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DA DWT-IDWT based Image Compression Implementation

P. Sushinder Reddy*, Harshali Soni** and Md. Sohail Afroze*

Department of Electronics and Communication Engineering,
**Teegala Krishna Reddy Engg. College, Hyderabad, (A.P.)*
***Acropolis Institute of Technology and Research, Indore, (M.P.)*

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ABSTRACT: Image compression is one of the major image processing techniques that is widely used in medical, automotive, consumer and military applications. Discrete wavelet transforms is the most popular transformation technique adopted for image compression. Complexity of DWT is always high due to large number of arithmetic operations. In this work a modified Distributive Arithmetic based DWT architecture is proposed and is implemented on FPGA. The modified approach consumes area of 6% on Virtex-II pro FPGA and operates at 134 MHz. The modified DA-DWT architecture has a latency of 44 clock cycles and a throughput of 4 clock cycles. This design is twice faster than the reference design and is thus suitable for applications that require high speed image processing algorithms.

Keywords: Discrete Wavelet Transforms (DWT), Distributive Arithmetic (DA), Poly-phase structure, and convolution

I. INTRODUCTION

During last decade there has been enormous increase in digital images. This type of information gives rise to high transmission and storage cost. To store these images or make them available over networks, compression techniques are needed. To illustrate the need for compression, some examples are given:

• To store a color image of moderate size, e.g. 512x512 pixels, one needs 0.75 MB of disk space.

• A 35 mm slide digitized with a resolution of 12 µm requires 18 MB disk space.

• One second of digital PAL video requires 27 MB.

Digital images can be compressed by eliminating redundant information. There are three types of Redundancy that can be exploited by image compression systems.

• Spatial redundancy: in almost all natural images the values of neighboring pixels are strongly correlated.

• Spectral redundancy: in images composed of more than one spectral band the spectral values for the same pixel location are often correlated.

• Temporal redundancy: adjacent frames in video sequence often show very little change.

Therefore, the development of reliable and fast compression techniques for several quality levels has become an important research topic. Many algorithm have been proposed in literature and some of them have been standardized. Mainly compression methods can be divided into two classes; lossless and lossy compression techniques:

• Lossless compression guarantees that the original signal can be reconstructed without any errors. This is important for application like compression of text or medical images.

• Lossy compression gives higher compression rates. But exact data cannot be reconstructed. Human visual system is not sensitive or has low sensitivity to some kind of errors. That's why the compression potential is much higher when small reconstruction errors are allowed.

Compressing an image is significantly different from compressing raw binary data. Of course, general purpose compression programs can be used to compress images, but the result is less than optimal. This is because images have certain statistical properties which can be exploited by encoders specifically designed for them. Also, some of the finer details in the image can be sacrificed for the sake of saving a little more bandwidth or storage space. This also means that lossy compression techniques can be used in this area.

Methods for lossy compression:

- Reducing the color space to the most common colors in the image. The selected colors are specified in the color palette in the header of the compressed image. Each pixel just references the index of a color in the color palette. This method can be combined with dithering to avoid posterization.

Chroma sub sampling. This takes advantage of the fact that the human eye perceives spatial changes of brightness more sharply than those of color, by averaging or dropping some of the chrominance information in the image.

Transform coding. This is the most commonly used method. In particular, a Fourier-related transform such as the Discrete Cosine Transform (DCT) is widely used. The more recently developed wavelet transform is also used extensively, followed by quantization and entropy coding.

Although the Fourier transform has been the mainstay of transform-based digital signal processing since time immemorial, a more recent transformation, called the wavelet transform, is making strides in DSP applications following some of its unique advantages.

Wavelets have their energy concentrated in time. Sinusoids (Fourier Transform) are useful in analyzing periodic and time-invariant phenomena, while wavelets are well suited for the analysis of transient, time-varying signals. Since most of the real-life signals encountered are time varying in nature, the Wavelet Transform suits very well for many applications.

II. EXPERIMENTAL SETUP

The project execution is done in 3 phases as shown in fig. 1. Where MATLAB model in which we simulate using Simulink and check for results, after that we design the same using Xilinx HDL model and results are verified. The operation is also verified on FPGA by dumping the code to it and viewing the result on monitor.

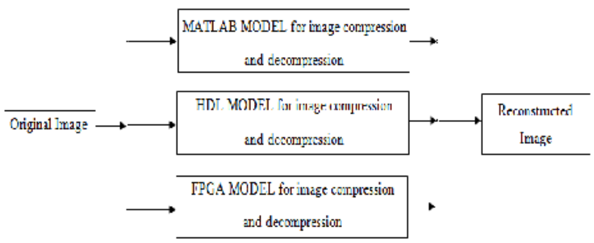

Fig. 1.

III. WAVELET TRANSFORM

The Continuous Wavelet Transform (CWT) is provided by equation , where x(t) is the signal to be analyzed. ψ(t) is the mother wavelet or the basis function. All the wavelet functions used in the transformation are derived from the mother wavelet through translation (shifting) and scaling (dilation or compression).

$$X_{WT}(\tau,s)=\frac{1}{\sqrt{|s|}}\int x(t)\cdot\psi^{*}\left(\frac{t-\tau}{s}\right)dt$$

The mother wavelet used to generate all the basis functions is designed based on some desired characteristics associated with that function. The translation parameter τ relates to the location of the wavelet function as it is shifted through the signal. Thus, it corresponds to the time information in the Wavelet Transform. The scale parameter is defined as |1/frequency| and corresponds to frequency information. Scaling either dilates (expands) or compresses a signal. Large scales (low frequencies) dilate the signal and provide detailed information hidden in the signal, while small scales (high frequencies) compress the signal and provide global information about the signal. Notice that the Wavelet Transform merely performs the convolution operation of the signal and the basis function. The above analysis becomes very useful as in most practical applications, high frequencies (low scales) do not last for a long duration, but instead, appear as short bursts, while low frequencies (high scales) usually last for entire duration of the signal.

The Wavelet Series is obtained by discretizing CWT. This aids in computation of CWT using computers and is obtained by sampling the time-scale plane. The sampling rate can be changed accordingly with scale change without violating the Nyquist criterion. Nyquist criterion states that, the minimum sampling rate that allows reconstruction of the original signal is 2ω radians, where ω is the highest frequency in the signal. Therefore, as the scale goes higher (lower frequencies), the sampling rate can be decreased thus reducing the number of computations.

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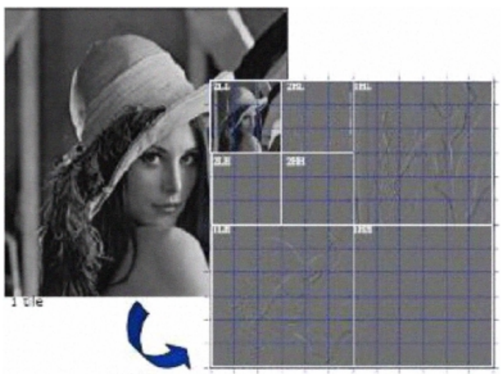
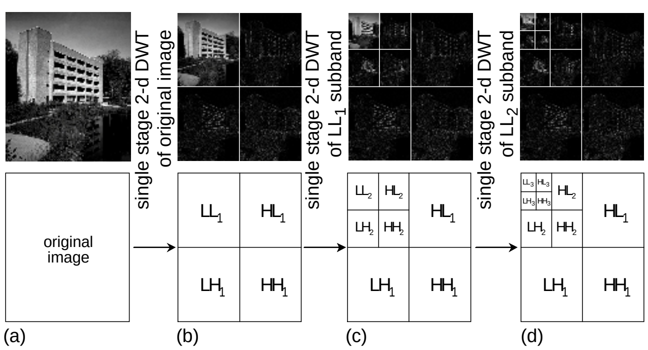
IV. DECOMPOSITION

The DWT represents the signal in dynamic sub-band decomposition. Generation of the DWT in a wavelet packet allows sub-band analysis without the constraint of dynamic decomposition. The discrete wavelet packet transform (DWPT) performs an adaptive decomposition of frequency axis. The specific decomposition will be selected according to an optimization criterion. The Discrete Wavelet Transform (DWT), based on time-scale representation, provides efficient multi-resolution sub-band decomposition of signals. It has become a powerful tool for signal processing and finds numerous applications in various fields such as audio compression, pattern recognition, texture discrimination, computer graphics etc. Specifically the 2-D DWT and its counterpart 2-D Inverse DWT (IDWT) play a significant role in many image/video coding applications. Lossless image compression plays a vital role in medical applications.

DWT schemes had been widely used for medical image coding due to the fact that DWT supports features like progressive image transmission, ease of compressed image manipulation, region of interest of coding, etc. Lifting based DWT scheme that reduces memory requirements and communications between processors has been proposed in this project.

The DWT has several different hardware implementations, of which the lifting-based architecture is providing to be most popular – due to its efficient use of resources. The lifting-based DWT algorithms are implemented and analysed in terms of area, speed and power consumptions.



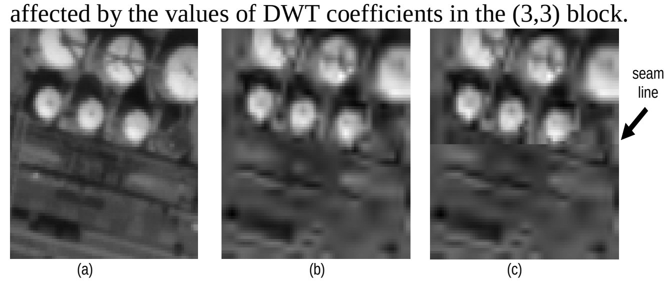


Three-Level 2-d DWT Decomposition of an Image

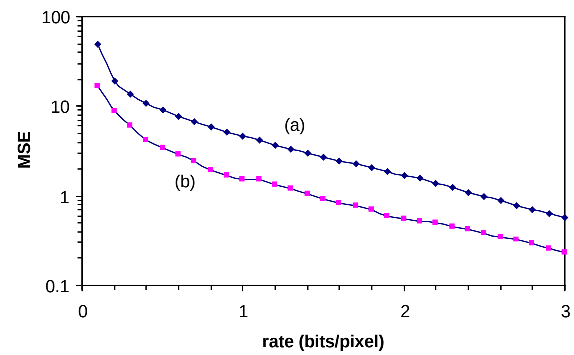
V. Effect of Block Errors

Partitioning the set of blocks into segments that are independently compressed allows for more efficient memory use and provides robustness to data loss or errors. These benefits could also be achieved by simply partitioning the original image into separate smaller images that are compressed independently. However, such an image-domain partitioning strategy can lead to noticeable boundaries between adjacent segments when lossy compression is used, even when adjacent segments are compressed to the same quality level and no data loss or corruption occurs. Figure illustrates this effect. reconstruction (b) was produced using segments defined in the DWT domain, as in the present Recommendation. Reconstruction (c), produced by partitioning the original image into two smaller images that were separately compressed, has a noticeable horizontal seam between the upper and lower halves. All segments were compressed to the same quality level.

A block is identified by the coordinates (r,c) of the DC coefficient (at row r and column c) within the LL_3 subband, with the upper left DWT coefficient in the subband having coordinates $(0,0)$. In an image with width w and height *h*, the pixels that may be affected by the values of DWT coefficients in block (r,c) are confined to a rectangular region of the reconstructed image with upper left corner $(\max\{8r-21,0\},\max\{8c-21,0\})$ and lower right corner $(\min\{8r+29,h-1\},\min\{8c+29,w-1\})$. For example, figure **Error! Reference source not found.** illustrates the set of pixels that may be affected by corruptions to block (3,3). In figure **Error! Reference source not found.**, the shaded square bounds the region of pixels that may be affected by the values of DWT coefficients in the (3,3) block.



VI. RESULTS



Rate Distortion Performance on Transposed Version.

VII. CONCLUSION

Comparing the 9/7M and 9/7F filters, the 9/7M filter provides better compression performance, especially for lossless compression and at high bit rates. At low bit rates, i.e., high compression ratios, the 9/7F tends to perform somewhat better, but this does not justify a preference over the 9/7M, especially since users who are primarily interested in low rate compression might be inclined to use the float DWT.

The 5/3 filter has the lowest computational complexity. However, the 9/7M has moderately higher complexity and provides significantly better lossy compression effectiveness.

For these reasons, the 9/7M was considered the best compromise in terms of complexity and performance and was therefore selected as the integer DWT for the Recommendation. The formulation of the recommended 9/7M filter described in reference [1] has a slight difference in the rounding operations than what is in reference **Error! Reference source not found.**. The formulation in reference [1] reduces mean-error bias during reconstruction.

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