.

1.2 Existing methods

1. A 3D-DCT Real-Time Video Compression System for Low Complexity Single-Chip VLSI Implementation by Andreas Burg, Roni Keller and Juergen Wassner in 2000. Implemented through No motion estimation is required, greatly reducing the number of en/decoding operations per pixel, En- and Decoder are symmetric with almost identical structure and complexity, which facilitates their joint implementation, The complexity of the implementation is independent of the compression ratio. And Drawbacks are Motion estimation process is computationally intensive, Its real time implementation is difficult and costly.
2. Video signals transparency in consequence of 3D-DCT transform by Tomas Fryza and stanislav hanus in 2003.
   Implemented on Transparency elimination and Drawbacks are Increase coder complexity, Increase bit rate and
   Decrease picture luminance.
3. Motion analysis in 3D DCT domain and its application to video coding by N.Boinovi and J.Konrad in 2005.
   Implemented in The spectral footprint in video coding, DCT coefficient quantization and motion-adaptive scanning,
   And Proposed a motion estimation method based on plane fitting to high-energy DCT coefficients. Drawbacks are
   Implementation of the algorithm requires large amounts of memory as temporary storage, since eight frames must be
   stored in buffers at any one time. It is likely that a significant improvement in the degree of compression achieved could
   be obtained through the use of run-length coding.
4. Video Compression using the Three Dimensional Discrete Cosine Transform(3D-DCT) by G.M.P Servais in 1997.
   Implemented through The 3D-DCT based compression technique in this method is conceptually simple, This is numerous fast techniques for implementing the 2D and 1D transforms exist, both in hardware and software.
   Drawbacks are For Lower rates it clearly outperforms MPEG-2, although it is outperformed by MPEG- 4, Visually this coder produces sequences very similar to MPEG-4 at lower bit rates, while outperforming MPEG-2 at higher bit rates.

II. METHODOLOGY

The fundamental idea is to represent a video sequence with highly correlated form. Thus we need to expose both spatial and temporal redundancy in video signal. The video cube is the input of our encoder, which is a number of frames.

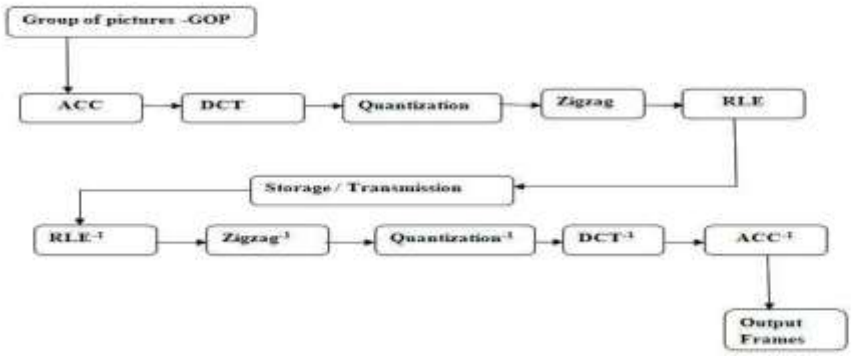

Figure 3: Block Diagram

This video cube will decomposed in to temporal frames which will be gathered into one 2D frame. The next step consists of coding the obtained frame. Normally, the variation of the 3D video signal is much less in the temporal domain than the spatial domain; the pixels in 3D video signal are more correlated in temporal domain.

A. **Group of pictures:** In video coding, a **group of pictures**, or **GOP structure**, specifies the order in which intra- and inter-frames are arranged. The GOP is a group of successive pictures within a coded video stream. Each coded video stream consists of successive GOPs. From the pictures contained in it, the visible frames are generated.

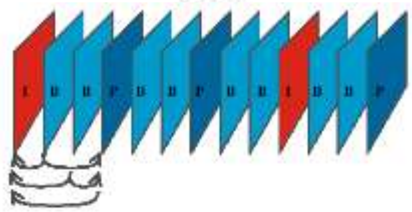

Figure 4: Group of frames

A GOP can contain the following picture types:

1. I-picture or I-frame (intra coded picture) - reference picture, which represents a fixed image and which is independent of other picture types. Each GOP begins with this type of picture.
2. P-picture or P-frame (predictive coded picture) - contains motion-compensated difference information from the preceding I- or P-frame.
3. B-picture or B-frame (bidirectionally predictive coded picture) - contains difference information from the preceding and following I- or P-frame within a GOP.
4. D-picture or D-frame (DC direct coded picture) - serves the fast advance.

B. Accordion Representation: Accordion representation is formed by collecting the video cube pixels which have the same column rank and these frames have a stronger correlation compare to spatial frames. To improve correlation in the representation we reverse the direction of event frames. This tends to put in spatial adjacency that the pixels having the same coordinate in the different frames of the video cube. The following example i.e., Figure clearly projecting the Accordion representation also minimizes the distance between the pixels correlated in the source. Figure shows the strong correlation obtained in the .Accordion representation. Made of 4 frames which are extracted from Miss America Sequence.

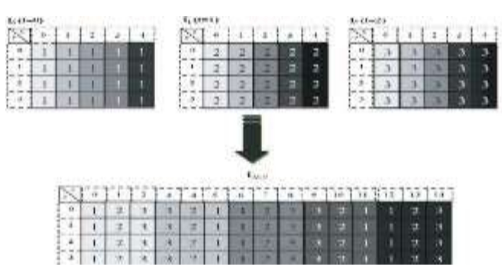

Figure 5 : Accordion representation example

Figure 6: Accordion representation example of Miss America

C. Discrete Cosine Transform:- The Discrete Cosine Transform (DCT) attempts to decorrelate the image data. After decorrelation each transform coefficient can be encoded independently without losing compression efficiency. This section describes the DCT and some of its important properties. The most common DCT definition of a 1-D sequence of length N is

$$C(u) = \alpha(u)\sum_{x=0}^{N-1} f(x)\cos\left[\frac{(2x+1)u\pi}{2N}\right]$$

For u=0, 1, 2…N-1. Similarly, the inverse transformation is defined as

$$f(x)=\sum_{u=0}^{N-1}\alpha(u)\ C\ (u)\cos\left[\frac{(2x+1)u\pi}{2N}\right]$$

For x=0, 1, 2…N-1.Where a*(u)* is defined as

$$\alpha(u)=\begin{cases} u=\sqrt{\frac{1}{N}} & for\, u=0 \\ u=\sqrt{\frac{2}{N}} & for\quad u\neq 0 \end{cases}$$

It is clear that for u = 0, $C(u=0)=\sqrt{\frac{1}{N}}\sum_{x=0}^{N-1}f(x)$.Thus, the first transform coefficient is the average value of the sample sequence. In literature, this value is referred to as the *DC Coefficient*. All other transform coefficients are called the *AC Coefficient.*

The plot of $\sum_{x=0}^{N-1}\cos\left[\frac{(2x+1)u\pi}{2N}\right]$ for *N* =7 and varying values of *u* is shown in Figure. In accordance with our previous observation, the first the top-left waveform (u = 0) renders a constant (DC) value, whereas, all other waveforms (*u* = 1, 2,… ,7) give waveforms at progressively increasing frequencies [13]. These waveforms are called the *cosine basis function*. Note that these basis functions are orthogonal. Hence, multiplication of any waveform in Figure 3 with another waveform followed by a summation over all sample points yields a zero (scalar) value, whereas multiplication of any waveform in Figure 3 with itself followed by a summation yields a constant (scalar) value. Orthogonal waveforms are independent, that is, none of the basis functions can be represented as a combination of other basis functions.If the input sequence has more than *N* sample points then it can be divided into sub-sequences of length *N* and DCT can be applied to these chunks independently. Here, a very important point to note is that in each such computation the values of the basis function points will not change. Only the values of ( ) *f x* will change in each sub-sequence. This is a very important property, since it shows that the basis functions can be pre-computed offline and then multiplied with the sub-sequences. This reduces the number of mathematical operations (i.e., multiplications and additions) thereby rendering computation efficiency.

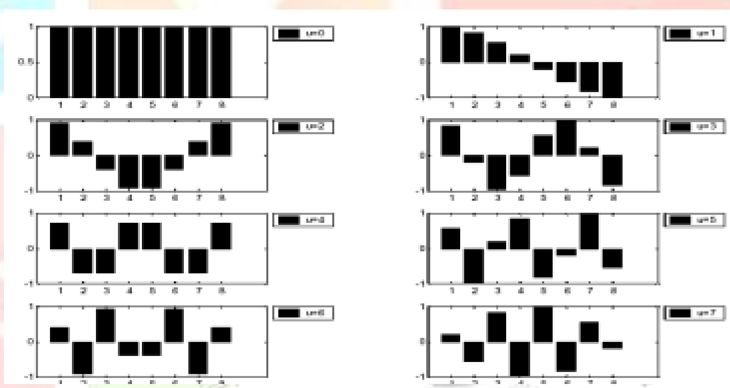

Figure 7: One dimensional cosine basis function (*N*=8).

2-D DCT: The objective of this document is to study the efficacy of DCT on images. This necessitates the extension of ideas presented in the last section to a two-dimensional space. The 2-D DCT is a direct extension of the 1-D case and is given by

$$C(u,v)=\alpha(u)\alpha(v)\sum_{u=0}^{N-1}\sum_{v=0}^{N-1}f(x,y)\cos\left[\frac{(2x+1)u\pi}{2N}\right]\cos\left[\frac{(2y+1)v\pi}{2N}\right]$$

For u,v=0,1,2, ……,N- 1. The inverse transform is defined as

$$f(x,y)=\sum_{u=0}^{N-1}\sum_{v=0}^{N-1}\alpha(u)\alpha(v)\,C(u,v)\cos\left[\frac{(2x+1)u\pi}{2N}\right]\cos\left[\frac{(2y+1)v\pi}{2N}\right]$$

For *x, y*= 0, 1, 2… *N-1*. The 2-D basis functions can be generated by multiplying the horizontally oriented 1-D basis functions with vertically oriented set of the same functions.

3-D DCT: The discrete cosine transform (DCT) has energy packing efficiency close to that of the optimal Karhunen-Loeve transform. In addition, it is signal independent and can be computed efficiently by fast algorithms. For these reasons, the DCT is widely used in image and video compression. Since the common three-dimensional DCT kernel is separable, the 3D DCT is usually obtained by applying the one-dimensional DCT along each of the three dimensions. Thus, the N ×N ×N 3D DCT can be defined as

$$C(u,v,w) = \alpha(u)\alpha(v)\alpha(w) \sum_{u=0}^{N-1}\sum_{v=0}^{N-1}\sum_{w=0}^{N-1} f(x,y,z) \cos\left[\frac{(2x+1)u\pi}{2N}\right] \cos\left[\frac{(2y+1)v\pi}{2N}\right] \cos\left[\frac{(2z+1)w\pi}{2N}\right]$$

For u,v,w=,1,2,……N-1.

Where $\alpha(u)$ is defined as

$$\alpha(u) = \begin{cases} u = \sqrt{\frac{1}{N}} & for\, u = 0 \\ u = \sqrt{\frac{2}{N}} & for \quad u \neq 0 \end{cases}$$

Similarly $\alpha(v)$ & $\alpha(w)$.

The inverse transform is defined as

$$f(x,y,z) = \sum_{u=0}^{N-1}\sum_{v=0}^{N-1}\sum_{w=0}^{N-1} \alpha(u)\alpha(v)\alpha(w)\, C(u,v,w) \cos\left[\frac{(2x+1)u\pi}{2N}\right] \cos\left[\frac{(2y+1)v\pi}{2N}\right] \cos\left[\frac{(2z+1)w\pi}{2N}\right]$$

For x,y,z=0,1,2,…….N-1.

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Similarly $\alpha(v)$ & $\alpha(w)$.

D. Quantization: - Quantization, involved in image processing, is a lossy compression technique achieved by compressing a range of values to a single quantum value. When the number of discrete symbols in a given stream is reduced, the stream becomes more compressible. For example, reducing the number of colors required to represent a digital image makes it possible to reduce its file size. Specific applications include DCT data quantization in JPEG and DWT data quantization in JPEG 2000.

E. Zigzag:- A zigzag is a pattern made up of small corners at variable angles, though constant within the zigzag, tracing a path between two parallel lines; it can be described as both jagged and fairly regular. Traditionally a "zig" points in the left direction (/) and a "zag" points right (\). From the point of view of symmetry, a regular zigzag can be generated from a simple motif like a line segment by repeated application of a glide reflection.

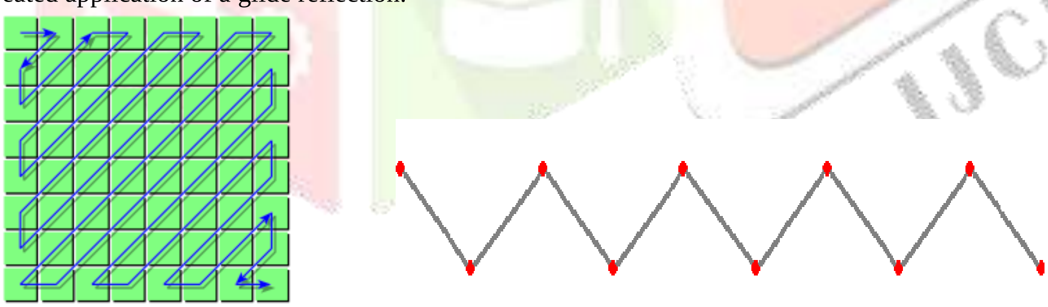

Figure 7: Zig Zag image

Proposed Method Advantages:

1. The proposed method transforms the 3D features to 2D ones, which enormously reduce the Processing complexity.
2. The proposed encoder and decoder are symmetric with almost identical structure and complexity, which facilitates their joint implementation.
3. It exploits the temporal redundancies more than the space redundancies.
4. Offers flexibility that makes it possible to be adapted to different requirements of video applications: The latency time, the compression ratio and the size of required memory depend on the value of the GOP parameter.
5. The proposed method allows the random frame access.

III. RESULTS

This section verifies the performance of the proposed new low complexity DCT based video compression model. We summarize the experimental results with some analysis and comments. By understanding the performance of the proposed method with different

GOP value the best compression rate is obtained with GOP=8. Here Figure 8 GUI model is created to integrate the encoder and decoder sections. Figure 9 shows the progress of frame separation from video sequence. Encoder model is shown in Figure 10 and Figure 11 is the example Accordion representation for one GOP video cube. Figure 12: GUI for Decoding and Validation Process. Figure 13: GUI for Reconstructed output validation, then history of entire simulation is specified as **ans.** Finally Figure 14 shows the plot between Frame number Vs PSNR (dB) and Figure 15 shows the plot between Bit Rate Vs PSNR (dB).

Figure 8: GUI Model

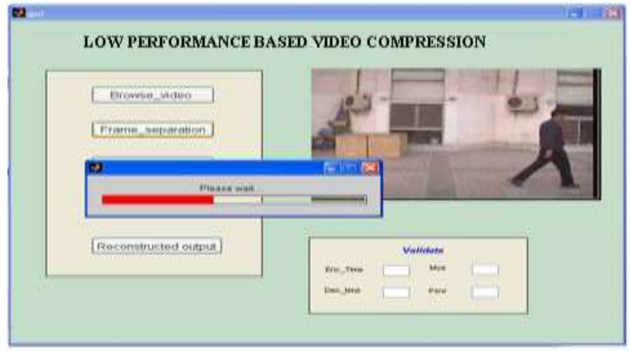

Figure 9: Frame Separation Model

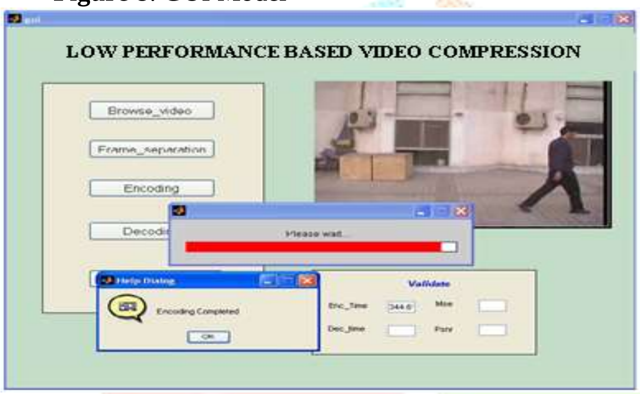

Figure 10: Encoding Model

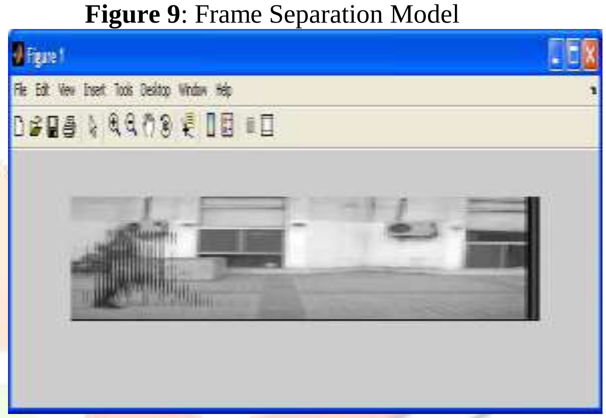

Figure 11: Accordion Representation example (Hall Monitor)

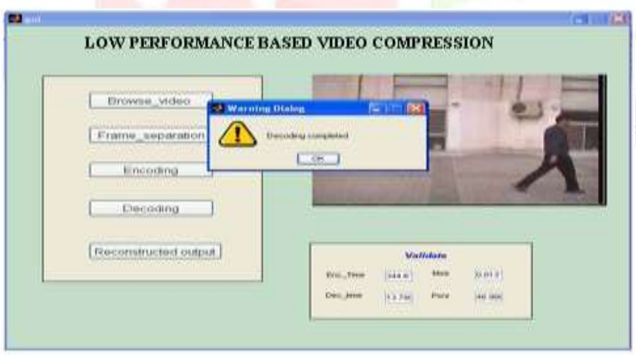

Figure 12: GUI for Decoding and Validation Process

Figure 13: GUI for Reconstructed output validation

Peak signal-to-noise ratio:- 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 codecs (e.g., for image compression). 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×n monochrome images I and K where one of the images is considered a noisy approximation.

The MSE is defined as: $MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2$

The PSNR is defined as: $PSNR = 10.\log_{10}[\frac{MAX_I^2}{MSE}] \quad =20.\log_{10}[\frac{MAX_I}{\sqrt{MSE}}]$

Here, 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, 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. Typical values for the PSNR in lossy image and video compression are between 30 and 50 dB, where higher is better. Acceptable values for wireless transmission quality loss are considered to be about 20 dB to 25 dB.

When the two images are identical the MSE will be equal to zero, resulting in an infinite PSNR.

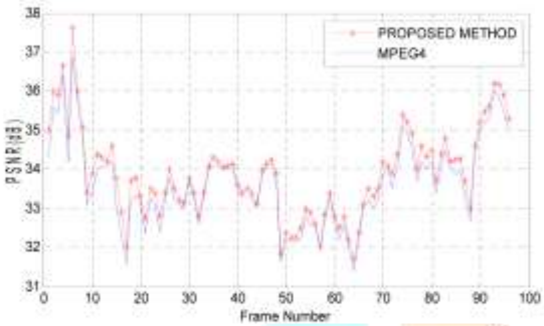

Figure 14: frame number vs PSNR (db)

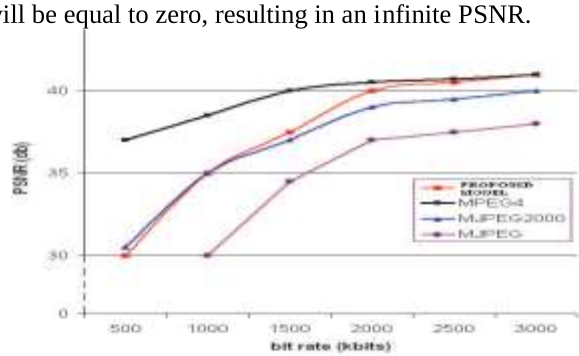

Figure 15: Bit Rate vs PSNR (db)

Data compression ratio : Data compression ratio, also known as compression power, is a computer-science term used to quantify the reduction in data-representation size produced by a data compression algorithm. The data compression ratio is analogous to the physical compression ratio used to measure physical compression of substances, and is defined in the same way, as the ratio between the compressed size and the uncompressed size:

$$\text{Compression Ratio} = \frac{\text{Compressed Size}}{\text{Uncompressed Size}}$$

Thus a representation that compresses a 10MB file to 2MB has a compression ratio of 2/10 = 0.2, often notated as an explicit ratio, 1:5 (read "one to five"), or as an implicit ratio, 1/5. Note that this formulation applies equally for compression, where the uncompressed size is that of the original; and for decompression, where the uncompressed size is that of the reproduction. Sometimes the space savings is given instead, which is defined as the reduction in size relative to the uncompressed size:

$$\text{Space savings} = 1 - \frac{\text{Compressed Size}}{\text{Uncompressed Size}}$$

Thus a representation that compresses a 10MB file to 2MB would yield a space savings of 1 - 2/10 = 0.8, often notated as a percentage, 80%. For signals of indefinite size, such as streaming audio and video, the compression ratio is defined in terms of uncompressed and compressed data rates instead of data sizes:

$$\text{Compression Ratio} = \frac{\text{Compressed Date Rate}}{\text{Uncompressed Date Rate}}$$

When the uncompressed data rate is known, the compression ratio can be inferred from the compressed data rate.

IV. CONCLUSION & FUTURE SCOPE

In this project, we successfully extended and implemented a new low complexity DCT based video compression algorithm on MATLAB and provided experimental results to show that our method is better than the existing methods. We not only improved the coding efficiency in the proposed encoding algorithm but also it reduces complexity. As discussed in the experimental section, proposed method provides benefits of rate-PSNR performance at the good quality of base layer and low quality of enhancement layer. With the apparent gains in compression efficiency we foresee that the proposed method could open new horizons in video compression domain; it strongly exploits temporal redundancy with the minimum of processing complexity which facilitates its implementation in video embedded systems.

It presents some useful functions and features which can be exploited in some domains as video surveillance. In high bit rate, it gives the best compromise between quality and complexity. It provides better performance than MJPEG and MJPEG2000 almost in different bit rate values. Over 2000kb/s bit rate values; our compression method performance becomes comparable to the MPEG 4 standard especially for low motion sequences.

FUTURE SCOPE:- Wavelet transform techniques have been investigated for low bit rate coding. Wavelet based coding has better performance than traditional DCT based coding. Much lower bit rate and reasonable performance are reported based on the application of these techniques to still images. A combination of wavelet transform and vector quantisation gives better performance.

Wavelet transform decomposes the image into a multi frequency channel representation, each component of which has its own frequency characteristics and spatial orientation features that can be efficiently used for coding. Wavelet based coding has two main advantages: it is highly scaleable and a fully embedded bit stream can be easily generated. The main advantage over standard techniques such as MPEG is that video construction is achieved in a fully embedded fashion. Encoding and decoding process can stop at a predetermined bit rate. The encoded stream can be scaled to produce the desired spatial resolution and frame rate as well as the required bit rate. Vector quantization makes use of the correlation and the redundancy between nearby pixels or between frequency bands. Wavelet transform with vector quantization exploits the residual correlation among different layers if the wavelet transform domain using block rearrangement to improve the coding efficiency. Further improvements can also be made by developing the adaptive threshold techniques for classification based on the contrast sensitivity characteristics of the human visual system. Joint coding of the wavelet transform with trellis coded quantization as a joint source channel coding is an area to be considered.

Additional video coding research applying the wavelet transform on a very low bit rate communication channel is performed. The efficiency of motion compensated prediction can be improved by overlapped motion compensation in which the candidate regions from the previous frame are windowed to obtain a pixel value in the predicted frame. Since the wavelet transform generates multiple frequency bands, multi-frequency motion estimation is available for the transformed frame. It also provides a representation of the global motion structure. Also, the motion vectors in lower frequency bands are predicted with the more specific details of higher frequency bands. This hierarchical motion estimation can also be implemented with the segmentation technique that utilizes edge boundaries from the zero crossing points in the wavelet transform domain. Each frequency band can be classified as temporal activity macro blocks or no temporal activity macro-blocks. The lowest band may be coded using DCT, and the other bands may be coded using vector quantization or trellis coded quantization.

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