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AN EFFICIENT TECHNIQUE USING LIFTING BASED 3-D DWT FOR BIO-MEDICAL IMAGE COMPRESSION

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ABSTRACT

Compression technique is significant in day to day scenario for smooth transmission of data. By utilizing this technique the bandwidth utilization is reduced. Even compression techniques help us for efficient memory utilization to make overall data transmission better. Data size in different cases is quite huge and difficult to send without compressing it. In the bio- medical arena, it is applicable because of the large image size, but at the same time it is having its own challenges in terms of data loss. While reconstructing the image, the possibility of data loss or quality loss comes into picture. Though there are many techniques which suggest lossless compression and decompression but still refinement is required. There are techniques using discrete wavelet transform to do the lossless image compression. The recent one is the Three-Dimensional Discrete Wavelet Transform (3-D DWT). In this research work, a lifting based Discrete Wavelet Transform architecture for three dimensional images is presented. The proposed architecture has been implemented on Xilinx Virtex-6 Series Field-Programmable Gate Array (FPGA). Implementation results show the efficiency of proposed system in terms of power consumption and operating frequency. The proposed architecture of Discrete Wavelet Transform achieves a maximum operating frequency of 298 MHz with a power consumption of 7 mW.

Keywords: *Discrete Wavelet Transform (DWT), Discrete Cosine Transform (DCT), Peak-Signal-to-Noise Ratio (PSNR), Very-Large-Scale Integration (VLSI), Lifting scheme.*

1. INTRODUCTION

The measure of medicinal analytic information delivered by doctor's facilities has expanded exponentially. A healing center produces numerous terabytes of advanced information every year, and all of which must be kept and documented [1]. Besides, for telemedicine applications, transmitting a lot of computerized information through a transmission capacity restricted station turns into a substantial weight. An advanced system can be utilized to understand both the stockpiling and the transmission issues. Among numerous sign sources, the storage of medicinal images has an incredible interest [2]. The objective of image compression can be a solitary image or an arrangement of images. In restorative image grouping called the volumetric therapeutic image (VMI) or three-dimensional medicinal information, adjoining images in the arrangement are generally profoundly comparative in pixel dissemination, edge appropriation and elements. Such image arrangements are delivered by a mixed bag of modalities, including attractive reverberation imaging such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Positron Emission Tomography (PET), particular ultrasound 3-D images, and endoscopy images. The measure of the VMI information is corresponding to the volume characterized by the result of a casing size and the grouping length. The two noteworthy sorts of compression techniques used for therapeutic images are lossless and lossy. A lossless strategy safeguards all the data in an image.

Research on image coding and compression techniques is a highly active area. The main research target is to get higher compression ratios with minimum loss of quality. For identification of disease and surgical planning medical imaging is being used, and long-term storage is needed for profiling patient's data. To avoid loss of critical medical information, lossless compressions of the medical images are indispensable. Recent advances in therapeutic imaging and telecom frameworks require effective pace, determination and constant memory enhancement with most extreme equipment usage. The 3-D Discrete Wavelet

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Transform is broadly utilized strategy for these medical imaging frameworks on account of immaculate reconstruction property. DWT can decompose the input data into sub groups of even and odd samples. DWT construction modeling, by and large, diminishes the memory necessities and expands the pace of correspondence by separating the picture into the blocks [3]. A strategy for actualizing lifting based DWT has been proposed due to its numerous points of interest over convolution based one. Also, a few Very-Large-Scale Integration (VLSI) architectures have been proposed for processing the 3-D- Discrete Wavelet Transform. They are primarily taking into account convolution method and lifting scheme. The lifting scheme has many advantages compared to the convolution based methods. Lifting scheme can decrease the computational complexity in decomposing the high and low pass signals and hence this requires less multipliers and adders than the convolution method [4].

In this paper, a lifting based Discrete Wavelet Transform for therapeutic picture, without any change in the image quality is proposed. The proposed algorithm has been examined and compared with the existing systems. The rest of the paper is organized as follows: section 2 discusses the past work done by distinctive creators, section 3 explains the basics of wavelet transform, section 4 discusses the proposed strategy utilizing lifting based DWT, and section 5 shows the test and results, lastly section 6 winds up the paper with the conclusion.

2. RELATED WORK

To study and analyze more about the medical image compression techniques, the following literature survey is done and discussed in this section. Because of the limitations on the bandwidth and storage capacity, a medical image needs to be compressed before the transmission process or the storage process. There are many medical image compression techniques that are evolving every day. Hence it is necessary to study a literature about it, to understand the techniques also to use the appropriate methods during compression of medical images. Sukhwinder Singh, Vinod Kumar, H.K. Verma have jointly proposed a novel technique for medical image compression called adaptive threshold-based block classification. In this paper, the authors introduce a computational algorithm to classify the blocks based on the adaptive threshold value of the variance. Also this method can be applied to all kind of medical images. As the result of this, CT, an X-ray and ultrasound image are used to evaluate the performance and compares the derived results to the Joint Photographic Experts Group (JPEG) respective to the quality indices [5]. J. Jyotheswar, Sudipta Mahapatra have proposed a paper on efficient FPGA implementation of DWT and modified Set Partitioning in Hierarchical Trees (SPIHT) for lossless image compression. Here the DWT architecture which is based on the lifting scheme, was used to exploit the correlation between the image pixels. Also a modified SPIHT algorithm was used to encode the wavelet coefficients. The result shows that the algorithm promotes good compression ratio and better Peak-Signal-to-Noise Ratio (PSNR) with 3-D medical images. The authors have evaluated the algorithm using various parameters regarding the encoding process, like usage of various wavelets features, the counts of the times that the wavelet function is used, choosing of the threshold value, also selection of the quantization methods and the entropy encoder. Parameters like 3D-conscious run-length, hexadecimal coding and the arithmetic coding were used to obtain the better performance when compared to the existing ones. Result shows a good compression ratio and a good quality of the reconstructed video. Also when comparing this scheme with the Moving Picture Experts Group (MPEG-2) and Embedded Zerotree Wavelet (EZW), it promotes better compression ratios of 119% and 46% respectively for the same PSNR value [6]. Yen-Yu Chen has designed a novel medical image compression technique called Discrete Cosine Transform (DCT) based sub-band decomposition and modified SPIHT data organization. Here 8×8 Discrete Cosine Transform approach was used for making the sub-band decomposition. Also the modified SPIHT was used for managing the data and the entropy coding. The detailed features of an image were stored in the translation function. In this method, high-frequency sub-bands are used in good number for reducing the redundancy by promoting the algorithm with modified SPIHT. Results showed that the quality of the reconstructed medical image has been increased in the Peak Signal-to-Noise Ratio (PSNR) value [7]. R. Srikanth and A. G. Ramakrishnan has put forth a method for medical image compression called contextual encoding in uniform and adaptive mesh based lossless compression of Magnetic Resonance Imaging (MRI). Here a mesh based coding technique for 3-D brain Magnetic Resonance images was used which promotes the rejection of the irrelevant background that leads to meshing of the brain part of the image, performs the content-based mesh method with the spatial edges and

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optical flow. Also generates solution to an aperture problem at the edges, this paper focuses mainly on the lossless coding of the images, and then compares the performance of both the uniform and adaptive mesh-based methods. Result showed nominal range of bit rates when compared with three-dimensional wavelet-based techniques. The mesh based method is efficient in compression of 3-D brain computed tomography and the adaptive mesh based method gives good result than that of the uniform mesh-based methods with high complexity [8]. Aaron T. Deever and Sheila S. Hemami have proposed a method called lossless image compression with projection-based and adaptive reversible integer wavelet transforms. Here, a projection based scheme is introduced to reduce the first-order entropy of transform coefficients and to increase the performance of reversible integer wavelet transforms. Also the projection method has been framed for predicting a wavelet transform coefficient. This technique promotes optimal fixed prediction methods for the lifting based wavelet transforms. On the other side, the projection technique was emphasized for an adaptive prediction method which differentiates the final prediction process of lifting based transform on basis of modeling context. The result showed that, the projection technique poses very good performance on reversible integer wavelet transforms with the superior lossless compression when compared to current fixed and adaptive lifting based transform [9]. Zixiang Xiong et. al. have jointly proposed a technique called lossy to lossless compression using 3D wavelet transforms. In this technique the authors exhibits a 3-D integer wavelet packet transform structure that supports implicit bit shifting of wavelet coefficients for the process of approximation of a 3-D unitary transformation [10]. index. 3-D medical image compression using 3-D wavelet coders was developed by N. Sriraam and R. Shyamsunder. Daubechies 4, Daubechies 6, Cohen–Daubechies–Feauveau 9/7 and Cohen–Daubechies–Feauveau 5/3 are the four wavelet transforms that were used in this method with the encoders like 3-D SPIHT, 3-D Set Partitioned Embedded Block Coder (SPECK) and 3-D Binary Set Splitting with K-d trees (BISK) to find out the best wavelet–encoder combination. Two versions of wavelet transform known as symmetric and decoupled wavelet transform has been used. Magnetic Resonance Images (MRI) and X-Ray Angiograms (XA) are used for testing the algorithm. The best compression result possessed by the 3-D Cohen–Daubechies–Feauveau 9/7 symmetric wavelet with the 3-D SPIHT encoder [11].

3. DISCRETE WAVELET TRANSFORM

Discrete wavelet transform is a multiresolution analysis tool with excellent characteristics in the time and frequency domains. Discrete Wavelet Transforms is based on the sub-band coding. This method is used in image processing because it has some good features like coding efficiency and image restoration compared with the traditional discrete cosine transform. Also it is easy to obtain high compression ratio and hence widely used in signal processing and image compression. Many architectures have been proposed for the implementation of discrete wavelet transform. The basic concepts of the one dimensional (1-D), two dimensional (2-D) and three dimensional (3-D) Discrete Wavelet Transforms is explained in the following section.

3.1. One Dimensional Discrete Wavelet Transform (1-D DWT)

In the one dimensional discrete wavelet transform, the input discrete signal is filtered at each level of transformation. It produces two filtered output which are subsampled to achieve the high pass and low pass sub-bands. These low pass and high pass sub-bands represented as $y_L(n)$ and $y_H(n)$ are given in equation (1) and (2).

$$y_L(n) = \sum_{i=0}^{\frac{N}{2}-1} h(2n-i).x(i) \quad (1)$$

$$y_H(n) = \sum_{i=0}^{\frac{N}{2}-1} g(2n-i).x(i) \quad (2)$$

Figure 1. shows the general block diagram of a subband transformation. The forward transform uses two analysis filter, low pass and high pass followed by subsampling. The output of the subband transformation are obtained as the detail (Y_L) and approximate signal (Y_H).

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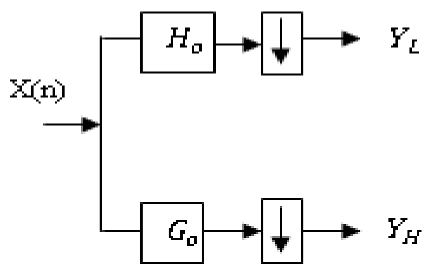

Figure 1: 1-D Discrete Wavelet Transform

Signal Analysis

3.2. Two Dimensional Discrete Wavelet Transform (2-D DWT)

The basic idea of a two dimensional discrete wavelet transform is similar to 1-D architecture. A 2-D Discrete Wavelet Transform shown in figure 2, can be seen as a 1-Dimensional wavelet transform which transform along the rows and then a 1-Dimensional wavelet transform along the column. The 2-D Discrete Wavelet Transform operates in a straightforward manner by inserting array transposition between the two 1-D DWT. The output of the two dimensional discrete wavelet transform results in four subsamples. These subsamples are represented as the approximate and detail coefficients, given as Y_{LL},Y_{LH},Y_{HL} and Y_{HH}.

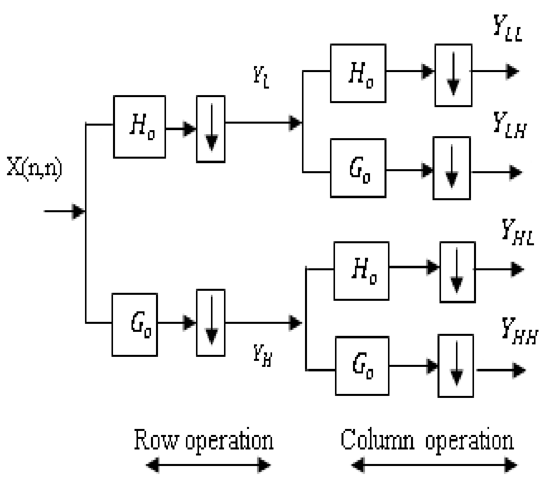

Figure 2: 2-D Discrete Wavelet Transform

3.3. Three Dimensional Discrete Wavelet Transform (3-D DWT)

The 3-D DWT can be considered as a combination of three 1-D DWT in the X, Y and Z directions. First, the process transforms the data in the X-direction. Next, the low and high pass outputs both given to other filter pairs, which transforms the data in the Y-direction. These four output streams go to the next four filter pairs, performing the final transform in the Z-direction. The process results in 8 data streams, 7 detailed coefficients and 1 approximate coefficient as shown in figure.3. After one-level of 3-D discrete wavelet transform, the image is decomposed into Y_{LLL}, Y_{LLH}, Y_{LHL}, Y_{LHH}, Y_{HLL}, Y_{HLH}, Y_{HHL} Y_{HHH}.

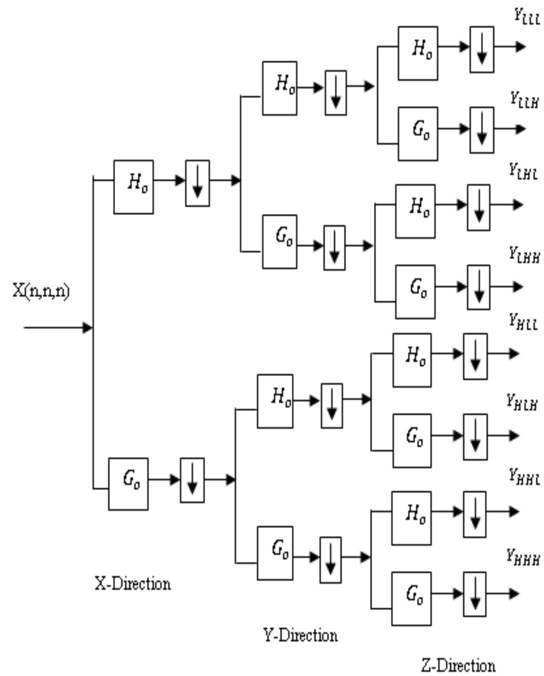

Figure.3. 3-Dimensional Discrete Wavelet Transform

4. PROPOSED MODEL FOR IMAGE COMPRESSION

In this section, the proposed architecture for medical image compression by using lifting scheme is discussed. The proposed architecture utilizes the Le Gall's 5/3 filter with lifting scheme. This architecture performs arithmetic operation on the samples which reduces the complexities of the design. The main advantage of the design is that it does not require any multipliers. All the multiplication operations are done by using shift and rotate operations, hence this architecture require lesser memory. In next sections the detailed discussion with mathematical model is presented.

4.1. Lifting Based Discrete Wavelet Transform

DWT was traditionally implemented by convolution or FIR filter bank structures, resulting in both, a large number of arithmetic computations and a large storage. Lifting scheme is a new

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generation technique to construct biorthogonal wavelets different from the convolution method, with low complexity and buffers. The polyphase matrix is represented as given in eqn. (3),

$$\tilde{P}(z) = \begin{bmatrix} \tilde{h}_e(z) & \tilde{h}_o(z) \\ \tilde{g}_e(z) & \tilde{g}_o(z) \end{bmatrix} \quad (3)$$

The $\tilde{h}_e(z)$ and $\tilde{h}_o(z)$ denote the even and odd polyphase components of the low pass analysis filter and $\tilde{g}_e(z)$ and $\tilde{g}_o(z)$ denote the even and odd polyphase components of the high pass analysis filter. With the polyphase matrix, the wavelet decomposition is expressed as given in eqn. (4):

$$\begin{bmatrix} LP(z) \\ HP(z) \end{bmatrix} = \tilde{P}(z) \begin{bmatrix} X_e(z) \\ X_o(z) \end{bmatrix} \quad (4)$$

$LP(z)$ represents the low pass coefficients, $HP(z)$ denotes the high pass coefficients, $X_e(z)$ represents the even polyphase components, $X_o(z)$ represents odd polyphase components and $\tilde{P}(z)$ is the polyphase matrix.

Lifting scheme of the proposed architecture is illustrated in Fig 4. $\tilde{P}(z)$ can be factorized into a series of matrix multiplications with alternating lower and upper triangular matrices as given in eqn.(5)

$$\tilde{P}(z) = \prod_{i=1}^{m} \left\{ \begin{bmatrix} 1 & 0 \\ \tilde{t}(z) & 1 \end{bmatrix} \begin{bmatrix} 1 & \tilde{s}(z) \\ 0 & 1 \end{bmatrix} \begin{bmatrix} K & 0 \\ 0 & \frac{1}{k} \end{bmatrix} \right\} \quad (5)$$

where K is a constant and m is the number of predict and update steps. The $\tilde{t}_i(z)$ is predictor and $\tilde{s}_i(z)$ is updater unit.

According to the lifting scheme the polyphase matrix is transformed into elementary matrix by performing factoring which reduces the complexity. The forward lifting scheme is presented in figure 4. This scheme consists of three major stages: (i) Split (ii) Predict (iii) update.

Input x_i is given to the split stage, here the data is divided into two parts which are even indexes $even^{j+1}$ and odd indexes odd^{j+1}. This operation is shown in the figure 4.

The next step is called prediction stage. In this stage even and odd coefficients are correlated with each other so that the prediction can be done on the original data. In other words, the prediction is applied on the even data by using prediction operator $\tilde{t}_i(z)$ and the obtained results are subtracted from the odd coefficients which give the detailed coefficients, as given in equation (6).

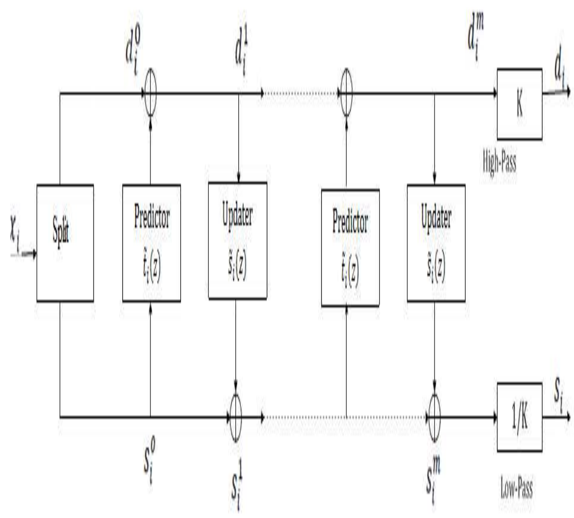

Figure 4: Forward Lifting Scheme

In the updation stage, update operator is applied to the odd coefficients and added to the even coefficients which is given in equation (7).

$$d^{j+1} = odd^{j+1} - \tilde{t}_i(z)(even^{j+1}) \quad (6)$$

$$s^{j+1} = even^{j+1} + \tilde{s}_i(z)(d^{j+1}) \quad (7)$$

In the final stage of lifting, we perform the normalization on the approximation data which is done by performing scaling by factor K and detailed coefficients are normalized by performing scaling by factor $1/K$. Below given equations show the mathematical model for these stages,

The first stage computation of prediction stage and update stage is given by equation (8) and (9), equation (10) and (11) does the computation of the predict stage and update stage for the second stage computation.

$$d_i^1 = d_i^0 + \alpha(s_i^0 + s_{i+1}^0) \quad (8)$$

$$s_i^1 = s_i^0 + \beta(d_{i-1}^1 + d_i^1) \quad (9)$$

$$d_i^2 = d_i^1 + \gamma(s_i^0 + s_{i+1}^0) \quad (10)$$

$$s_i^2 = s_i^1 + \zeta(d_{i-1}^2 + d_i^2) \quad (11)$$

$$d_i = d_i^2.K \quad (12)$$

$$s_i = s_i^2.\frac{1}{K} \quad (13)$$

Equation (12) and (13) shows the scaling stage. $\alpha, \beta, \gamma, \zeta$ are the coefficients for the lifting scheme and the values of the coefficients are -1/2, 1/4,0, and 1 respectively.

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The proposed system concentrates mainly on the memory issues of the input image. The size of medical image is very huge which requires more space to store the data, hence an architecture with reduced memory is required. To overcome this memory issue and for handling the huge image data, an efficient memory architecture which is based on the dynamic memory access is proposed in this research work. The proposed memory handling architecture is shown in figure 5.

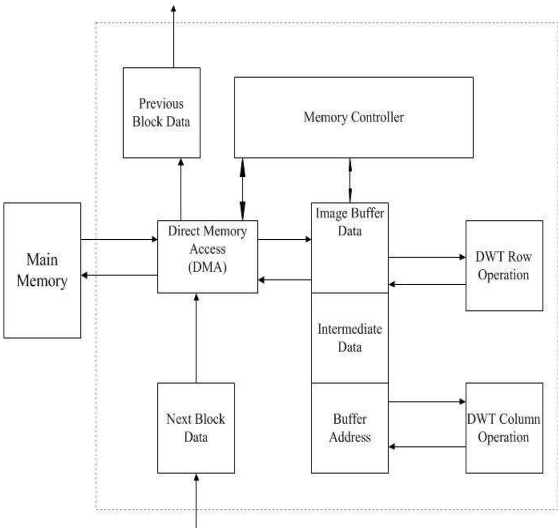

Figure 5: Proposed Memory Access Architecture

The proposed architecture contains memory controller block, Row wise DWT kernel block, buffers for the data block, and Column wise DWT kernel block. To address the data it contains the parameters such as pixel counting, block data, data start address, row counter and column counter. The proposed memory architecture utilizes interleaving between DWT model and image data elements which reduces the memory overhead with parallel computations. These addresses are passed to memory access block which passes the address to the discrete wavelet transform units.

The image information is stored in the primary memory (off-chip) and stacked to the line buffer. This information is sent line by line through the direct memory access. The row coefficients are computed and saved in the line buffers. After completing all the row operations, the computation of the column coefficient is performed. All the row and column operations are finished in a pipelined way. The calculated discrete wavelet transform information is stored back to the fundamental memory through the direct memory access. Then the computed coefficients are stored in the memory (on-chip). The next set of data is sent to the processing unit and all the discrete wavelet transform coefficients at each level are computed. The DWT processing unit passes its upper transitional limit information to the following top neighboring unit and gets lower transitional limit information from the following lower unit to finish the DWT calculations. Figure. 6 demonstrates the pipeline and stream of limit information (states) for a two nearby DWT handling units.

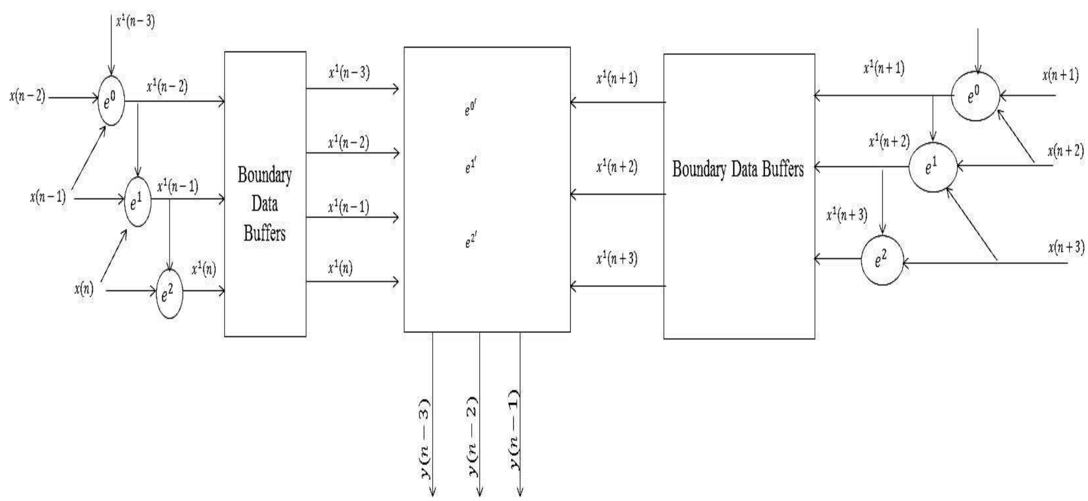

Figure 6: Proposed Pipelined Computation Method for DWT

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5. RESULTS AND DISCUSSION

The results of the proposed method for medical image compression is discussed in this section. The aim of this method is to achieve the better performance results in terms of power, frequency and slices with less memory storage. This method is applied for the forward and inverse lifting DWT scheme. The prototype is realized using the Xilinx Virtex6 series FPGA and targeted to the device Xilinx xc6vcx75t-2ff484. The resources utilized by the FPGA implementation interms of the number of flip-flops, 4-input Look-Up-Table (LUTs) and the bonded Input Output Blocks (IOBs) are given in table 1. The maximum operating frequency is 298MHz.

Table 1:Synthesis Results

	Used	Available
Number of Slices	337	93120
Number of Slice Flip-Flops	670	46560
Number of 4-Input LUTs	221	786
Number of bonded IOBs	44	240
Frequency	298 MHz	

The power consumption results are presented in table 2. The power consumption of the FPGA device on which the circuit is implemented is measured to have a total power of 1300mW.

Table 2: Power Consumption Summary

Power Summary		
Total Power	Dynamic Power	Static Power
1300 mW	7 mW	1293 mW

The power utilization and the operating frequency of the proposed and other existing architectures, are given in Table 3. The existing architectures are designed for the one dimensional discrete wavelet transform and two dimensional discrete wavelet transform. In this research work, a lifting based three dimensional discrete wavelet transform architecture is proposed. The power consumption is the least among the existing systems for an operating frequency of 298MHz. The table 3 gives a comparison of the various technology used for the implementation of the Discrete Wavelet transform.

Table 3: Comparison Table

	Wahid et al. [12]	Islam et al. [13]	Madishetty et al. [14]	Madishetty et al. [15]	Proposed
Architecture	1-D/ 2-D	1-D	2-D	1-D/2-D	3-D
Dynamic Power (mW)	15.94 / 22.29	4.51	38	61	7
Max. Freq.(MHz)	148	100	282.50	168.83	298

6. CONCLUSION

The Discrete Wavelet Transform gives a multi-resolution representation of images. The Discrete Wavelet Transform has been executed utilizing filter banks. In this work lifting based Discrete Wavelet Transform is executed. This architecture is realized using VHDL code and implemented on the Xilinx Virtex-6 series FPGA utilizing a 64 x 64 therapeutic image. The image is compressed through the proposed design. This architecture empowers quick calculation of discrete wavelet transform with parallel and pipeline processing. It consumes less power and has low memory requirements.

REFRENCES:

[1] Jaffar Iqbal Barbhuiya, A.H.M.; Laskar, T.A.; Hemachandran, K., "An Approach for Color Image Compression of JPEG and PNG Images Using DCT and DWT," *International Conference on Computational Intelligence and Communication Networks,* Vol., no.6, 14-16 Nov. 2014, pp.129-133.

[2] Baviskar, A.; Ashtekar, S.; Chintawar, A., "Performance evaluation of high quality image compression techniques," *International Conference on Advances in Computing, Communications and Informatics (ICACCI),* 24-27 Sept. 2014, pp.1986-1990

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[3] Sunil, B.M., Raj.C.P., "Analysis of Wavelet for 3D-DWT Volumetric Image Compression," *International Conference on Emerging Trends in Engineering and Technology (ICETET),* 2010, 19-21 Nov. 2010, pp.180-185,

[4] Daubechies. I and Sweldens.W, "Factoring Wavelet Transforms Into Lifting Steps," *Journal Fourier Anal. Application.,* Vol.4, 1998, pp.247-269.

[5] Sukhwinder Singh, Vinod Kumar, H.K.Verma , "Adaptive threshold based block classification in medical image compression for teleradiology", *Computers in Biology and Medicine*, Vol.37, 2007, pp. 811 – 819..

[6] J. Jyotheswar, Sudipta Mahapatra, "Efficient FPGA implementation of DWT and modified SPIHT for lossless image compression", *Journal of Systems Architecture,* Vol.53, 2007, pp.369–378,

[7] Yen-Yu Chen, "Medical image compression using DCT-based sub band decomposition and modified SPIHT data organization", *International journal of medical informatics,* Vol.76, 2007, pp. 717–725,

[8] R. Srikanth, A.G. Ramakrishnan, "Contextual encoding in uniform and adaptive mesh based lossless compression of MR images", *IEEE Transactions on Medical Imaging,* Vol. 24, 2005, pp.1199–1206.

[9] A.T. Deever, S.S. Hemami, "Lossless image compression with projection-based and adaptive reversible integer wavelet transforms", *IEEE Transactions on Image Processing.* Vol.12, 2003, pp.489–499.

[10] Z. Xiong, X. Wu, S. Cheng, J. Hua, "Lossy to lossless compression of medical volumetric data using 3D integer wavelet transforms", *IEEE Transactions on Medical Imaging*, Vol.22, 2003, pp.459–470.

[11] N. Sriraam, R. Shyamsunder. "3-D medical image compression using 3-D wavelet coders", Elsevier on Digital Image Processing, Vol.21, 2010, pp.100-109.

[12] K. Wahid, V. Dimitrov, and G. Jullien, "VLSI architectures of Daubechies wavelets for algebraic integers," *J. Circuits, Syst., Comput.,* vol. 13, no. 6, 2004, pp. 1251–1270.

[13] M. A. Islam and K. A. Wahid, "Area-and power-efficient design of Daubechies wavelet transforms using folded AIQ mapping," *IEEE Trans. Circuits Syst. II*, vol. 57, no. 9, Sept. 2010, pp. 716 –720.

[14] S. K. Madishetty, A. Madanayake, R. J. Cintra, V. S. Dimitrov, and D. H. Mugler, "VLSI architectures for the 4-tap and 6-tap 2-D Daubechies wavelet filters using algebraic integers," IEEE Trans. Circuits Syst. I, vol. 60, no. 6, June 2013, pp.1455–1468.

[15] S. Madishetty, A. Madanayake, R. Cintra, and V. Dimitrov, "Precise VLSI architecture for AI based 1-d/2-d daub-6 wavelet filter banks with low Adder-count," *IEEE Trans. Circuits Syst. I*, vol.61, no.7, 2014, pp. 1984–1993.