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DWT Based Biomedical Image Compression

Jallu Sateesh[1], Muddapu Harika[2]

[1]*Assistant Professor, Department of Electronics and Communication Engineering, JNTUK, UCEV, Vizianagaram, India*

[2]*Assistant Professor, Department of Electronics and Communication Engineering, SITAM College of Engineering, Vizianagaram, India*

***Abstract*: Image compression technique is one of the application of image processing which resolves the problem of storage and transmission bandwidth. Image compression may be lossy or lossless and is dependent on the selected technique. In the proposed methodology we have considered biomedical images of dicom image format and applied discrete wavelet transform for different dataset samples of different modalities. We have considered Daubechies, Biorthogonal and Symlet families for analysis. Objective parameters considered for quantitative analysis are compression ratio (CR), peak signal to noise ratio (PSNR) and mean square error(MSE). Reverse biorthogonal filter of order 5.5 of biorthogonal family gives best results with high PSNR, low MSE and good CR. Dicom files we have considered are of different sizes and had achieved the CR of maximum 20. For our work we considered a sample set of 15 images of each modality (i.e., MRI, CT, X-RAY).**

***Keywords*: DWT, Dicom, Daubechies, Reverse biorthogonal, Symlet, CR, PSNR, MSE.**

1. Introduction

Wide advancements in digital technology has accelerated the development of image processing software and need for better compression algorithms. Image compression is the vital research area and the use of any compression algorithm depends on representation of the transformed image and its usefulness for certain application though

higher compression ratios are obtained. When a series of images or an image of huge data is to be transmitted, it requires processing. Image contains large data hidden in its picture elements called pixels which are highly correlated. The wavelet theory has been used widely with better features and thus use of wavelet based image compression is primary objective of this paper.

A. Image compression

Image compression is helpful for deep analysis of any image. It reduces the storage space and transmission bandwidth which is necessary for many image processing applications. Image compression is a technique where size of the image is reduced in order to facilitate more images fit into a memory space or a single disk. There are mainly two categories of image compression and their major objective is to reconstruct original image without loss of numerical values:

- Lossless compression
- Lossy compression

Lossless compression: In lossless type of compression, image data not varies but only some redundant data is removed. The reconstructed image remains as the size of the original images even after compression. It is preferred in the certain areas where information should not be lost, for example medical imaging. These are expensive and hence are used in only required areas based on cost and their usage. Lossless compression algorithms include Run Length coding, Huffman coding, Arithmetic coding and Dictionary based coding.

Lossy compression: Compared to lossless compression in lossy methods the compression rates are high as the random noise is being removed through lossy techniques. The reconstructed may not the replica of original one and lossy compression techniques include transformation coding, Vector Quantization, Fractal coding, Block truncation coding and Sub-band coding.

B. Discrete Wavelet Transform

Wavelets are the waveforms effectively of short duration with average values of zero and have an irregular shape. A signal can be divided into many sub parts which are shifted and scaled versions of their mother wavelet. A wavelet transform can be used for this decomposition and we can remove some of the details represented by their coefficients. A very small wavelet is used to remove fine details and large wavelets remove coarse details. There are many types of wavelets and are categorised into four families:

- Haar wavelet transform
- Daubechies wavelet transform
- Symlet wavelet transform
- Biorthogonal wavelet transform

In the proposed methodology we have considered a group of filters from each family i.e., haar(db1), db2, db3, db4, db5, db5, db6, db7, db8, db9, db10, sym2, sym8, sym15, sym25, (reverse biorthogonal) rbio1.5, rbio2.6, rbio3.3 and rbio5.5.

2. Medical image compression

Medical imaging technology had made doctors look deep into the parts effectively without having deep cuts through the body. Patient's data have been stored for medical diagnosis and for future use in digital form with advancements in image processing techniques. There are many issues being dealt using this technology on subjects related to heart, brain, lungs, knees, stomach etc. and also diagnosing cancer. Image compression has its significant role in medical imaging as it helps to diagnose a diseased part keenly by applying Region of Interest (ROI) based techniques.

A. Medical image formats

Medical image formats can be divided into two formats. One is intended to standardize images generated by diagnostic modalities (i.e., DICOM) and the other is born with aim to facilitate and strengthen post-processing analysis. The four major file formats used in medical imaging are,

- Analyse
- Nifti
- Minc
- Dicom (Digital Imaging and Communications in Medicine)

The limits and strengths of these file formats can be discussed using some common parameters like pixel depth, photometric interpretation, meta data and pixel data.

- Pixel depth is the number of bits used to encode the information of each pixel and it is a concept related to memory space necessary to represent in binary amount of information we want to store in the pixel.
- Photometric interpretation specifies how the pixel data should be interpreted for correct image display as monochrome or color image.
- Metadata are information that describes the image which is typically stored at the beginning of the file as header and contains atleast image matrix dimensions.
- Pixel data stores numerical values of the pixels.

B. Image parameters

For the analysis of output images, the objective parameters considered are CR (Compression Ratio), MSE (Mean Square Error) and PSNR (Peak Signal to Noise Ratio). Depending on the values obtained for these parameters the efficient filter for image compression can be identified. A detailed description of these parameters is given below;

CR: Ratio of uncompressed size of image to the compressed image size.

$$\text{CR}=\frac{\textit{Uncompressed size}}{\textit{Compressed size}}$$

MSE: Measure of average of squares of errors obtained during transformation.

$$\text{MSE}=\frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}[f(x,y)-f'(x,y)]^2$$

where f(x,y) is the original image pixel value and f'(x,y) is the compressed image pixel value.

PSNR: It is the ratio of maximum possible power of the signal to the power of corrupted noise.

$$\text{PSNR}=10\log\left(\frac{R^2}{MSE}\right)$$

Where R is the maximum fluctuation in the input data type.

3. Methodology

In the proposed method we have implemented different wavelet filters for biomedical images of dicom format in matlab and are transformed to JPEG format. For comparing the performance, we have considered certain objective parameters like CR (compression ratio), PSNR, MSE. The steps involved in matlab implementation are as follows:

- Start the process by browsing the dicom images from standard database.
- Apply first level DWT on the considered medical image.
- Calculate PSNR, MSE and CR for the transformed image.
- Then the final output image is displayed.
- Repeat the same procedure for different medical images of various modalities.

The medical images considered are of three different modalities (MRI, X-RAY and CT) for brain, knee and lungs. Considered brain images are of 110KB and are compressed to 5.5KB, knee images of 282KB are compressed to 14.1KB and the lung images of 514KB to 27.5KB.

The results are obtained for 10 daubechies filters (db1 (haar), db2, db3, db4, db5, db6, db7, db8, db9, db10), four symlet filters (sym2, sym5, sym8, sym15) and four reverse biorthogonal filters (rbio1.5, rbio2.6, rbio3.3, rbio5.5). Of these it can be concluded that rbio5.5 is giving better results for medical image compression.

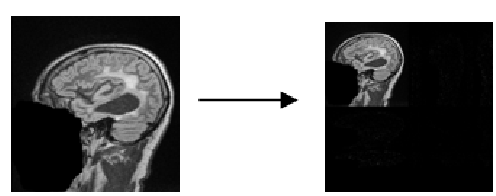
VLSI implementation is done for the rbio5.5 filter and also the performance metrics like resource utilization for targeting on artix7 FPGA and latency, timing constraints are obtained.

4. Results

A. MATLAB results

1) Results for brain images

The comparative analysis is done considering the parameters CR, MSE and PSNR. Table 1 gives the obtained results for transforming input DICOM image to JPEG image.



Original image (110KB) Transformed image (5.5KB)

Fig. 1. Original and transformed image (Brain)

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Table 1
Tabular representation for results of brain images

Wavelet filter	CR value	MSE value	PSNR value
db1	20.37201	31.60308	33.13351
db2	18.72101	36.48362	32.50982
db3	18.35327	33.46952	32.88431
db4	18.36243	32.52586	33.00852
db5	18.45856	32.00397	33.07877
db6	18.47076	32.70215	32.98504
db7	18.73169	34.07953	32.80587
db8	18.90259	32.32313	33.03567
db9	19.20776	47.94029	31.3238
db10	19.30695	32.99104	32.94684
rbio1.5	17.17834	33.12166	32.92968
rbio2.6	19.45496	35.35703	32.64605
rbio3.3	27.91748	59.71795	30.36975
rbio5.5	20.59479	31.26728	33.1799
sym2	18.72406	36.48362	32.50982
sym5	17.88788	31.56077	33.13933
sym8	17.93823	31.97259	33.08303
sym15	18.39447	31.75809	33.11226

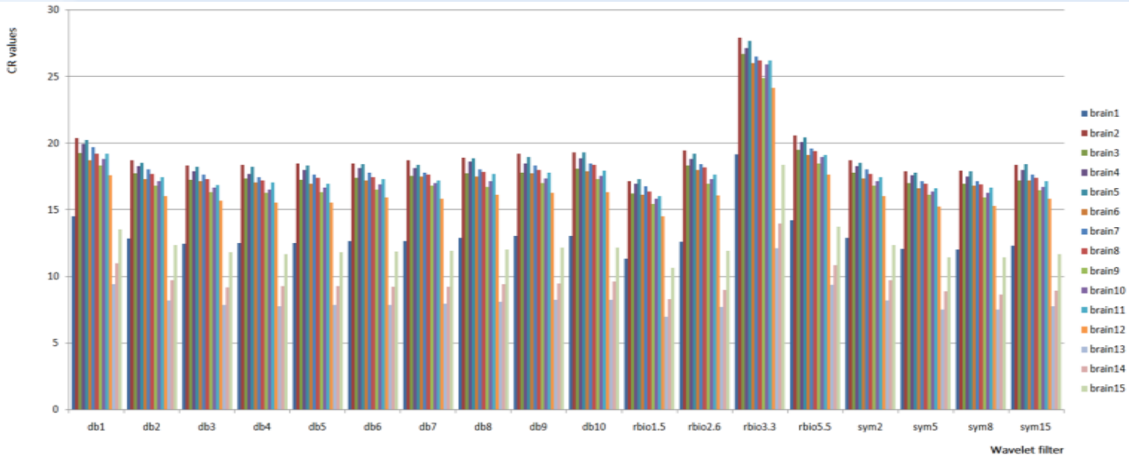

Fig. 2(a). CR values

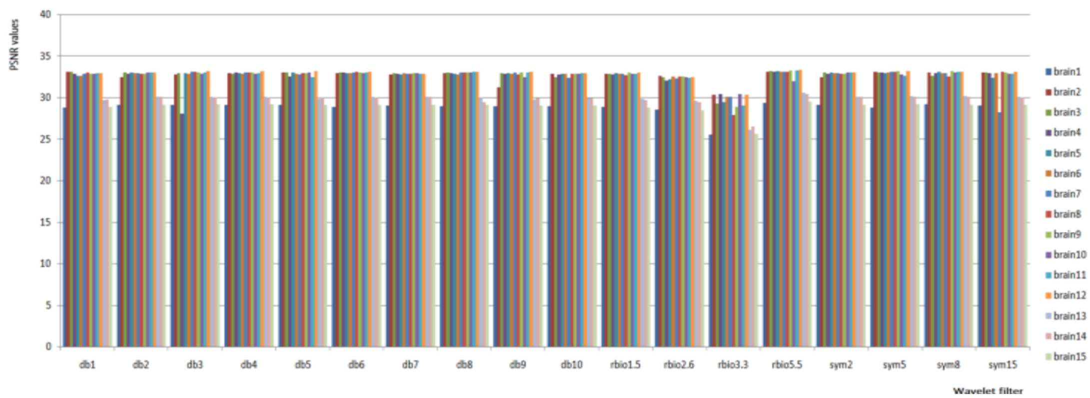

Fig. 2(b). PSNR values

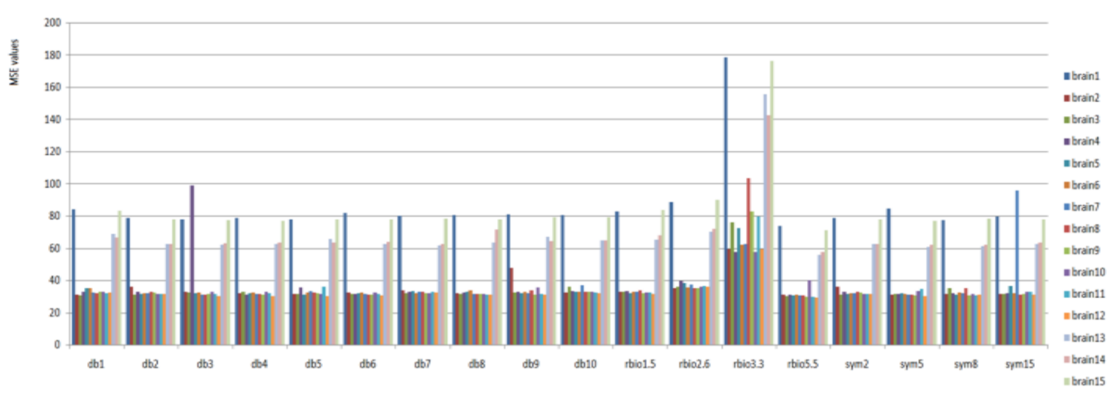

Fig. 2(c). MSE values

Figures 2 (a), (b), (c) are the observed outputs for sample set of 15 DICOM brain images. Though CR value is good for rbio3.3 filter taking into consideration that PSNR should be maximum and MSE should be minimum, rbio5.5 filter meets the specified requirements.

2) Results for Knee images

The comparative analysis is done considering the parameters CR, MSE and PSNR. Table 2 gives the obtained results for transforming input DICOM image to JPEG image.

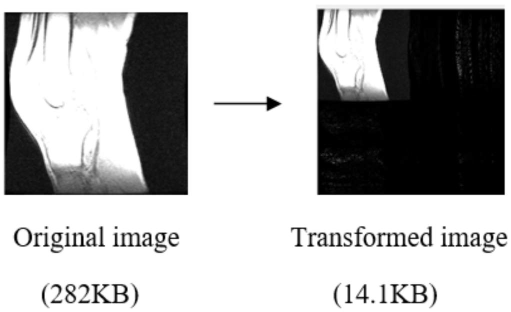

Fig. 3. Original and transformed image (Knee)

Table 2
Tabular representation for results of knee images

Wavelet filter	CR value	MSE value	PSNR value
db1	10.41718	189.3324	25.35855
db2	9.00116	171.0128	25.80052
db3	8.630371	164.1242	25.97908
db4	8.586121	166.7549	25.91002
db5	8.590698	159.2751	26.10933
db6	8.67157	158.7073	26.12484
db7	8.659363	160.8234	26.06731
db8	8.976746	164.4704	25.96993
db9	8.869934	162.4139	26.02457
db10	9.056091	161.0978	26.05991
rbio1.5	7.609558	180.9386	25.55549
rbio2.6	8.360291	200.6761	25.10585
rbio3.3	13.0661	571.298	20.56218
rbio5.5	10.00214	146.5733	26.47026
sym2	9.002686	171.0128	25.80052
sym5	8.413696	161.7141	26.04333
sym8	8.274841	157.4422	26.15959
sym15	8.529663	160.9717	26.06331

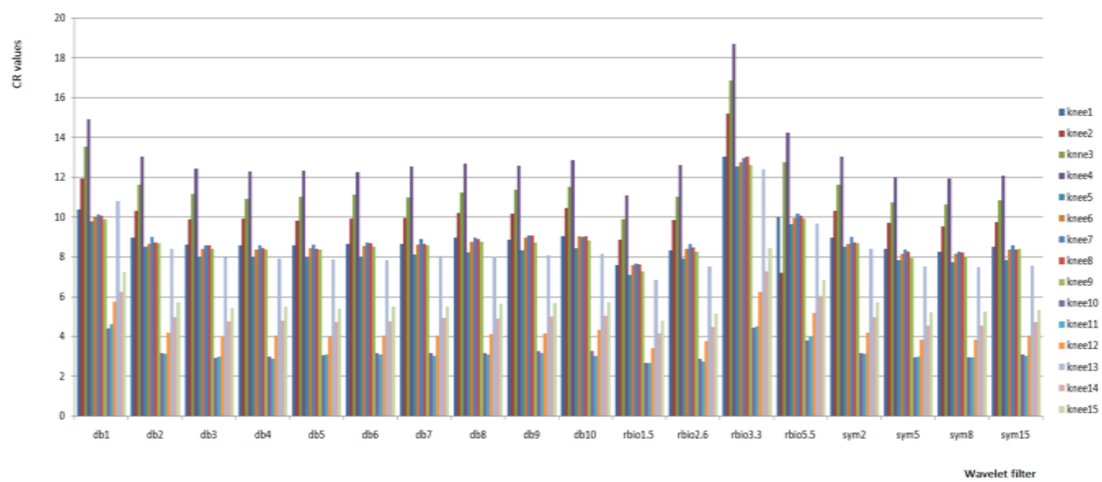

Fig. 4(a). CR values

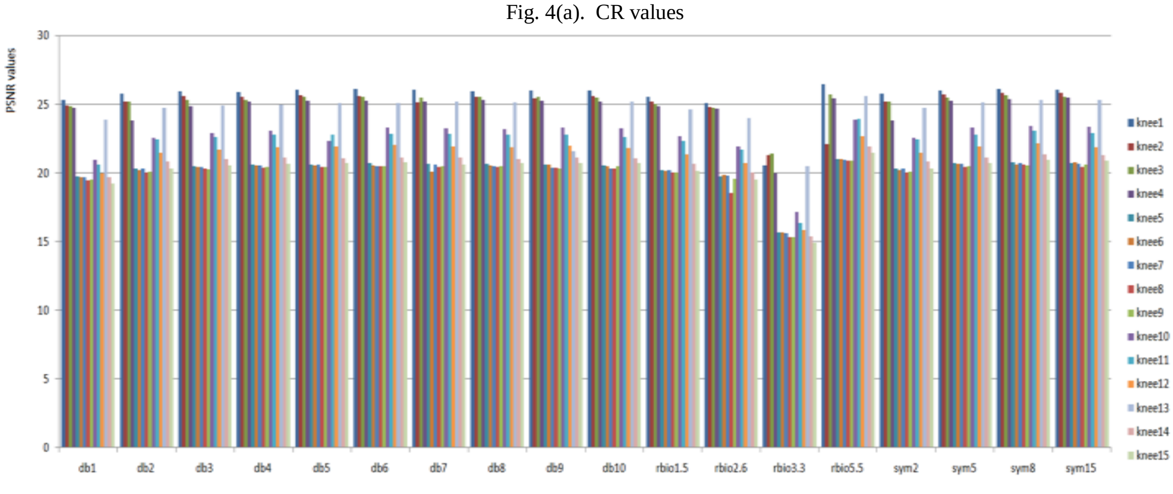

Fig. 4(b). PSNR values

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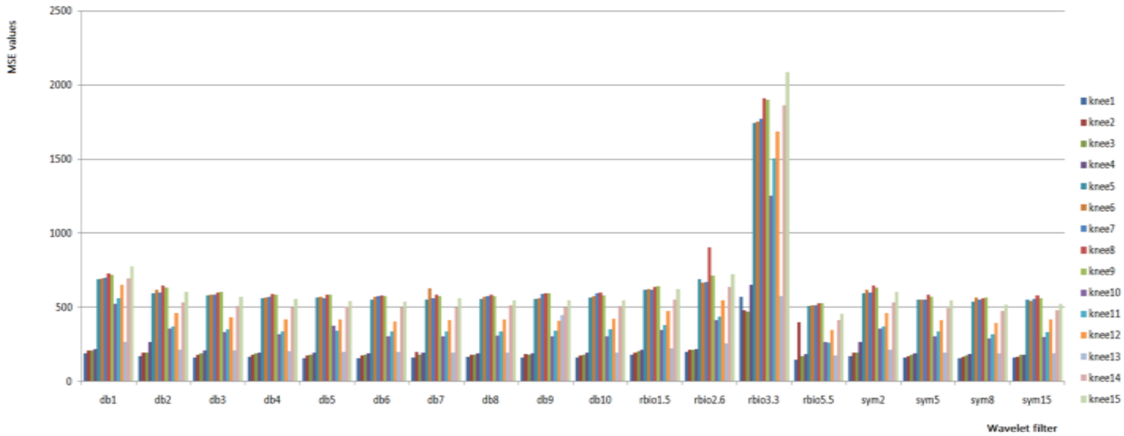

Fig. 4(c). MSE values

Figures 4 (a), (b), (c) are the observed outputs for sample set of 15 dicom knee images. From these we can conclude rbio5.5 gives better results compared to all other filters considered, though rbio3.3 is good considering CR values.

3) Results for lung images

The comparative analysis is done considering the parameters CR, MSE and PSNR. Table 3 gives the obtained results for transforming input DICOM image to JPEG image.

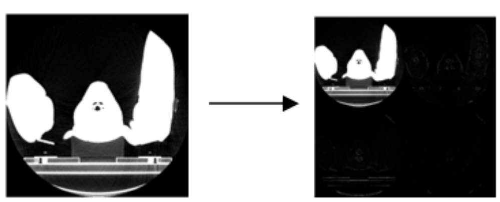

Fig. 5. Original and transformed image (Lung)

Table 3
Tabular representation for results of lung images

Wavelet filter	CR value	MSE value	PSNR value
db1	6.34613	501.2367	21.13038
db2	5.680084	474.5546	21.36794
db3	5.580139	463.9211	21.46636
db4	5.419922	455.7521	21.54352
db5	5.565643	457.4474	21.52739
db6	5.555725	468.5095	21.42362
db7	5.696869	465.9037	21.44784
db8	5.695724	477.1341	21.3444
db9	5.709839	487.8171	21.24823
db10	5.884933	480.4647	21.31419
rbio1.5	4.933167	493.9491	21.19398
rbio2.6	5.488205	568.8121	20.58111
rbio3.3	8.627319	1677.508	15.88416
rbio5.5	6.755066	389.5732	22.22491
sym2	5.680847	474.5546	21.36794
sym5	5.290222	445.8598	21.63882
sym8	5.228806	461.3038	21.49093
sym15	5.460358	472.1452	21.39005

Figures 6 (a), (b), (c) are the observed outputs for sample set of 15 DICOM lung images. From these we can conclude rbio5.5 gives better results compared to all other filters considered, though rbio3.3 is best for CR.

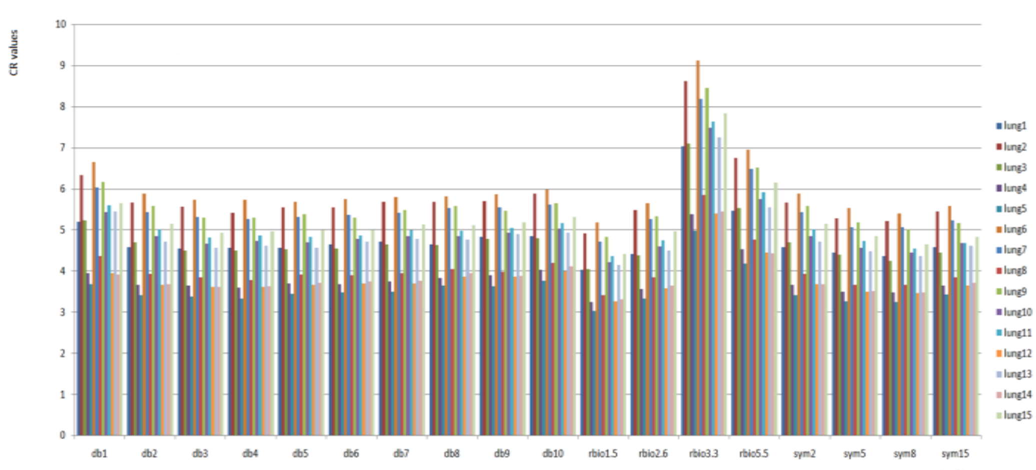

Fig. 6(a). CR values

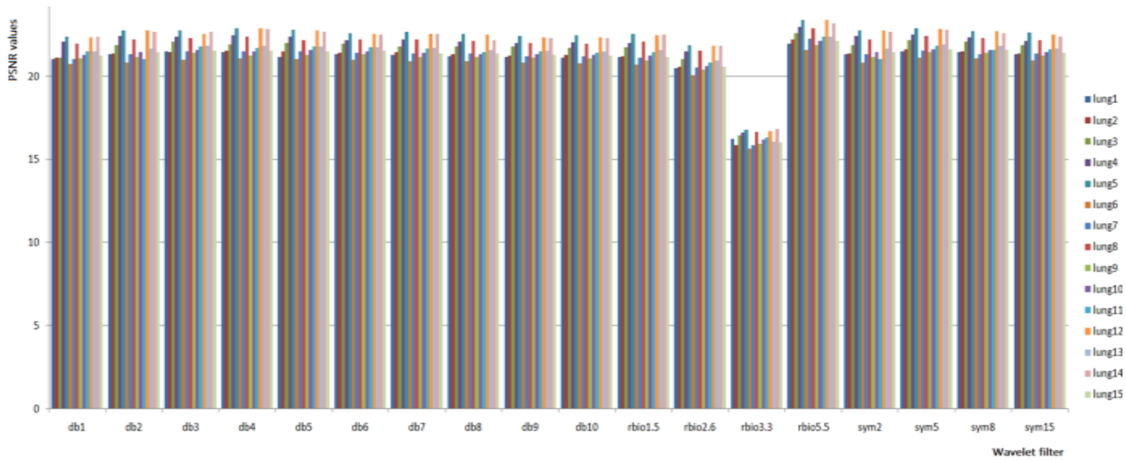

Fig. 6(b). PSNR values

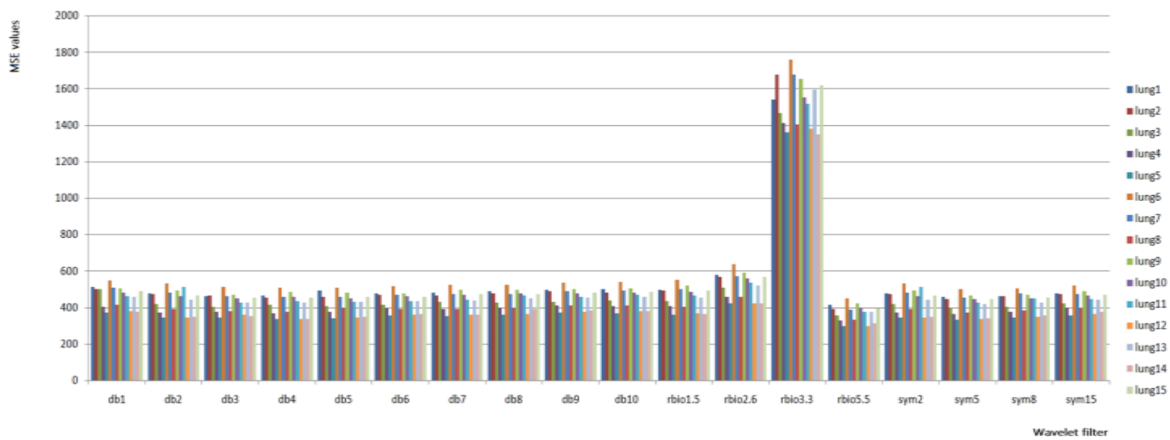

Fig. 6(c). MSE values

B. *VLSI implementation*

VLSI implementation is done for the rbio5.5 filter through Xilinx Vivado platform and is targeted on artix7 FPGA board. IP is generated for the rbio5.5 filter and the resource utilization for artix7, timing constraints and latency are obtained.

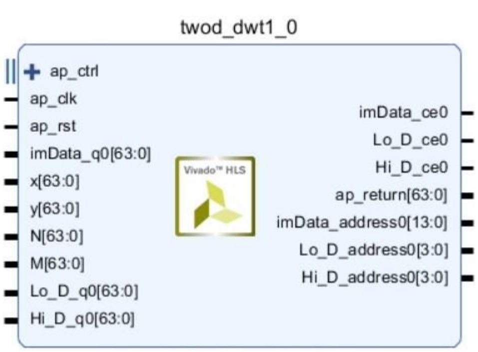

Fig. 7(a). twod_dwt1 rbio5.5 IP

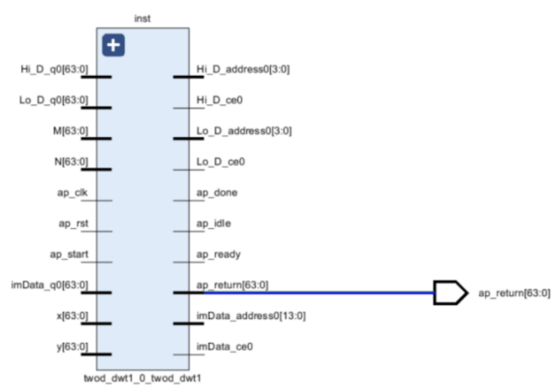

Fig. 7(b). Schematic diagram for rbio5.5 IP

Synthesis Report for 'rbio5.5 IP'
General Information:
Date: Mon Apr 2 14:40:18 2018
Version: 2017.2 (Build 1909853 on Thu Jun 15 18:55:24 MDT 2017)
Project: twod_dwt1
Solution: solution1
Product family: artix7
Target device: xc7a100tcsg324-1

1) Performance estimates

The performance estimates for the twod_dwt1 rbio5.5 IP generated are shown in table 4(a). Timing and latency are listed in the performance estimates.

Table 4(a)
Performance estimates for rbio5.5 IP
(i) Timing constraints

Timing(ns)			
Clock	Target	Estimated	Uncertainty
ap_clk	10.00	9 .66	1.25

(ii) Latency

Latency (clock cycles)			
Latency		Interval	
min	max	min	max
1157003	1157003	1157004	1157004

2) Utilization estimates

The number of BRAMs, DSP48E, flipflops, look up tables that are utilized are calculated to the total number of available resources for twod_dwt1 rbio5.5 IP and are shown in table 4 (b).

Table 4(b)
Utilization estimates summary for twod_dwt1 rbio5.5 IP

Name	RAM_18K	DSP48E	FF	LUT
DSP	-	-	-	-
Expression	-	-	553	455
FIFO	-	-	-	-
Instance	-	7	1840	1857
Memory	260	-	0	0
Multiplexer	-	-	-	916
Register	-	-	738	-
Total	260	7	3131	3228
Available	270	240	126800	63400
Utilization (%)	96	2	2	5

5. Conclusion and future work

From the above results we can conclude that reverse biorthogonal filter of order 5.5 gives the better result for biomedical image compression. The generated IP can be used directly in any image processing application as direct tool. The resources utilized and the latency, timing constraints can be reduced further by adding directive in the Vivado environment.

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