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VLSI Architecture for Fast Computation of 2D-Discrete Wavelet Transform and Low Power Feed Forward Neural Network Architecture for Image Compression

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Abstract: - Artificial Neural Networks (ANN) is significantly used in signal and image processing techniques for pattern recognition and template matching. Discrete Wavelet Transform (DWT) is combined with neural network to achieve higher compression if 2D data such as image. Image compression using neural network and DWT have shown superior results over classical techniques, with 70% higher compression and 20% improvement in Mean Square Error (MSE). Hardware complexity and power dissipation are the major challenges that have been addressed in this work for VLSI implementation. In this work VLSI architecture for neural network and DWT is designed to operate at frequency of 250 MHz and low power techniques are adopted to reduce power dissipation to less than 100mW. Daubechies wavelet filter and Haar wavelet filters are used for DWT, input layer with one hidden layer and output layer consisting of tansig and purelin function used for compression. Low power techniques and low power library in 65nm technology is used for VLSI implementation.

Key words: **-** *DWT, Neural Network, Image Compression, VLSI Implementation, High Speed, Low Power*

I. INTRODUCTION

Image compression is one of the most promising subjects in image processing. Images captured need to be stored or transmitted over long distances. Raw image occupies memory and hence need to be compressed. With the demand for high quality video on mobile platforms there is a need to compress raw images and reproduce the images without any degradation. Several standards such as JPEG200, MPEG-2/4 recommend use of Discrete Wavelet Transforms (DWT) for image transformation [1] which leads to compression, when encoded. Wavelets are a mathematical tool for hierarchically decomposing functions in multiple hierarchical sub bands with time scale resolutions. Image compression using Wavelet Transforms is a powerful method that is preferred by scientists to get the compressed images at higher compression ratios with higher PSNR values [2]. It is a popular transform used for some of the image compression standards in lossy compression methods. Unlike the discrete cosine transform, the wavelet transform is not Fourier-based and therefore wavelets do a better job of handling discontinuities in data.

On the other hand, Artificial Neural Networks (ANN) for image compression applications has marginally increased in recent years. Neural networks are inherent adaptive systems [3][4][5][6]; they are suitable for handling nonstationaries in image data. Artificial neural network can be employed with success to image compression. Image Compression using Neural Networks by Ivan Vilovic [7] reveals a direct solution method for image compression using the neural networks. An experience of using multilayer perceptron for image compression is also presented. The multilayer perceptron is used for transform coding of the image. Image compression with neural networks by J. Jiang [8] presents an extensive survey on the development of neural networks for image compression which covers three categories: direct image compression by neural networks; neural network implementation of existing techniques, and neural network based technology which provide improvement over traditional algorithms. Neural Networks-based Image Compression System by H. Nait Charif and Fathi. M. Salam [9] describes a practical and effective image compression system based on multilayer neural networks. The system consists of two multilayer neural networks that compress the image in two stages. The algorithms and architectures reported in these papers sub divided the images into sub blocks and the sub blocks are reorganized for processing. Reordering of sub blocks leads to blocking artifacts. Hence it is required to avoid reorganization of sub blocks. One of the methods was to combine neural networks with wavelets for image compression. Image compression using wavelet transform and a neural network was suggested previously [10]. Wavelet networks (WNs) were introduced by Zhang and Benveniste [11], [12] in 1992 as a combination of artificial neural networks and wavelet decomposition. Since then, however, WNs have received only little attention. In the wavelet networks, the basis radial functions in some RBF-networks are replaced by wavelets. Szu et al. [13], [14] have shown usage of WNs for signals representation and classification. They have explained how a set of WN, "a super wavelet", can be produced and the original ideas presented can be used for the assortment of model. Besides, they have mentioned the big compression of data achieved by such a representation of WN's. Zhang [15] has proved that the WN's can manipulate the non-linear regression of the moderately big dimension of entry with the data of training. Ramanaiah and Cyril [16] in their paper have reported the use of neural networks and wavelets for image compression. Murali and Dr. Satyanarayana [17] reports use of neural networks with DWT improves compression ratio by 70% and MSE by 20%. The complexities of hardware implementation on VLSI platform are not discussed in this paper. Murali andDr. Satyanarayana [18] reports the use of FPGA for implementation of neural network and DWT architecture, the design operates are 127 MHz and consumes 0.45 mW on Virtex-5 FPGAs. ASIC implementation of the algorithm proposed is reported as scope for future work. In this paper ASIC implementation of 2D-DWT architecture with ANN architecture is designed and implemented on ASIC platform using 65nm CMOS technology optimizing area, timing and power. Section II presents theoretical background on neural networks and DWT. Section III discusses the image compression architecture using DWT and ANN technique, section IV presents ASIC implementation of DWT-ANN, section V presents results and discussions and followed with conclusion in section VI.

II. NEURAL NETWORKS AND DWT

In this section, neural network architecture for image compression is discussed. Feed forward neural network architecture and back propagation algorithm for training is presented. DWT based image transformation and compression is also presented in this section. Compression is one of the major subject of research, the need for compression is discussed as follows [17]: Uncompressed video of size 640 x 480 resolution, with each pixel of 8 bit (1 bytes), with 24 fps occupies 307.2 Kbytes per image (frame) or 7.37 Mbytes per second or 442 Mbytes per minute or 26.5 Gbytes per hour. If the frame rate is increased from 24 fps to 30 fps, then for 640 x 480 resolution, 24 bit (3 bytes) colour, 30 fps occupies 921.6 Kbytes per image (frame) or 27.6 Mbytes per second or 1.66 Gbytes per minute or 99.5 Gbytes per hour. Given a 100 Gigabyte disk can store about 1-4 hours of high quality video, with channel data rate of 64Kbits/sec – 40 – 438 secs/per frame transmission. For HDTV with 720 x 1280 pixels/frame, progressive scanning at 60 frames/s: 1.3Gb/s – with 20Mb/s available – 70% compression required – 0.35bpp. In this work we propose a novel architecture based on neural network and DWT [18].

2.1 Feed Forward Neural Network Architecture for Image Compression

An Artificial Neural Network (ANN) is an information- processing paradigm that is inspired by the way biological nervous systems, such as the Brian, process information [16]. The key element of this paradigm is the novel structure of the information processing system. The basic architecture for image compression using neural network is shown in figure 1. The network has input layer, hidden layer and output layer. Inputs from the image are fed into the network, which are passed through the multi layered neural network. The input to the network is the original image and the output obtained is the reconstructed image. The output obtained at the hidden layer is the compressed image. The network is used for image compression by breaking it in two parts as shown in the Figure 1. The transmitter encodes and then transmits the output of the hidden layer (only 16 values as compared to the 64 values of the original image). The receiver receives and decodes the 16 hidden outputs and generates the 64 outputs. Since the network is implementing an identity map, the output at the receiver is an exact reconstruction of the original image.

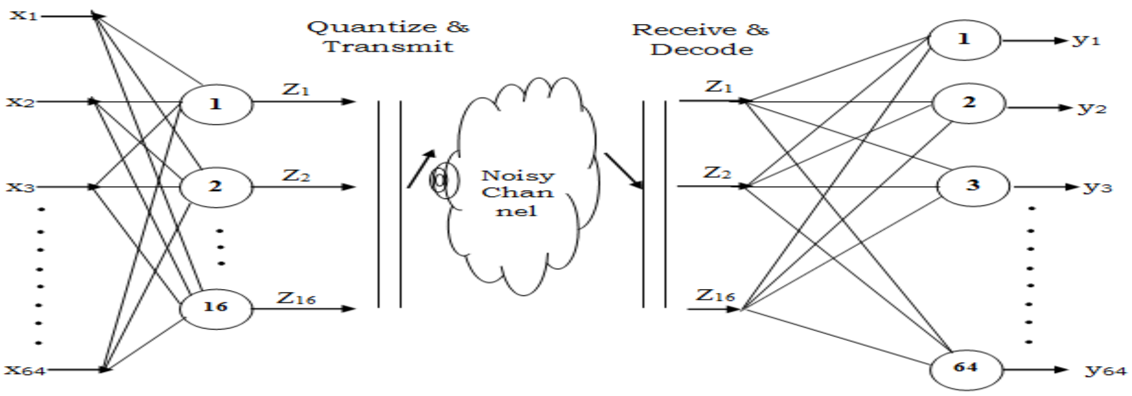


Figure 1: Feed forward multilayered neural network architecture

Three layers, one input layer, one output layer and one hidden layer, are designed. The input layer and output layer are fully connected to the hidden layer. Compression is achieved by designing the network such that the number of neurons at the hidden layer is less than that of neurons at both input and the output layers. The input image is split up into blocks or vectors of 8 X8, 4 X 4 or 16 X 16 pixels. Back-propagation is one of the neural networks which are directly applied to image compression coding [20][21][22]. In the previous sections theory on the basic structure of the neuron was considered. The essence of the neural networks lies in the way the weights are updated. The updating of the weights is through a definite algorithm. In this paper Back Propagation (BP) algorithm is studied and implemented.

2.2 DWT architecture for image compression

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 [24][25][26] etc. Specifically the 2-D DWT and its counterpart 2-D Inverse DWT (IDWT) play a significant role in many image/video coding applications. Figure 2 shows the DWT architecture, the input image is decomposed into high pass and low pass components using HPF and LPF filters giving rise to the first level of hierarchy. The process is continued until multiple hierarchies are obtained. A1 and D1 are the approximation and detail filters.

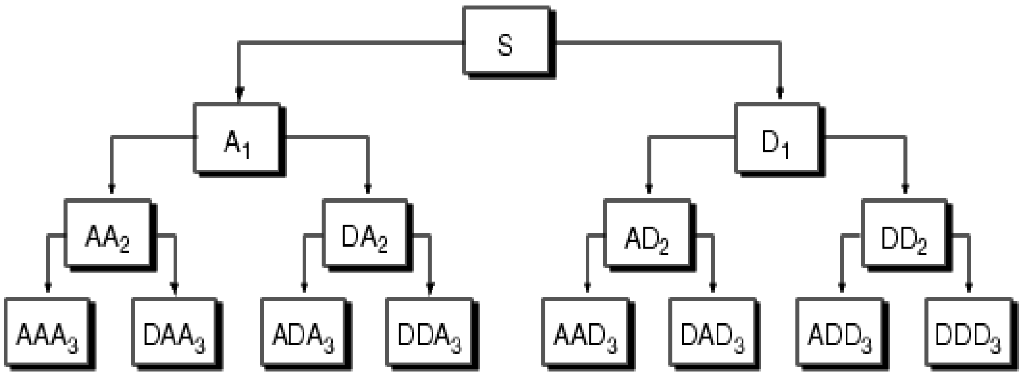


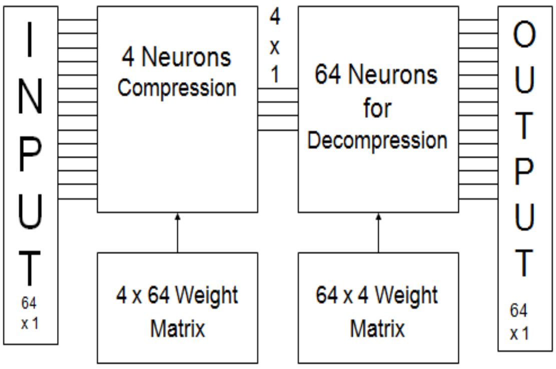
Figure 2: DWT decomposition

Figure 3 shows the decomposition results. The barbera image is first decomposed into four sub bands of LL, LH, HL and HH. Further the LL sub band is decomposed into four more sub bands as shown in the figure. The LL component has the maximum information content as shown in figure 3, the other higher order sub bands contain the edges in the vertical, horizontal and diagonal directions. An image of size N X N is decomposed to N/2 X N/2 of four sub bands. Choosing the LL sub band and rejecting the other sub bands at the first level compresses the image by 75%. Thus DWT assists in compression. Furhter encoding increases compression ratio.

Figure 3 DWT decomposition of barbera image into hierarchical sub bands

III. ANN WITH DWT FOR IMAGE COMPRESSION

Basic architecture for image compression using neural network is shown in the above figure 4. The input image of size 64 x 1 is multiplied by 4 x 64 weight matrixes to obtain the compressed output of 4 x 1, at the receiver 4 x 1 is decompressed to 64 x 1 by multiplying the compressed matrix by 64 x 4. The table in figure 4 shows the compression ratio that can be achieved by choosing the sizes of hidden layer.



Network size	Size of hidden layer	Compression ratio
64-64-64	64	0%
64-32-64	32	50%
64-16-64	16	75%
64-08-64	08	87.5%
64-04-64	04	93.75%
64-01-64	01	98.5%

Figure 4: Neural network based image compression

Prior to use of NN for compression it is required to perform training of the network, in this work we have used back propagation training algorithm for obtaining the optimum weights and biases for the NN architecture. Based on the training, barbera image is compressed and decompressed; Figure 5 shows the input image, compressed image and decompressed image.

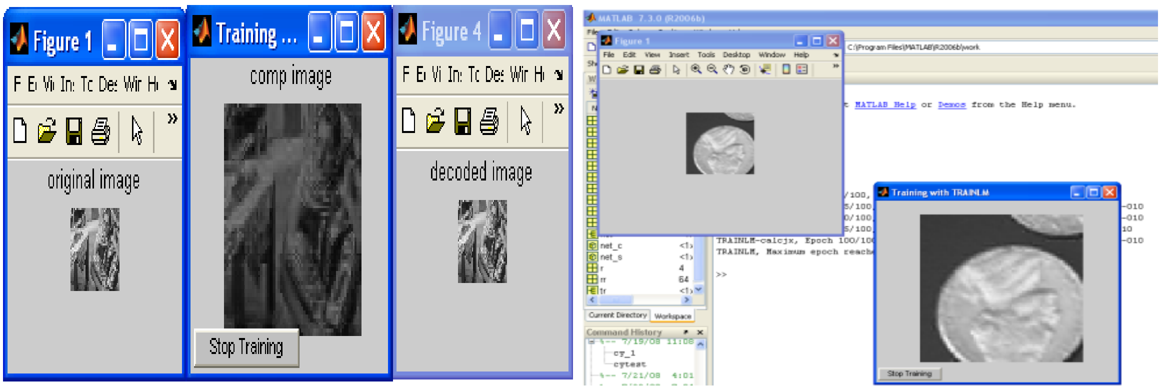


Figure 5: NN based image compression and decompression

Figure 5 also shows the input image and the decompressed image of coins image using neural network architecture. From the decompressed results shown, we find the checker blocks error, which exists on the decompressed image. As the input image is sub divided into 8 x 8 blocks and rearranged to 64 x 1 input matrixes, the checker block arises. This is one of the limitations of NN based compression. Another major limitation is the maximum compression ration which is less than 100%, in order to achieve compression more than 100% and to eliminate checker box errors or blocking artifacts we proposed DWT combined with NN architecture for image compression.

3.1 Image Compression using DWT-ANN

Most of the image compression techniques use either neural networks for compression or DWT (Discrete wavelet Transform) based transformation for compression. In order to overcome the limitations of NN architecture in this work, DWT is used for image decomposition and an N X N image is decomposed using DWT into hierarchical blocks the decomposition is carried out until the sub block is of size 8 x 8. For a image of size 64 x 64, first level decomposition gives rise to 32 x 32 (four sub bands) of sub blocks, further decomposition leads to 16 x 16 (sixteen sub bands), which can further decamped to 8 x 8 at the third hierarchy. The third level of hierarchy there are 64 sub blocks each of size 8 x 8. Figure 6 shows the decomposition levels of input image of size 64 x 64.

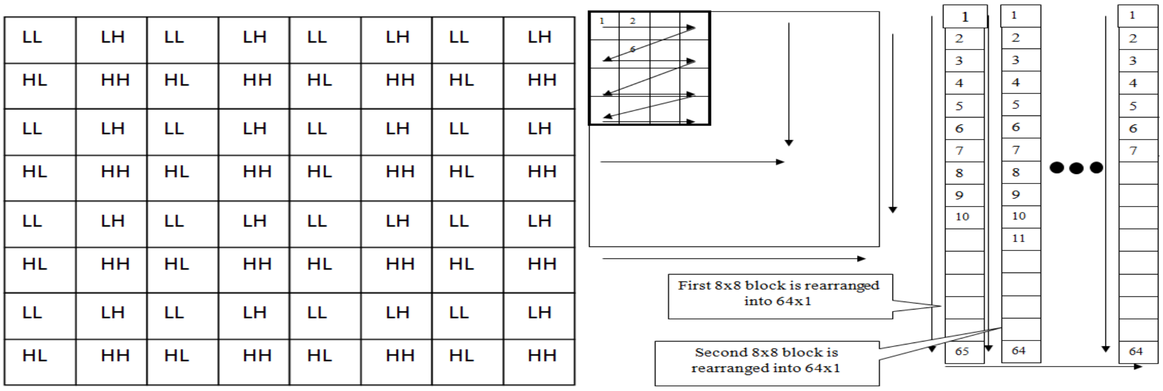


Figure 6: Decomposition of image into sub blocks using DWT

Sub blocks of 8 x 8 are rearranged to 64 x 1 block are combined together into a rearranged matrix size as shown in figure 6. The rearranged matrix is used to train the NN architecture based on back propagation algorithm. In order to train the NN architecture and to obtain optimum weights it is required to select appropriate images [17][18]. The training vectors play a vital role in NN architecture for image compression. The NN architecture consisting of input layer, hidden layer and output layer. The network functions such as tansig and purelin are used to realize feed forward neural network architecture [18]. In this work, hybrid neural network architecture is realized using DWT combined with ANN. The hybrid architecture is discussed in the research paper [Ramanaiah and Cyril]. The NN based compression using analog VLSI is presented in the research paper [Cyril and Pinjare]. Based on the two different papers neural network architecture is developed and is trained to compress and decompress multiple images. The DWT based image compression algorithm is combined with neural network architecture. There are several wavelet filters and neural network functions. It is required to choose appropriate wavelets and appropriate neural network functions. In this work an experimental setup is modeled using Matlab to choose appropriate wavelet and appropriate neural network function. Based on the above parameters chosen the Hybrid Compression Algorithm is developed and is shown in Figure 7.

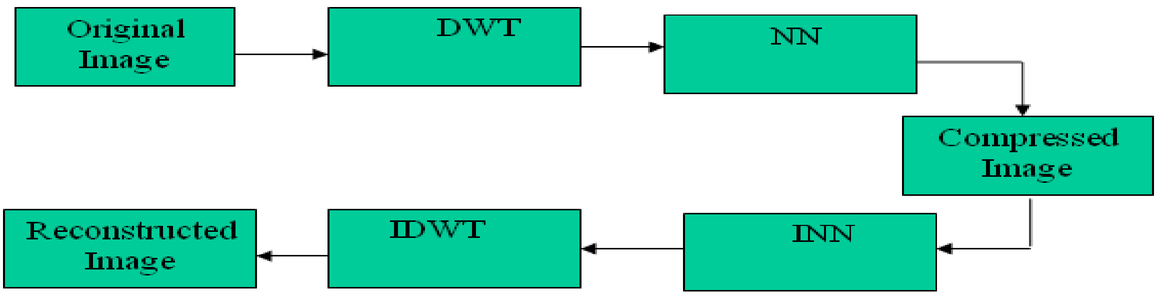


Figure 7: Proposed hybrid algorithms for image compression

Several images are considered for training the network, the input image is resized to 256 x 256, the resized image is transformed using DWT, 2D DWT function is used for the transformation. There is several wavelet functions, in this work Haar and dB4 wavelet functions are used. The input image is decomposed to obtain the sub band components using several stages of DWT. The DWT process is stopped until the sub band size is 8 x 8. The decomposed sub band components are rearranged to column vectors; the rearranged vectors are concatenated to matrix and are set at the input to the neural network. The hidden layer is realized using 4 neurons and tansig function. The weights are biases obtained after training are used to compress the input to the required size and is further processed using weights and biases in the output layer to decompress. The decompressed is further converted from vector to blocks of sub bands. The sub band components are grouped together and are transformed using inverse DWT. The transformation is done using multiple hierarchies and the original image is reconstructed. The input image and the output image is used to compute MSE, PSNR. The selection of network parameters and performances are discussed in the next section.

IV. ASIC IMPLEMENTATION OF DWT-ANN ARCHITECTURE

Synthesis is a complex task consisting of many phases and requires various inputs in order to produce a functionally correct netlist. Synthesis includes the following main tasks: reading in the design, setting constraints, optimizing the design, analyzing the results and saving the design database. The first task in synthesis is to read the design into Design Compiler memory. Reading in an HDL design description consists of two tasks: *analyzing* and *elaborating* the description. The next task is to set the design constraints. Constraints are the instructions that the designer gives to Design Compiler. They define, the synthesis tool can or cannot do with the design or how the tool behaves. Usually this information can be derived from the design specifications (*e.g.* from *timing specification*). There are basically two types of design constraints: Design Rule Constraints and Optimization Constraints. Optimization constraints are explicit constraints (set by the designer). They describe the design goals (area, timing, power and so on) the designer has set for the design and work as instructions to perform synthesis. The top level model is constrained with the following parameters: clock master_clock (rise edge) of 4.00ns, library setup of -0.05ns, data required time of 3.95ns, data arrival time of -3.95 ns, the slack is found to be 0.00 indicating that the design is able to meet timing constraints. The area report obtained using 65nm low power library from TSMC indicates that the number of ports is 2, number of nets is 714, number of cells is 16, number of references is16, Combinational area occupied by the design is 870596.656057 um^2, Non-combinational area occupied by the design is 329587.191422 um^2 and the total design area occupied is 1200183.847480 um^2. The power report obtained after synthesis indicates that the total dynamic power is 86.8380 mW, cell internal power is 85.6360 mW, net switching power is 1.2021 mW and cell leakage power is 362.3151 uW at load capacitance of 1pF and operating voltage of 1.08V. The synthesized netlist for the compressor unit is shown in Figure 8 (below).

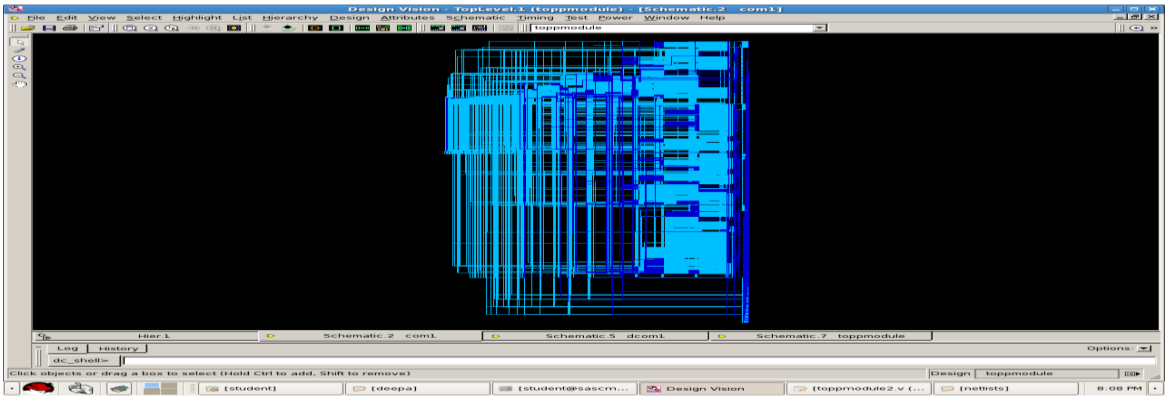


Figure 8: Synthesized netlist for compressor unit

Figure 9 (below) shows the synthesized netlist for the decompressor unit.

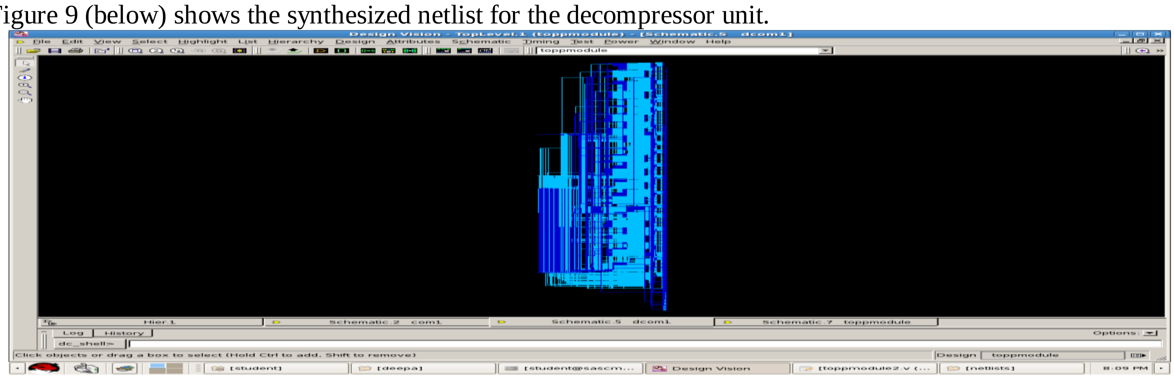


Figure 9: Synthesized netlist of decompressor unit

Figure 10 (below) shows the synthesized netlist of adder circuits used in the design to realize the compressor and decompressor unit.

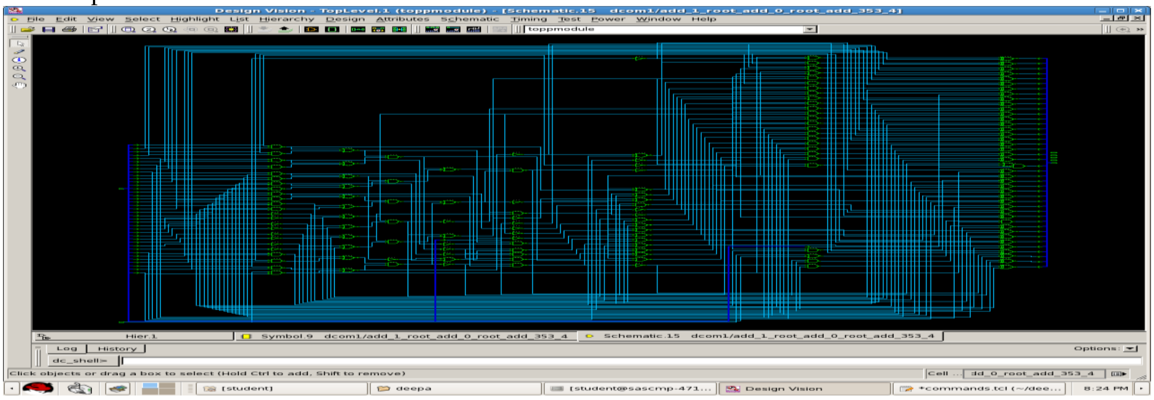


Figure 10: Synthesized netlist of 14-bit Carry Save Adder

Figure 11 (below) shows the synthesized netlist of Wallace tree multiplier used for design of compressor and decompressor unit.

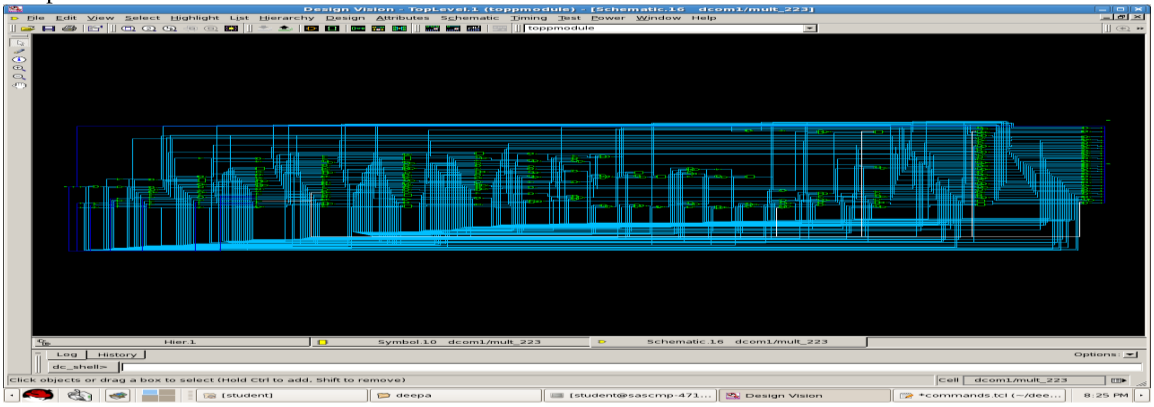


Figure 11: Synthesized netlist of Wallace tree multiplier

V. RESULTS AND DISCUSSION

Figure 12 shows the results of image compression and decompression using the proposed hybrid architecture model. The input image is transformed into four sub bands in the first level decomposition, further is decomposed to second level of hierarchy and is shown in figure 12. The decomposed image is rearranged into column matrix, and is shown in figure 12. The compressed data using NN architecture is decompressed using output layer. The output obtained is further rearranged to sub blocks and is inverse transformed using inverse DWT. The output obtained is shown in figure 13, along with the reconstructed image.

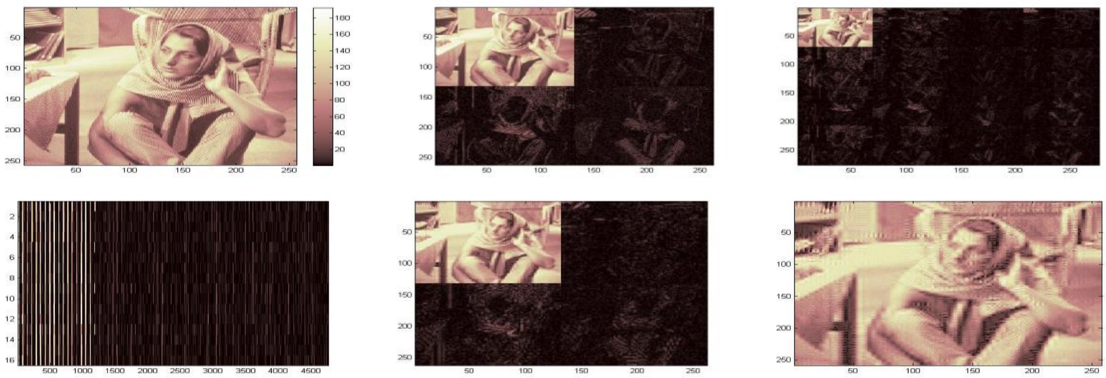


Figure 12: Results of hybrid Neural Network Architecture

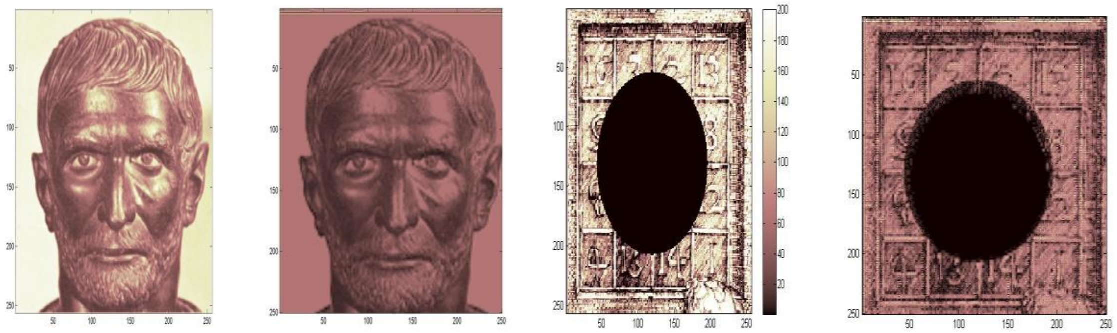


Figure 13: Input Image and Reconstructed Image

The following table summarizes the MSE results for various test images using the hybrid architecture. The results compare the performances of NN architecture, reference design and the present work. With the choice of appropriate wavelet filters (Haar, db4), choice of decomposition levels, number of hidden layers and network function the proposed architecture is superior compared with all the other architectures.

Sl. No.	*Test Image*	*Image MSE (With NN only)*	*Reference*	*Image MSE (With NN and DWT)*
1	Camera man	321	301	262
2	Board	1590	1289	958
3	Cell	39	34	26
4	Circuit	24	21	14
5	Lena	201	190	100
6	Sun	278	149	115
7	Girl	67	51	42
8	Blue hills	38	31	22
9	Sunset	51	47	39
10	Water lilies	56	42	31
11	Winter	89	52	47
12	Drawing	260	232	170
13	College	180	126	97
14	Garden	163	145	87
15	My photo	320	234	197
16	Holi	289	256	175
17	Bhagavad geetha	98	78	65
18	Devine couple	143	101	80
19	Krishna	29	19	7
20	Goddess	76	53	45

Table 1: MSE results for various test images and comparison

From the results presented in table for all the 20 images considered proposed network achieves less MSE compared with the reference design. The input image is decomposed using DWT and is compressed using NN architecture, this introduces delay and hence high speed architectures are required to implement for real time applications.

VI. CONCLUSION

Use of NN for image compression has superior advantage compared with classical techniques; however the NN architecture requires image to be decomposed to several blocks of each 8 x 8, and hence introduces blocking artifact errors and checker box errors in the reconstructed image. In order to overcome the checker errors in this work, we have used DWT for image decomposition prior to image compression using NN architecture. In this work, we proposed a hybrid architecture that combines NN with DWT and the input image is used to train the network. The network architecture is used to compress and decompress several images and it is proven to achieve better MSE compared with reference design. The hybrid technique uses hidden layer consisting of tansig function and output layer with purelin function to achieve better MSE. The proposed architecture is suitable for real time application of image compression and decompression.

VII. ACKNOWLEDGMENTS

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