Wavelet based Video Compression techniques for Industrial monitoring applications

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Abstract. The principle of industrial machine monitoring and vehicle camera transmission system are focusing on this paper. Video compression is widely used in many industrial applications like continuous monitoring of machines which consumes more storage by capturing every motion detection in machine, hence video coding is highly recommended for video compression without any loss in the actual video. By using wavelet transform delivers the superior localization both in frequency and time domain and its results showcases the better performance while comparing with discrete cosine transform. A comparative analysis has been carried on Video compression using Haar and orthogonal (Daubechies) wavelet. Duplicate coefficients of discrete wavelet transform is reduced by using quantization technique. It aims to attain minimum error while preserving the high peak signal to noise ratio and image quality in the acceptable range. Using PSNR as measure of quality, this paper shows that Daubechies wavelet provides the better quality of video compared to Haar wavelet. Evaluation of performance is depends upon on compression ratio, PSNR, MSE, and SSIM.

Keywords: Machine monitoring, Discrete Wavelet Transform, Video Coding, Haar, Orthogonal Wavelets, Compression Ratio PSNR.

I. Literature Review
Video coding using serializer and deserializer to transmit the data and pixel clock signal of the frontend camera module over long distances and decoding of the pixel clock results in 74MHZ with no phase error. And also it achieved long distance and lossless video signal when the vehicle is driving [1].

B.Wang [2] shows the better performance in motion compensation. Comparatively wavelet transform is the best way for sequencing the image and video. To obtain a high compression ratio, the input picture is broken into multilayer DWT. The multilevel 2D-DWT is very computational and it is incorporated in VLSI systems to match the timing requirements of real world applications.

Video coding with multiple channel and the recent improvements were discussed for the optimizing purpose, Kirill S [3]. DWT will perform the image compression based on the rows and columns of the frame. DWT algorithms iterate on columns first, then rows by reversing the sequence of rows and columns and in similar way, the IDWT technique is performed to finish the picture reconstruction. Hasna presents a lifting-based 2D DWT VLSI architecture that is extensively pipelined and distributed, with lifting coefficients recorded in fixed point [2:14] format.

Highly pipelined architecture improves the design, resulting in faster performance. A further video compression technique is the Hybrid (DCT-DWT) algorithm. Arithmetic coding can obtain a high
compression rate. The actual perception of temporal direction fragmentation may be used to produce 3-D coding of picture frames, but with significantly fewer queuing required.

Nithin[4] proposed motion compensation techniques along with discrete sign coding and Haar Wavelet Transform. Dandu proposed a Transcoding process to segregate the video into digital tracks, to eliminate the high RGB and redundant pixels decoding can be done at each individual track. And proposed a new pipelining strategy to perform various transform types with threshold rate of 2 pixel/cycle by zero-column dropout for enhanced performance. For an area-efficient implementation, a high-density SRAM-based flip memory is employed. The suggested system offers a design strategy for developing memory-efficient framework for multilevel 2-D DWT.

II. Discrete Wavelet Transform
Discrete wavelet transforms have a higher temporal resolution than the Fourier transforms and cosine transforms because they capture both spatial as well as phase characteristics. This may be deployed well to examine the sudden changes, but the former approach does not display the exact changes in reconstruction. Wavelets are aimed to accomplish better frequency accuracy for moderate picture intensity and high temporal resolution for image edges. Haar and Daubechies wavelets are employed for video compression in this work.

A. Haar Wavelet
Haar transform has the orthogonal property which is used for analyzing the frequency components present. By using haar wavelet, multiplications can be avoided. Paring up of input values may store the difference and sum can be processed to provide the next level, which leads to $2^{n-1}$ differences and a final sum.

The scaling and wavelet functions are defined as

$$\phi(x) = h_0 \phi(2x) + h_1 \phi(2x-1)$$

$$\psi(x) = h_1 \phi(2x) - h_0 \phi(2x-1)$$

$$h_0 = h_1 = \frac{1}{\sqrt{2}}$$

B. Daubechies wavelets
Daubechies wavelets are characterized in an indistinguishable way from the Haar wavelet by performing running midpoints and contrasts by means of scalar items with scaling sand wavelets functions. Such as Haar transform, it may be extended to as many levels as the signal length separated by two. The distinction between the Haar and Daub4 transforms is how the scaling signals and wavelets are defined. Scaling and wavelet functions are defined as follows:

$$\phi(x) = h_0 \phi(2x) + h_1 \phi(2x-1) + h_2 \phi(2x-2) + h_3 \phi(2x-3)$$

$$\psi(x) = h_0 \phi(2x-1) - h_1 \phi(2x) + h_2 \phi(2x+1) - h_3 \phi(2x+2)$$

$$h_0 \approx 0.48296; h_1 \approx 0.83652; h_2 \approx 0.22414; h_3 \approx -0.12941$$

C. Video Coding

![Figure 1. Block of Video coding](image-url)
Each frame undergoes various wavelet transforms as described in section II. After removing nearly three-quarters of the information from the DWT, we further simplify the result by quantizing. Quantization is a lossy compression system where the scope of qualities can be adjusted off to the single quantum esteem. Eliminating high frequency components can limit the amount of information, which is subsequently rounded to the nearest integer or reduced to 0.

**D. Multilevel Decomposition**

2-D Discrete Wavelet Transformation transforms the picture from the spatial domain to frequency domain. This can be achieved by applying 1-D discrete wavelet transform (DWT) which undergoes row wise and column wise decomposition to produce 2D image.

![Figure 2. One level 2D DWT](image)

As illustrated in Figure 2. There are four coefficients included in decomposition such as approximation, horizontal, vertical and diagonal. Decomposition can be performed up to three levels. The average information is included in the low-low frequency components, whereas the other components has its details. By keeping only the approximate coefficients, the detailed coefficients are set to zero without any loss of information in image, therefore low-low components can be sufficient to perfectly reconstruct the image. This helps in achieving good compression rate at this level.

III. Performance Metrics

**A. Compression ratio**

Compression ratio shows the size of minimized data and storage is given by compression ratio.

$$\text{Compression Ratio} = \frac{\text{Uncompressed Size}}{\text{Compressed Size}}$$  \hspace{1cm} (5)

**B. Mean Square Error**

Mean Square Error is error difference between the original and reconstructed image.

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [X(i,j) - Y(i,j)]^2$$ \hspace{1cm} (6)

**C. Peak Signal-To-Noise Ratio**

Peak signal to noise ratio (PSNR) which characterizes the amount of distortion in lossy compression. The quality of the image is measured using PSNR value [5].

$$\text{PSNR} = 20 \times \log_{10}(255^2/MSE)$$ \hspace{1cm} (7)
D. Structural Similarity Index Matrix
The methodology for assessing superior quality on structural information deterioration. It compares the balanced local patterns of pixel intensities for brightness and contrast. The structural information in an image is defined by the SSIM index as the characteristics which shows the framework of objects in the frame.

IV. Experimental result and Discussion
Hockey and Rhinos video frames of size 256 x 256 can be used for this experiment. Haar and Daubechies wavelet were performed for the process of compression.

The decompressed video frame of Hockey and Rhinos obtained for Haar wavelet was shown in Figure 3 and Figure 4 respectively. The observations was based on the performance measure parameter including Compression ratio, Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE) and SSIM. The compression ratio obtained by applying haar wavelet is 48. Other metrics like PSNR, MSE and SSIM are tabulated in TABLE I.
Figure 6. Video II: Rhinos Unzipped Video Frame

The unzipped video frame of Hockey and Rhinos obtained for Daubechies wavelet was shown in Figure 5 and Figure 6. The compression ratio obtained by applying Daubechies wavelet is 53. Several quality measures (CR, MSE, PSNR, and SSIM) presented in this section were designed to evaluate the compression's quality. We ran our suggested method via MATLAB2014b.

A. Comparing with existing DCT architecture

Existing DCT architecture is used to perform the efficient VLSI architecture in terms of energy and area. The pipeline idea was used to handle all transform ratios at a nominal throughput of 2 pixels/cycle. The folded design requires 1.69 times the power of the full parallel architecture. While comparing the synthesis result of DCT, DWT proved that it has high compression ratio.

B. Comparing with Haar and Daub4 DWT architecture

The quality metrics of Haar wavelet are tabulated with two set of inputs as shown above in Table I where both results in minimum error with high PSNR value. The results shows better performance while compared with DCT.

| Table I. Performance Metrics of Haar Wavelet |
|---------------------------------------------|
| Quality Metrics | MSE | PSNR(dB) | SSIM |
| Frames         | Video I | Video II | Video I | Video II | Both |
|---              |        |          |        |          |      |
| 1              | 0.4790  | 0.5626   | 54.5245 | 53.1269  | 0.8  |
| 4              | 0.4785  | 0.5628   | 54.5330 | 53.1243  | 0.8  |
| 8              | 0.4784  | 0.5628   | 54.5348 | 53.1276  | 0.8  |
| 12             | 0.4790  | 0.5624   | 54.5346 | 53.1291  | 0.8  |
| 24             | 0.4784  | 0.5627   | 54.5342 | 53.1247  | 0.8  |
| 48             | 0.4788  | 0.5619   | 54.5274 | 53.1374  | 0.8  |
| 60             | 0.4790  | 0.5617   | 54.5238 | 53.1403  | 0.8  |
| 77             | 0.4789  | 0.5614   | 54.5252 | 53.1449  | 0.8  |

The quality metrics of Daub4 wavelet are tabulated with two set of inputs as shown above in Table II where both results in minimum error with high PSNR value than the Haar wavelet. SSIM shows the similarity between the input and output file. From both Table I and Table II, we infer that PSNR value ranges from 50 dB to 80 dB shows the high quality of the reconstructed image.
Table II. Performance Metrics of Daub4 Wavelet

| Quality Metrics | MSE | PSNR(dB) | SSIM |
|----------------|-----|---------|------|
| Frames         | Video I | Video II | Video I | Video II | Both |
| 1              | 0.0731 | 0.1420 | 71.006 | 65.195 | 0.9 |
| 4              | 0.0616 | 0.1400 | 72.412 | 65.212 | 0.9 |
| 8              | 0.0656 | 0.1527 | 71.887 | 64.454 | 0.9 |
| 12             | 0.0678 | 0.1773 | 71.660 | 63.356 | 0.9 |
| 24             | 0.0999 | 0.1730 | 68.305 | 63.371 | 0.9 |
| 48             | 0.1059 | 0.1935 | 67.737 | 62.415 | 0.9 |
| 60             | 0.1003 | 0.1380 | 68.204 | 65.337 | 0.9 |
| 77             | 0.0559 | 0.1692 | 73.338 | 63.564 | 0.9 |

V. Conclusion

Video compression using Haar and Daubechies wavelets as the basis function along with the quality metrics of decompressed video frame have been obtained in this research for the size of 256x256. From the experimental results, while comparing with Haar wavelet Daubechies provides minimum error and acceptable PSNR range which plays good in video coding which can be very much useful monitoring applications like industrial machine monitoring, live streaming and also in medical applications. The analysis of results can be carried out based on the quality metrics like compression ratio, PSNR, MSE, and SSIM. When compared to DCT, the wavelet-based experiment performs better.

In the future, wavelet based video coding can be extended for video Steganography and for future digital television with high and ultrahigh definition. It can be implemented by utilizing alternative wavelets such as the Bi-orthogonal wavelet and the Coiflets filter.

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