

FFT Based Compression approach for Medical Images

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Abstract

In this new era, advances in the Image Processing have played an imperative role as catalyst in Medical Imaging. The Digital Medical Images are necessary for the fast and safe diagnosis in the medical field. The objective of medical image compression is to represent medical images reduced data so that they can be stored and transmitted competently. An efficacious diagnosis is possible only when the applied compression algorithm preserves all the required diagnostic information and the resolution of the image. In several medical imaging modalities the output is in the form of raw data and when the data size is relatively small it takes modest time to reconstruct the image. But if the raw data is excessive then the time of processing also increases. This provokes the probe for faster processing which also leads to large data size practical. A Fast Fourier Transform algorithm that is massively parallel and highly pipelined has been developed for processing of such medical images. Subsequently the architectures have been coded using Verilog Hardware Description Language in line with RTL guidelines, simulated and tested for medical images. The proposed algorithm is resulting in PSNR greater than 40dB indicating the quality of reconstructed images that are indistinguishable from original ones. The lower value of Mean Square Error between the compressed and original image confirms to good diagnostic quality of the medical images.

Keywords: Medical Imaging, FFT, IFFT, Huffman Coding, Compression, Verilog RTL Coding

INTRODUCTION

The Fast Fourier Transform is a mathematical operation generally used in many fields. In a number of medical applications; Fast Fourier Transform (FFT) is being used for reconstructing the images and to analyze them in frequency domain. Also FFT plays vital role in image processing applications such as filtering, compression and de noising by manipulating data in frequency domain. FFT is most popular in Medical Imaging applications being computationally fast and simple. Medical Imaging is a process that creates images of the human body and its parts that can be used for clinical purposes. The most common Medical Imaging modalities are Computer Tomography (CT), Magnetic Resonance Imaging (MRI), ultrasound and Optical Imaging Technologies which produces prohibitive amount of data. The images produced by these equipments are composed of pixels which the visual representation of functioning of the human organs. Also they

are the most important information of the patient and this information requires large amount of storage and transmission width. Medical Image Compression algorithms can express these medical images with less data based on asserting the significant information is retained. There are two ways of categorizing compression algorithms Lossless & Lossy Compression: The Lossless compression can reconstruct the original image exactly from the reconstructed image but results in less compression ratio hence used for text. The original and reconstructed images in this compression are numerically same and hence can achieve fair amount of compression. Whereas the Lossy Compression totally discards the redundant information and posses degradation related to the original. Also they result in higher compression and are used for Image and Video compression which appear to visually lossless.

FFT based compression is one such algorithm that can process the image fast along with compression in the transformed domain. The transformed domain contains both low and high frequency coefficients which are then quantized. Several quantized high frequency coefficient values are insignificant that are nearly equal to zero and these coefficients are removed from the transformed image. This pre processing procedure leads to the platform for the compression. The significant coefficients are then compressed using Huffman Coding technique. Huffman coding is a technique for the construction of minimum redundancy code. It is optimal prefix code generated from set of probabilities and has been used in various compression applications. These codes are of variable code length using integral number of bits [1]. The algorithm does compression by granting symbols to vary in length. Most occurring symbols are assigned shorter code length whereas the less occurring symbols are assigned with longer code length. These transformed and compressed codes that assigned with variable length are then stored on storage media for transmission. The compression ratio of the algorithm is calculated and the quality of reconstructed images are quantified using Power Signal Noise Ratio (PSNR). If the value of PSNR is above 40dB the original and reconstructed images are indistinguishable. At the decoder end the images are reconstructed by decompressing, inverse quantizing and by finding Inverse Fourier Transform (IFFT) of the transformed image. The divide-and-conquer approach of the FFT algorithm makes FPGAs an ideal solution because of their unhindered potential for parallelization [2]. This paper is structured as follows. In section 2 Medical Imaging Modalities is discussed, section 3 is discusses the block

diagrams of the proposed algorithm along with the highlights of the design implemented in the present work.

Quantization procedure and compression technique is explained in section 4 and development of the architecture for the proposed algorithm for FFT quantization and Inverse quantization steps in section 5. The simulation results and performance of the compression technique is unveiled in Section 6.

Medical Imaging System

Medical Imaging is gaining significant importance in health care sector as hospitals are moving towards digitization, Filmless Imaging and Tele medicines. This has lead to the great challenge of having compression algorithms that can reduce constancy evading the diagnostics errors but having high compression ratio for reduced storage and transmission bandwidth. Particularly in medical field, expedient diagnosis is possible only when the compression technique preserves the required diagnostic information.

The medical modalities produce images that require more space for storage which is difficult to manage and also demand high end network for transmission. Hence the purpose of Medical Image Compression is to express these images with less data to save storage space and transmission time asserting that the true information in the original image is preserved.

Medical Images are one of the most important data about patients and represent human body pictures in digital form. These images allow the doctors to view the internal portions of the body for easy diagnosis. It also helps in making keyhole surgeries to reach the internal parts of the body without much incision in to the body. They can be efficiently processed, objectively evaluated, and made available at many places at the same time by means of appropriate communication networks and protocols, such as Picture Archiving and Communication Systems (PACS) and the Digital Imaging and Communications in Medicine (DICOM) protocol, respectively [3]. The images in the form of X-ray, CT, MRI, Ultrasound contain immense data which requires large channel or storage capacity. Even with the advances in storage capacity and communication, the implementation cost limits the storage capacity. Mainly the implementation cost increase with the storage capacity and bandwidth and hence it affects the cost of medical imaging. Especially in case of telemedicine quick access to the patient data saves the time, cost and the life of patient. In such applications fast processing of data is very important that involves both reconstruction and compression of the medical images. There exist some of the techniques that produce imperceptible differences and acceptable fidelity that can result in lossy compression for medical images. The lossy compression with minor losses from the original file quality excluded.

In this paper an FFT based compression has been proposed and the performance of the algorithm is measured with the PSNR. The compression technique mainly consists of three main steps: First step is the Transformation which converts spatial domain image in to frequency domain that more

accurately reflects the information. The advantage of Transformation is that a set of Transformed samples is large enough to completely describe the spatial domain image. In the second step the frequency co efficient are then quantized to achieve higher compression at the cost of precision. The quantized data can be represented with lesser number of bits than the spatial domain data. Hence the quantization provides the platform for compression and act as the initial step in compression. The last step is the Entropy encoding which is type of lossless coding to compress digital data by representing frequently occurring patterns with few bits and rarely occurring patterns with many bits[3]. The encoded bits is the compressed data which can be stored using less storage and can be transmitted using lesser transmission width and time.

PROPOSED FFT BASED COMPRESSION APPROACH FOR MEDICAL IMAGES

Fourier Transform is a tool for solving many physical problems. FFT is used in most medical modalities for applications like the reconstruction of images from raw data, de noising and compression. FFT is a technique that eases the analysis of signal in frequency domain and an algorithm for fast computation of DFT. The real time applications in medical field require FFT for fast computation. The DFT of an image is given by

$$F(u, v) = \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} f(x, y) W_N^{-(ux+vy)} \quad (1)$$

for $x = 0, 1, 2, \dots, N-1$
 for $y = 0, 1, 2, \dots, N-1$

Inverse Fourier Transform is given by

$$f(x, y) = \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} F(u, v) W_N^{(ux+vy)} \quad (2)$$

for $u=0, 1, 2, \dots, N-1$
 for $v = 0, 1, 2, \dots, N-1$

The FFT relies on redundancy in the calculation of DFT and reduces the number of computations. The large reduction in calculation makes real time processing a reality. The transform of a signal packs the information from higher dimension space in to a lower dimension leading to compression through quantization and encoding. The key component in FFT computation is Twiddle factor represented by ω . Twiddle Factor is a rotating vector that increments based on the number of samples and has symmetry as it rotates encircle. This symmetry property of FFT is an advantage to draw the butterfly diagram which aids the fast computation of Discrete Fourier Transform (DFT). The twiddle factor is expressed as:

$$W_N = e^{-j(2\pi kn)/N} \quad (3)$$

The exponential term in the equation is rewritten using Euler's formula and expressed as Cosine and Sine matrix.

$$e^{-j\theta} = \cos \theta - j \sin \theta \quad (4)$$

The cosine and sine terms are expressed as (MXN) matrix for various values of (u, x) and (v, y) and these sine and cosine matrices along with their transposes are used as lookup table in the proposed algorithm. The image is accessed as 8*8 blocks and each block is multiplied with the lookup table elements correspondingly to find the sine and cosine transforms of the image. The proposed algorithm overcomes the irregularities of the twiddle factor by sine and cosine transforms. Then FFT of the image is computed by subtracting the sine, cosine and their transposes with the block of the image. The addition/subtraction and multiplication operations FFT/IFFT computations are achieved through pipeline and parallel operations that increase the speed of fast computations. The FFT/IFFT algorithm for color images have been developed by the present author and reported in earlier paper (4).

Design Flow of the proposed algorithm

The design flow starts with the MATLAB. The medical image is subdivided in to 8*8 blocks and stored in RAM for FFT computation. The spatial domain image is converted in to frequency domain by applying FFT to each block of the image. Thus obtained FFT co efficient values are compressed by applying quantization and Huffman encoding. In the reconstruction process decoding, inverse quantization and IFFT is applied. In this proposed work the architecture is based on parallel and pipeline approach for the computation of FFT and its inverse for blocks of the image under consideration.

With the purpose of better understanding of the proposed algorithm, a block level description is presented in Fig.1. The raw data produced by the medical modalities are too large and these images require more space for storage, management of which becomes very difficult. These images also demand for high end networks for their transmission such as in Telemedicine application [5]. They have to be pre processed before applying transforms. The pre processing is necessary to improve the input data by suppressing unwanted distortions or by enhancing some image features. Pre processing involves down sampling which is required to reduce the sampling rate. Because sampling rate is analogous to computation and memory requirement. Hence reduction in sampling rate leads to cheaper implementation and thus the cost of processing. In Medical Imaging the raw data is enormous and requires more time for processing and transmitting. Also RGB color images have high correlations among the primary color components containing lot of redundant data and hence energy of the image is varied significantly throughout the image. Hence RGB color image transmission is forbidden by the higher bandwidth. This leads to conversion of RGB image space in to other color spaces like YUV, YIQ and YCbCr for good performance in compression. Also, the human eyes are more sensitive to luminance than chrominance and the sampling rate required for chrominance is half that of the luminance. At

the encoder the RGB is down sampled to YCbCr 4:2:0 formats with almost no loss of characteristics in visual perception.

In a number of medical imaging systems FFT is used for the reconstruction of images from the raw data and also used in compression, de noising and filtering. FFT is efficient implementation of DFT and also turns complicated convolution operations in to simple multiplications. FFT does not change the information content of signal instead decomposes it to its sine and cosine components. The important property of FFT that any signal expressed using Fourier can be completely reconstructed using its inverse and this is because the transform is a complex number which has much greater range representation than spatial domain. Also performing some operations in frequency domain is much more efficient than doing the same in spatial domain. This enables efficient implementation of different operations and algorithms in signal processing fields.

The FFT coefficients are the frequency domain representation of a signal and hence the image is represented in frequency range from low to high. The images have compact representation in low frequency range than in high frequency range. Most of the significant information is present in low frequency coefficients and high frequency coefficients can be discarded by quantization with filtering.

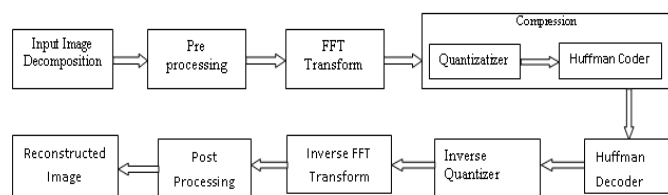


Figure 1. Block diagram of FFT Based Compression for Medical Image Processing

Quantization makes the algorithm lossy compression and the quantization matrix is designed in such a way that the elements near to zero are zeroed down and other elements are slimmed. Succeeding quantization, the co efficient are normalized to the nearest integer values and the inconsiderable coefficients are discarded without affecting the quality of the image.

These steps lead to compression in Transform domain that reduces the inter pixel redundancy of the image. This type is referred to as mappings which are reversible only if the original elements can be reconstructed from the transformed elements. This provides platform for compression by reducing the number of coefficients to be encoded for storage or transmission. Quantization and Normalization of Transformed coefficients preside to Psycho Visual redundancy. Normally human perception of information in an image does not pertain to quantitative analysis of every pixel of an image. Human eye does not respond with the same sensitivity to all visual information and certain information is ignored by human eye. Removing such information does not affect perception and they are related to sampling and quantization. Also in normal visual processing certain information has relatively less

importance than other information. This information is called as Psycho visually redundant which can eliminate without significantly hindering the quality of the image. In general, an observer searches for distinguishing features such as edges or textual regions and mentally combines them in to recognizable groupings [7].

In order to complete the interpretation process, the brain correlates these groupings with prior knowledge and does interpret the image. Psycho visual redundancy eliminates quantifiable visual information and this is possible because that information itself is not necessary for normal visual processing. Quantitative information is lost in this and hence referred as Quantization. Also the input values are mapped on to a limited number of output values that cannot be reconstructed resulting in Lossy compression. In Medical Imaging systems, reproducible means of quantifying and extent of information loss is highly prudent. In addition to that, adhering to the fidelity criteria is very much essential so that the information of interest is not lost.

FFT along with Quantization enabled us to lead a color channel in to a form where majority of data consists of few codes. A method that can loss lessly compress such codes is used for compression in this proposed algorithm. The next and the last step of compression is coding redundancy which is associated with the representation of information. This is the simplest and more popular compression that eliminates the redundancy in coding. There are different techniques available for the construction of minimum redundancy code with their own advantages and disadvantages.

Huffman coding is one such lossless compression technique that is based on frequency of occurrence of data. This technique was proposed by Dr. David A. Huffman in 1952 for the construction of minimum redundancy code. Huffman coding is greedy algorithm that focuses on occurrence of each data and it as binary string in an optimal way [8]. This technique attempts to reduce the amount of bits required to represent the data and hence it is a form of statistical coding.

An optimal prefix code is generated against a set of probabilities and is of variable code length using integral number of bits. The idea of Huffman coding is to reduce the average code length and thus the minimizing the size of reconstructed data than the original. The goal is achieved by varying the length of symbols, meaning shorter codes are assigned to more frequently occurring symbols and longer codes are assigned to less occurring symbols. Throughout encoding the code word lengths are not fixed like other codes. The length of assigned codes is based on the frequency of corresponding symbols. The longest code word may have L bits, where $L=2^B$. L represents the size of Huffman code book and B is the bits/pixel. Codes are stored in Code Book that can be constructed for each image. This Code Book and the encoded data are must for decoding at the receiving end. The assigned variable codes are called as Prefix codes meaning the codes assigned to one symbol are not used as prefix of other codes. This is done to avoid the ambiguity during decoding. Huffman coding technique is based on two observations [9].

- a. More frequently occurred symbols will have shorter code words than symbol that occur less frequently.
- b. The two symbols that occur least frequently will have the same length.

There are two major sections in Huffman Coding. The first step is to build a Huffman Tree from the symbols and second is to Transverse the tree and assigning codes to the symbols. The input to build the tree is an array of unique symbols along with their frequency of occurrence and output is Huffman Tree. Creating Huffman tree is simple and it requires a list of set of symbols and their frequencies.

The steps of the algorithm are summarized as follows.

a. Creating Huffman Tree

1. Sort the frequency list from highest to lowest.
2. Create a Parent node by summing the two lowest frequencies (probabilities).
3. The two elements are removed from the list and the new Parent node is inserted in to the tree.
4. Sort the list and again create new node by summing two lowest probabilities.
5. Repeat the steps from 2 to 4 until one element is left in list.
6. The last element in the list is the root and other nodes are the leaves of the Huffman tree.

b. Huffman Code Assignment

1. Transverse the formed Huffman Tree from the root.
2. Assign 0 to the lowest and 1 to the lower node in the tree.
3. Increment the code value and work back to get the code for the longest symbol.
4. Repeat the steps until all nodes are assigned.

The codes generated are stored in Code Book and used for decoding. Once the Huffman codes have been generated the image may be encoded simply by replacing each symbol with its code. Thus encoded medical image is stored on the storage media or can be transmitted over the channel for communication in Telemedicine. The encoded medical image requires less space than the original or the raw data as the image is compressed at various levels during processing. The encoded data is represented using lesser bits per pixel than the original image.

At the receiving end, the Decoder decodes the compressed image using the code book and the encoded data. The significance of Huffman decoding is its popular use in data, image and video compression [10]. For data transmission and reception the same encoding tree is used as the symbols have same frequencies of occurrence. The Decoding is achieved by accessing encoded data two bits at a time. When iterating the bit stream 00 bit pattern means go LEFT, 01 pattern means go LEFT MID, 10 pattern means go RIGHT MID and 11 pattern means go RIGHT in case of quaternary tree[11]. In this stage the Huffman codes are replaced with the symbols of the image on a way to the reconstruction. When the bit pattern matches

with the symbol parent tree then replace the bit pattern with that symbol. This procedure is repeated until the last bit of the codes. The decoded data is now inversely transformed to reconstruct the compressed image. The Inverse Fast Fourier Transform is computed using Eq.2 and image is converted back to the spatial domain. The Inverse FFT operation is very much similar to Fourier Transform operation except that the Sine and Cosine Transposes of the compressed image are added instead of subtracting. Thus obtained inversed image is now reverse or inversely quantized using the same quantization tables to obtain the reconstructed image. Since the image is reconstructed from its degraded version, the performance of the image compression algorithm needs to be assessed quantitatively. Also the Medical Image Processing applications require high quality images for the perfect diagnosis while maintaining the dimension of original and reconstructed image as same. The quality of the reconstructed image is measured using Image Quality Metrics.

DEVELOPMENT OF A NEAR LOSSLESS FFT COMPRESSION ALGORITHM FOR MEDICAL IMAGES

A near lossless FFT compression algorithm is developed using the flowchart presented in Fig.2 and Fig.4. An Algorithm has been developed using Flowcharts for processing FFT for Image compression and is presented in Fig. 2 to Fig. 6. To begin with initializes all registers and outputs of the design.

Read the input image data from memory and then decompose it to the 8x8 pixel blocks. The multiplicand and multiplier for finding the cosine and sine transforms are initialized. Next find the cosine and sine transforms of the image block by multiplying image block with cosine and sine matrices and then store the result in the corresponding product memories. Following multiplication, the transpose of cosine and sine of transforms of the same image block is calculated. The FFT of image is computed by the subtraction of the transforms in the next step of the algorithm. Later the FFT results are written on to FFT memory. During the next step the Quantization is done using the JPEG Quantization tables and the quantized coefficients are normalized. From the Normalized coefficients the Non Zero FFT Coefficients of image are extracted and the Compression Ratio of the image is calculated. These quantized non zero FFT coefficients are stored on to the memory for reconstruction in the proceeding steps.

The developed Flow chart for IQ IFFT for Image reconstruction is similar and is shown in Fig. 5 and Fig. 6. To begin with initializes all registers and outputs used in the design. At the decoding end, first decode the coded Huffman codes using Code Book. Make sure all the codes are decoded and stored on to the memory. Then read the decoded image data from memory and select 8x8 pixels block of image. Consequently initialize multiplicand and the multiplier memory for finding the cosine and sine transforms. Next read the quantization table and performs the inverse quantization of the decoded FFT coefficients of the image block by block. Then compute the cosine and sine transforms of the inverse

quantized decoded image block. Then do the multiplication of transformed image block with the Cosine and Sine Transpose matrices. Later store results on to the corresponding memories to find subtraction of the resultant matrices to on a way to the computation of Inverse Fast Fourier Transform of the image. Then write the result to the reconstructed image memory. Next repeat the same operation for G and B matrices of the image matrix.

For reconstruction concatenate the three color components R, G, B and writes the reconstructed image values to the memory so that the reconstructed image can be displayed.

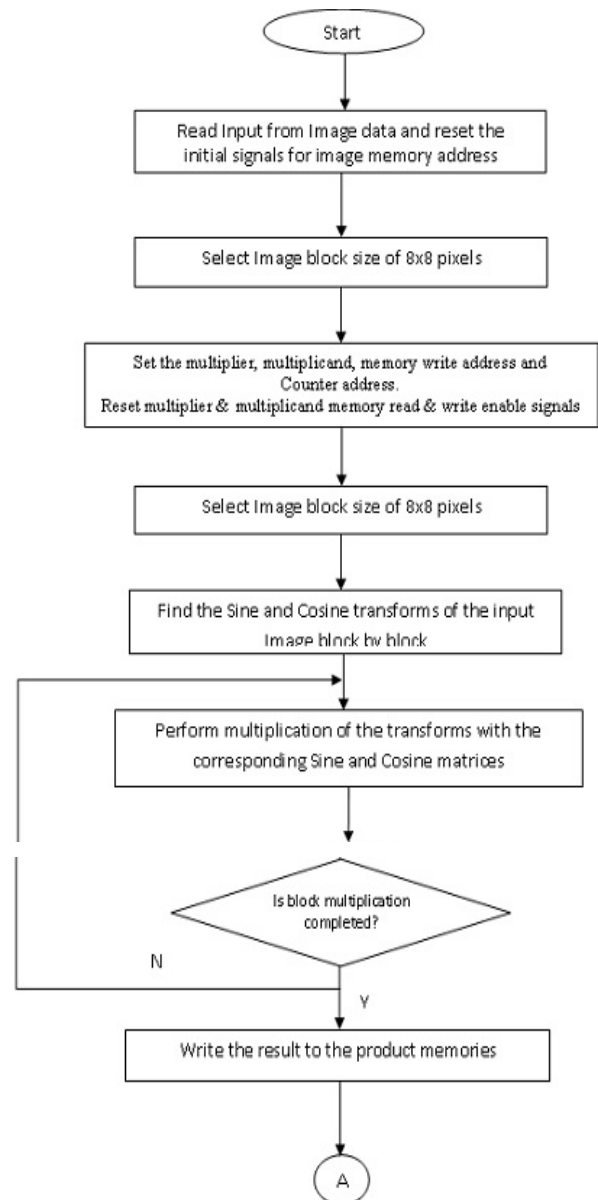


Figure 4. Flowchart of the FFT Based Compression approach for Medical Images (Continued)

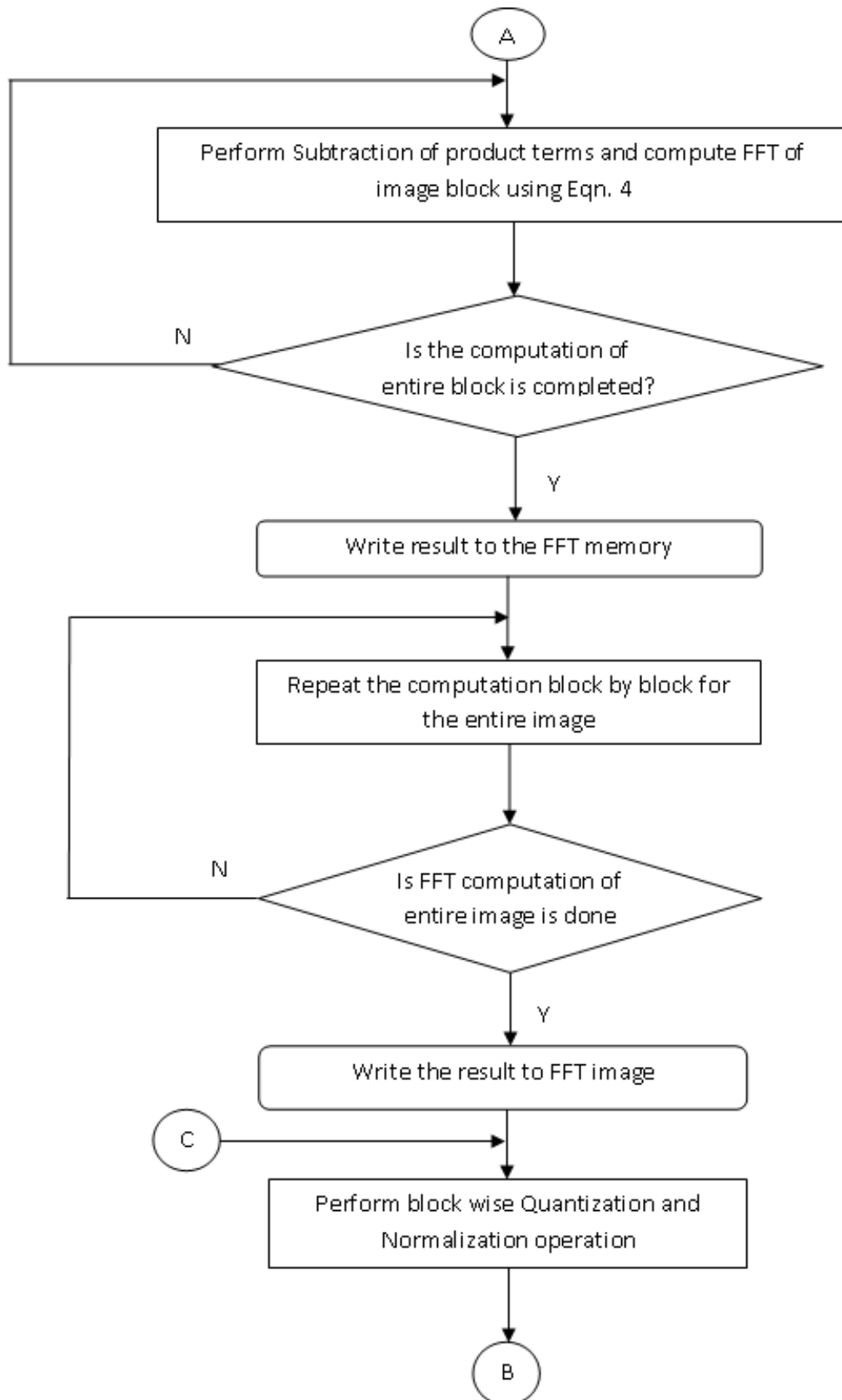


Figure 4. Flowchart of the FFT Based Compression approach for Medical Images (Continued)

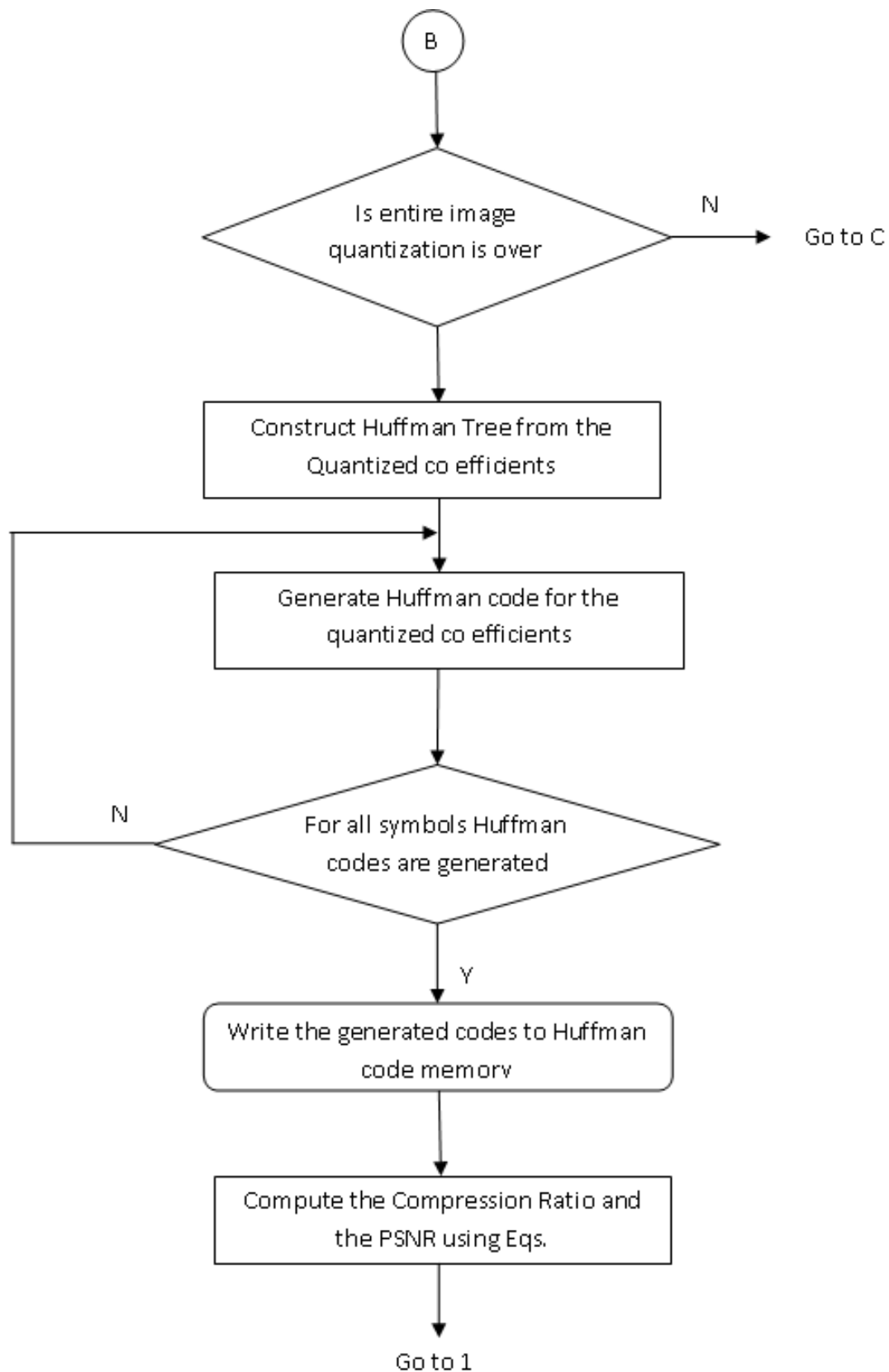
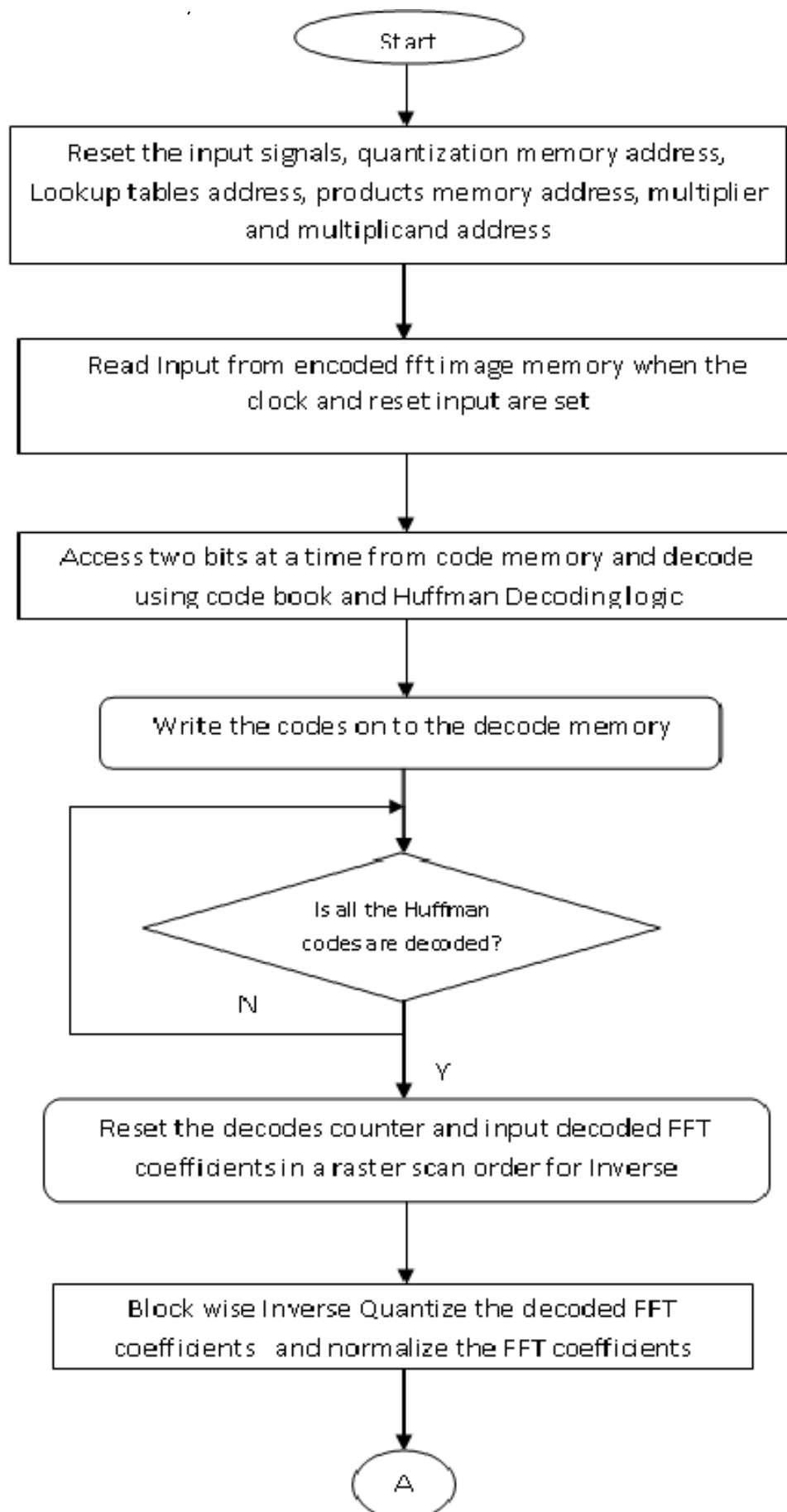


Figure 4. Flowchart of the FFT Based Compression approach for Medical Images (Continued)



FLOWCHART FOR IFFT COMPUTATION USING FFT BASED COMPRESSION APPROACH FOR MEDICAL IMAGES

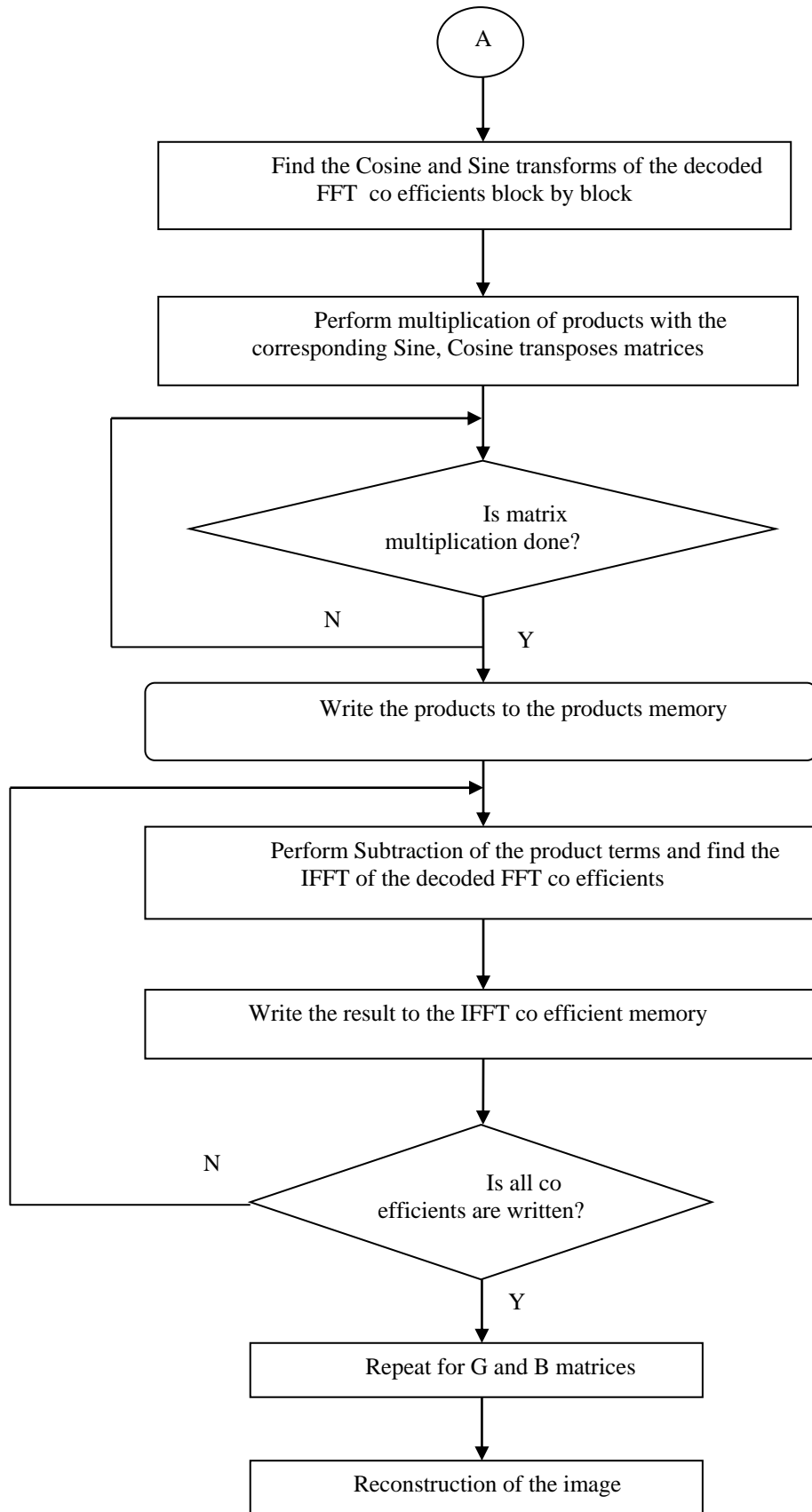


Figure 6. Flowchart for IFFT computation using FFT Based Compression approach

ARCHITECTURE OF THE PROPOSED FFT, QUANTIZATION AND THEIR INVERSE PROCESSORS

Compression of the image is conveying the information of an image in reduced amount of data while preserving as much of information as possible. Compression can be achieved by Quantization, Transformation, Encoding etc., As a matter of fact Quantization does not really give rise to compression of an image but only serves the stage for compression by zeroing the insignificant Quantized coefficients. The exact compression is carried in the next stage using Huffman Coding. Huffman tree is constructed using the quantized FFT coefficients and coding algorithm. Compression is achieved by assigning shorter codes to more frequently occurring symbols and longer codes to rarely occurring symbols. Then

the number of bits used to represent the image is reduced as more frequently occurring symbols are represented with shorter codes hence the reconstructed image is built with lesser bits. The schematic block diagrams of FFTQ compression and IQ IFFT decompression Processors as realized in the current work are shown in Fig. 10 and Fig. 11 respectively. The FFTQ Compression Processor performs the Fourier Transformation of the input image using cosine, sine transform and the transpose of the transforms of the image. The input is of 8*8 blocks structured by converting RGB image to YCbCr (4:2:0) standard format. YCbCr format represent the image with less number of pixels than compared to 4:2:2 formats, thus resulting in shorter processing time and higher compression. So this format of image is always preferred for storing in Image memory.

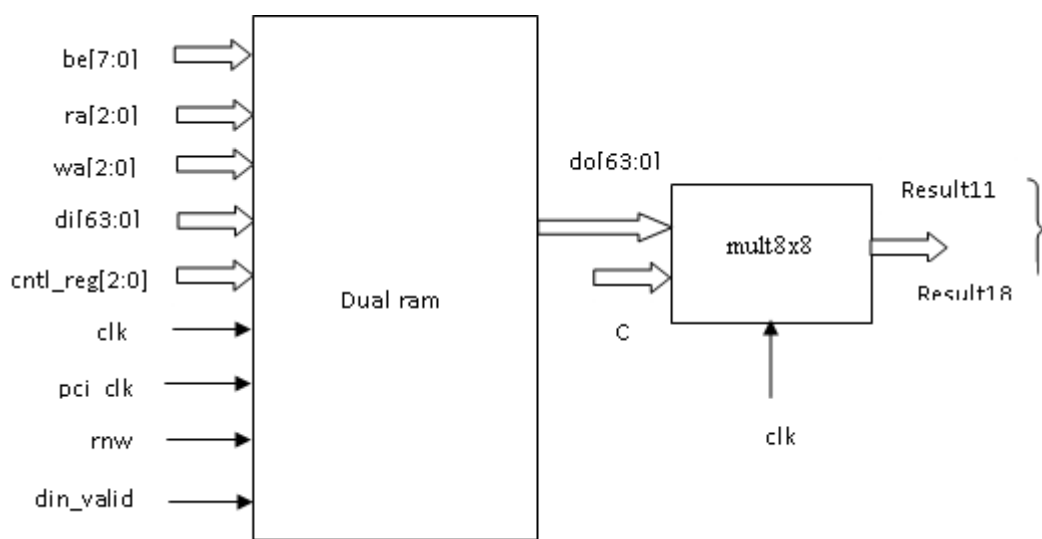


Figure 7. Architecture of the multiplier module for Cosine Transform

The Cosine and Sine look up tables saved memory are used in find the cosine and sine transform of the image by multiplying the image block with the cosine matrix and sine matrix respectively using Eq. 6. consequently the transpose of the transforms are found by the same multiplication method. The transforms and their transposes are fed to subtractor for finding the FFT of the image and that FFT co efficient are stored on to the FFT memory. In later procedure the insignificant FFT co efficient are removed by Quantization and Normalization leading optimization of memory. This optimization contributes towards compression in Encoder by zero downing all negligible values and reducing to magnitude of high frequency to less number of bits. Thus a stage for compression is done by Quantizer.

In addition, the real compression is accomplished by Variable Length Coding in which the bit stream representing an image is minimized. In this proposed algorithm Huffman Encoding

is preferred for compression because it needs less execution time than other coding [12]. In case of Medical Image processing, for real time applications and quick diagnosis time is more important than high compression ratio.

At the Decoder end, the Huffman codes are decoded using Huffman Code Book and the codes. Subsequently the decoded Coefficients are inversely quantized using the quantization Tables of JPEG algorithm.

The Inverse Transform of the decoded image is found very much similar to FFT computation except an adder occupies the subtractor and decoded image is fed as input in to the Inverse FFT processor. The Inverse Transform outputs the coefficients for the reconstructing the image using Eq.7. The same procedure is repeated for G and B matrices and all the three resultant IFFT matrices are concatenated to reconstruct the image.

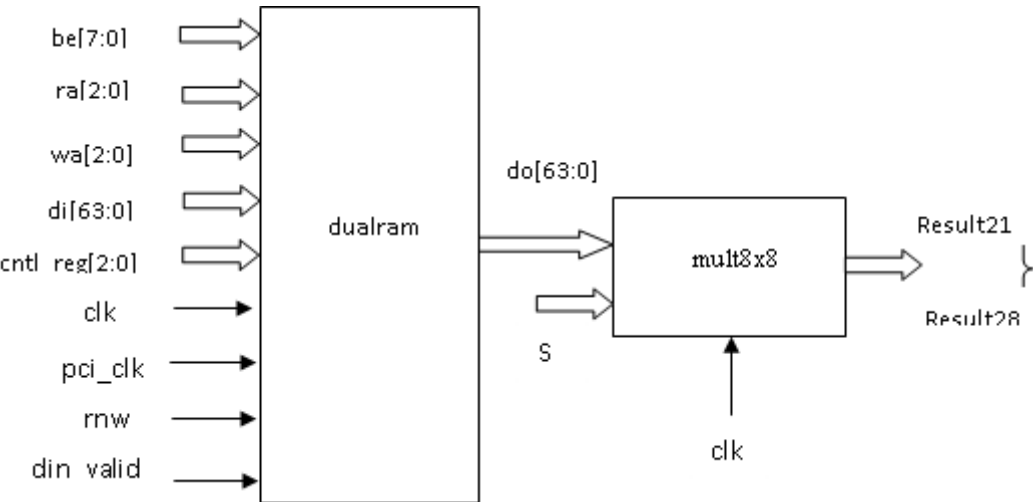


Figure 8. Architecture of the multiplier module for Sine Transform

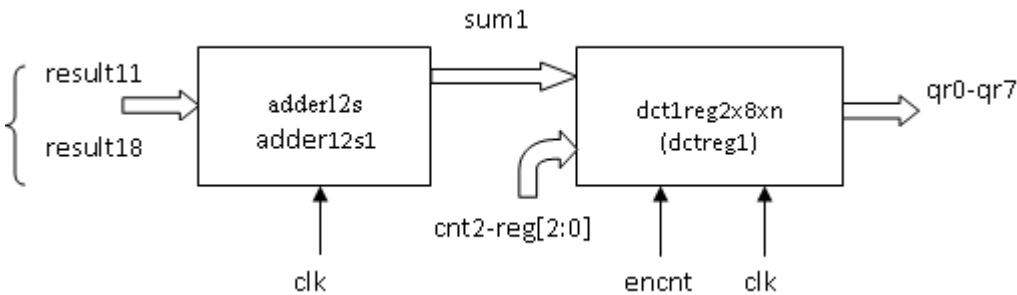


Figure 9. Architecture of the Adder module for Cosine Transform

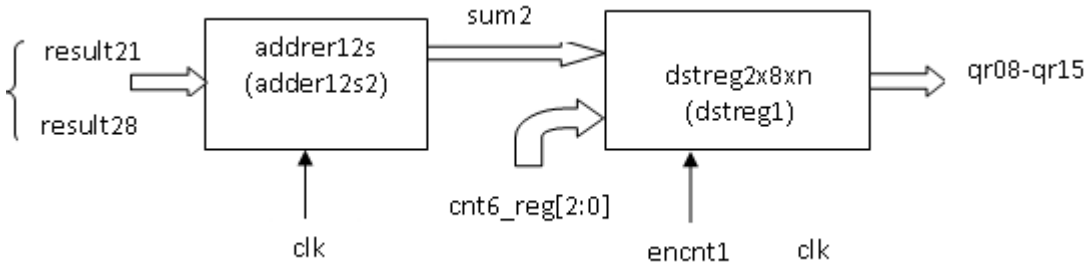


Figure 10. Architecture of the Adder module for Sine Transform

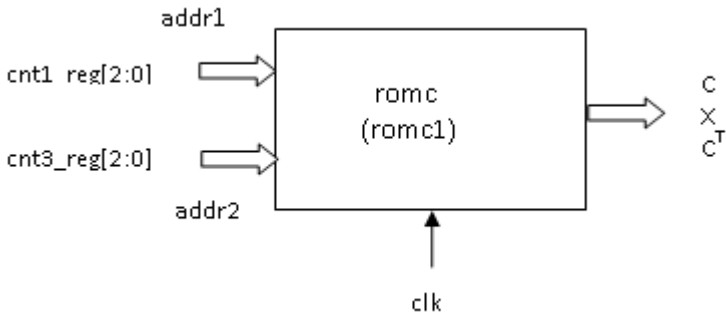


Figure 11. Architecture of the Cosine Transform memory module

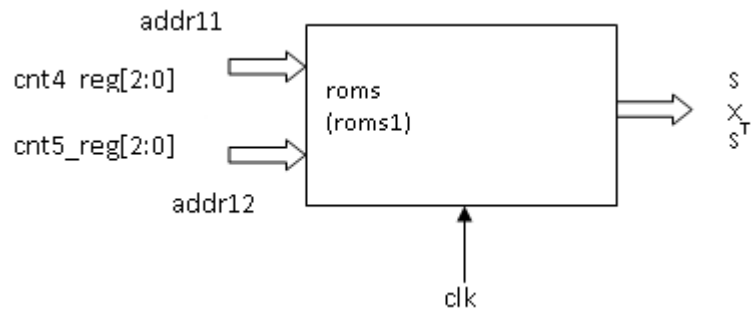


Figure 12. Architecture of the Sine Transform memory module

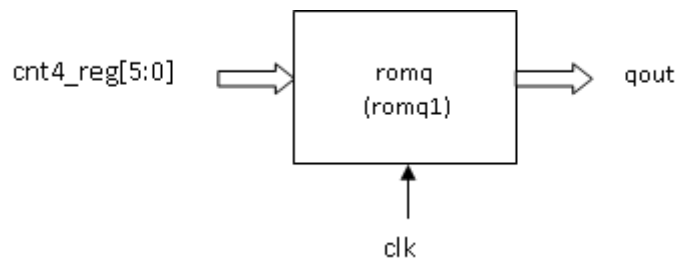


Figure 13. Architecture of the Quantization memory module

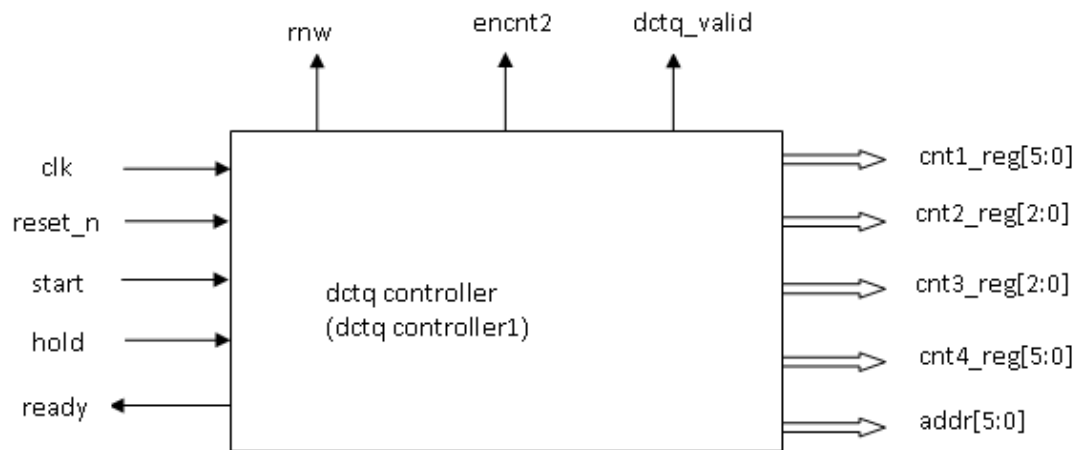


Figure 14. Architecture of the DCT Module

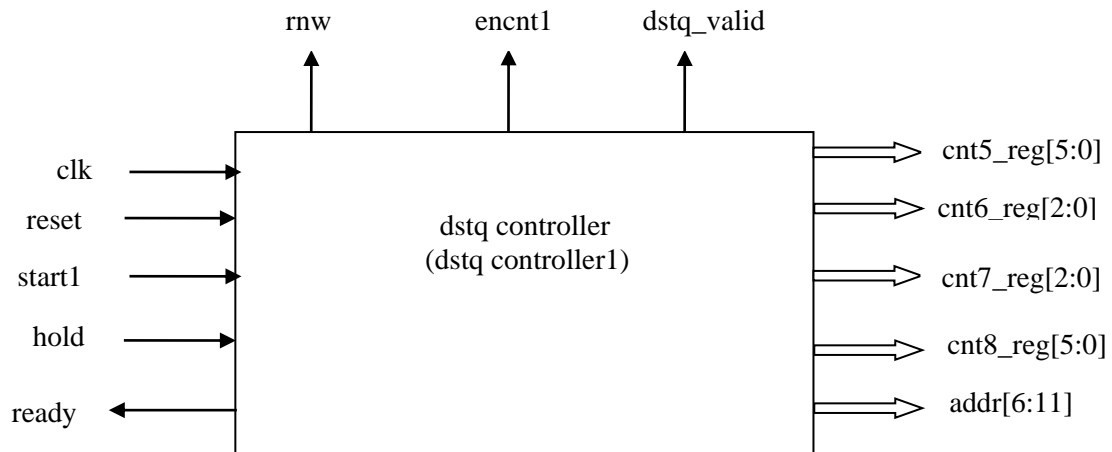


Figure 15. Architecture of the DST Module

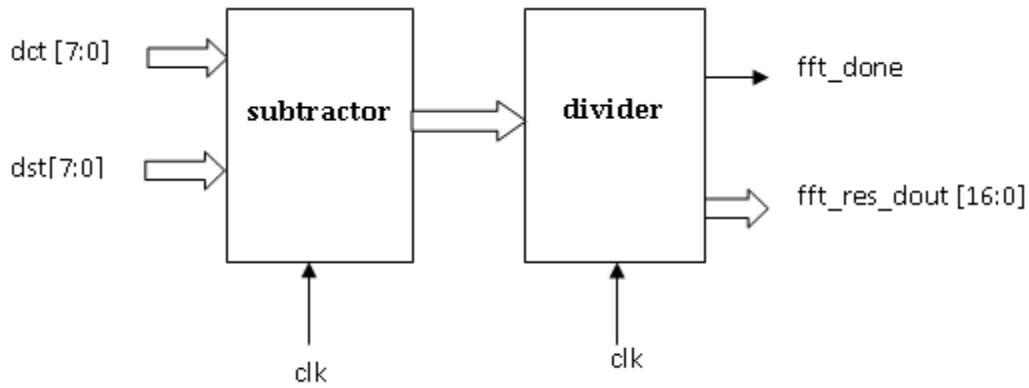


Figure 16. Architecture of the FFT Module

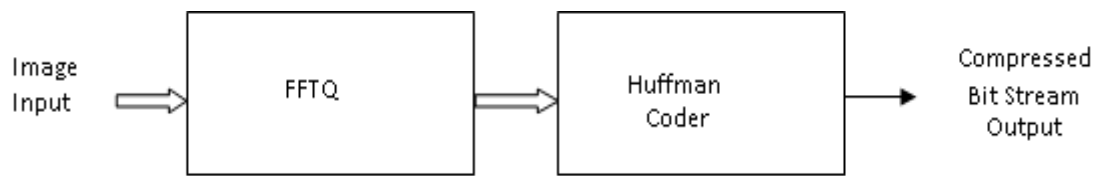


Figure 17. Architecture of the FFT based compression module

Metrics

Benchmarks in image data compression are the Compression Ratio, Mean Square Error(MSE) and Peak Signal to Noise Ratio(PSNR) (13).The main motive of compression is to reduce the number of bits required to represent the original image which is assigned using compression ratio (CR).It redefines the ability of compression of an algorithm.

$$CR = \frac{\text{Number_of_bits_in_Original Image}}{\text{Number_of_bits_in_Compressed Image}} \quad (5)$$

In accomplishing the motive, compression algorithms introduce some unacceptable effects such as raise in computational complexity, propagation delay and noise. The effect of distortion can be quantified by MSE and PSNR; also they compare restoration results for the image quality. The Mean Square Error is the cumulative error between the original and the reconstructed image(14). It is a signal fidelity measure by comparing two signals that gives a degree of similarity or conversely the distortion between them. On the whole it is assumed that one of the signals is purely original and the other is distorted by errors. The value of MSE between two identical images is zero. The MSE of two signals is represented by

$$MSE(x, y) = \frac{1}{N} \sum_{i=1}^N (x_i - y_i)^2 \quad (6)$$

Often MSE refers to the error signal that is the difference between the original and the reconstructed signal.MSE computation is simple, parameter free and inexpensive computation. It involves only one multiplication and two additions for one sample. The square error can be evaluated at

each sample means independent of samples and hence memory less. It remains the standard criterion for the assessment of signal quality and fidelity; it is the method of choice for comparing competing signal processing methods and systems, and, perhaps most importantly, it is the nearly ubiquitous preference of design engineers seeking to optimize signal processing algorithms [15].In Medical Image Processing the preferred MSE is less than 2 confirming to the resolution of the original image.

PSNR is also an error metric used to compare quality of compression. It is the ratio of maximum possible power value of a signal to the power of distorting noise that influences the quality of image. In Image Processing to accurately conclude better algorithm from a set of algorithms for compression PSNR is used. PSNR is one of the parameters that can be used to quantify image quality. PSNR parameter is often used as a benchmark level of similarity between reconstructed image and the original image[16]. As PSNR is a ratio of the signals, it demands the same dimension for original and compressed image. The mathematical formula for PSNR is given by

$$PSNR=20\log_{10}(255 / \text{sqrt}(MSE)) \quad (7)$$

For lossy image and video compression the typical PSNR values are 30 to 50 dB for 8 bits depth and for higher bit depth the values increase. For distortion and noise less images the MSE is zero and PSNR is infinity. The quality measurement between original and compressed is expressed in decibels as the signals have wide dynamic range[17]. The higher the PSNR value the higher the quality of reconstructed image. In Medical Imaging the required PSNR value to be maintained is 40dB.





RESULTS AND DISCUSSIONS

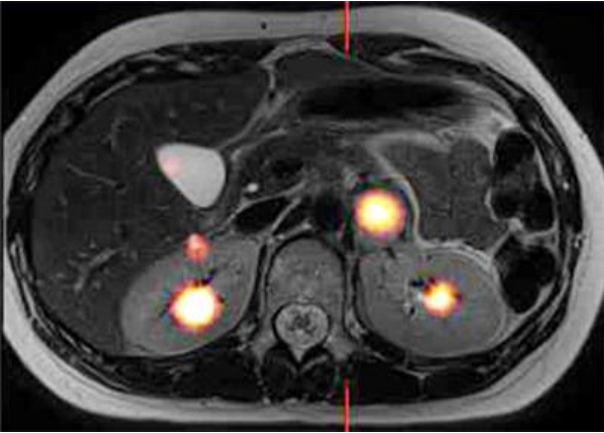
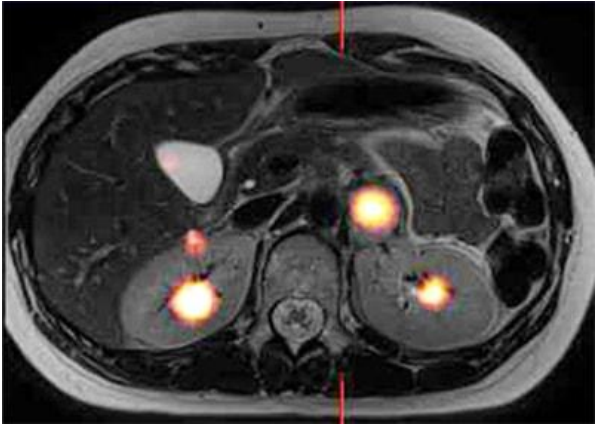


The proposed algorithm for FFT and IFFT compression for Medical Imaging has been first coded in matlab for the confirmation of the correct working of the algorithm. Followed by matlab coding the system has been coded in RTL complaint Verilog for FPGA implementation. The entire system is simulated using ModelSim and Synthesized using

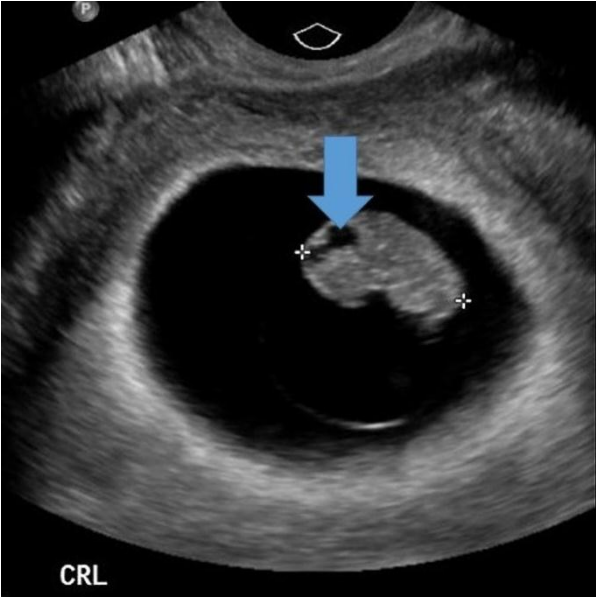
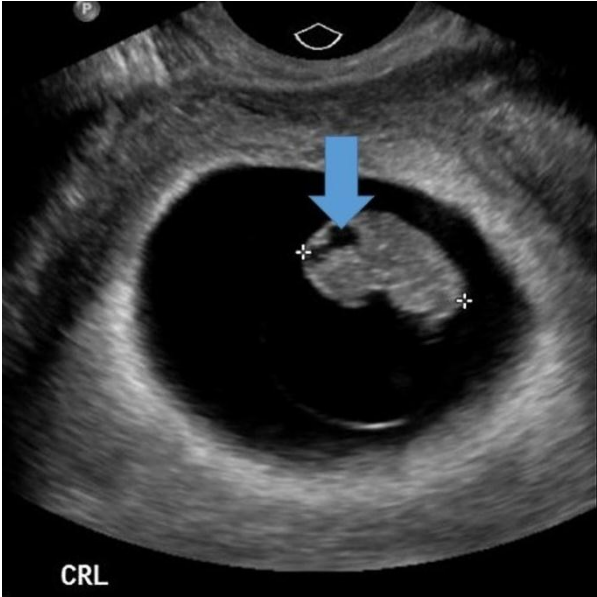
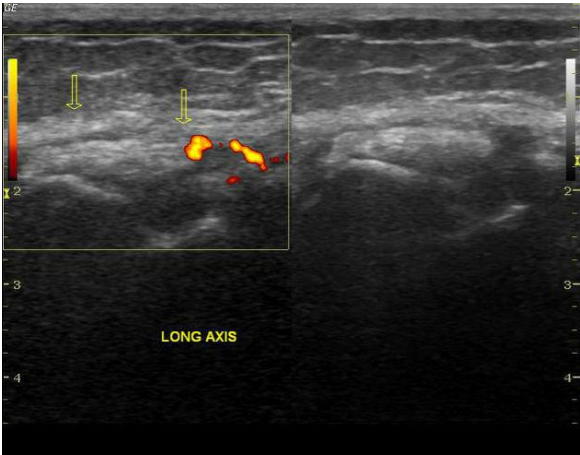
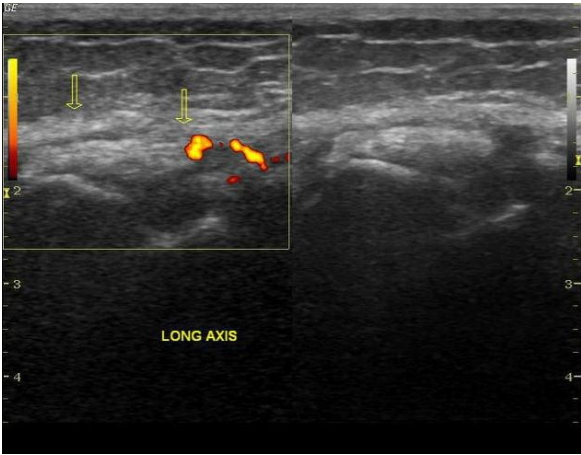
Xilinx ISE 14.5. Xilinx Spartan 6 xc6slx45-3fgg676 FPGA device is used as target board for implementation.

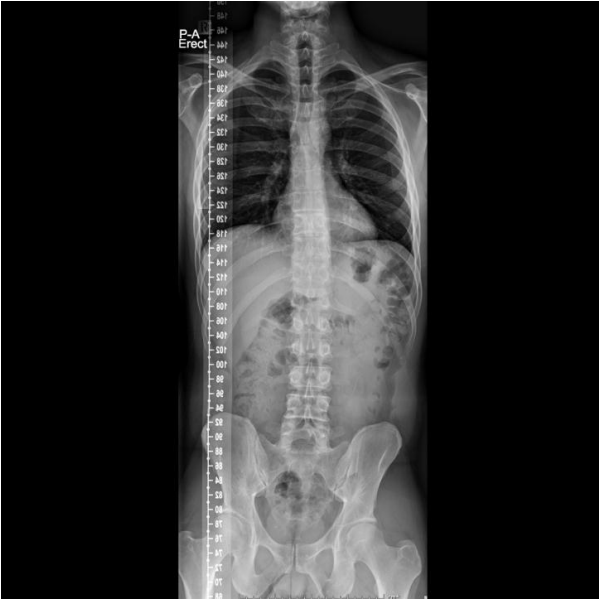
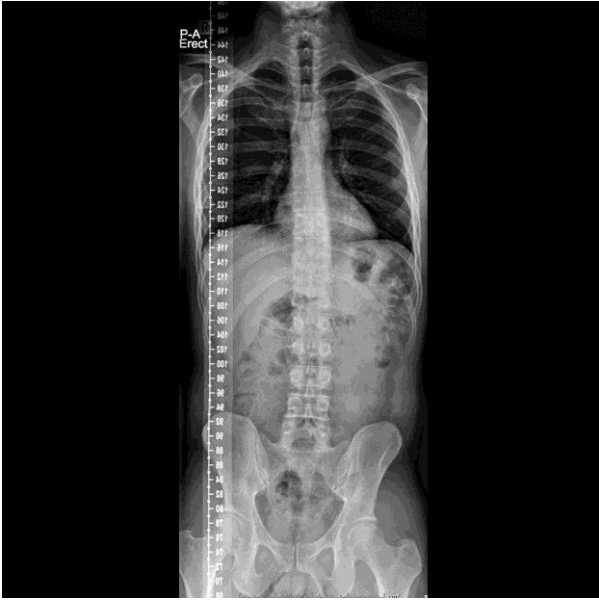

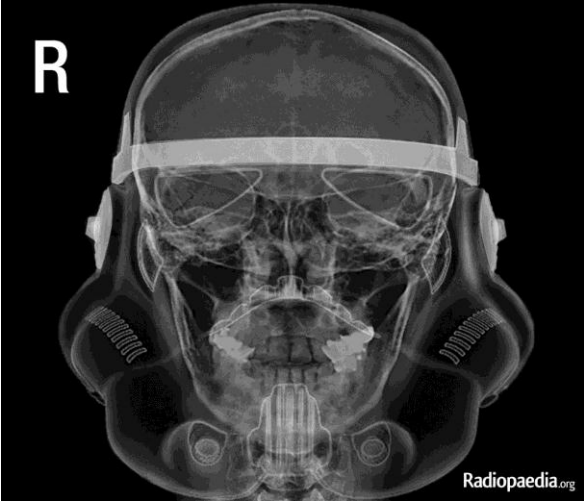
The result of the work was presented to Radiologists for their opinion on the quality of the images. It is found that they are hoping to use the technique as it has resulted in sufficient diagnostic quality of the medical images and also good compression ratio.

Table 1. Shows Original Image, Reconstructed Image and the Performance metrics/ Results of the FFT based Image compression approach for Medical images

SSl.No	Medical Images (Original Image)	Reconstructed Image
Computer Tomography Images		
1	<div><p>Abdomen Image Compression Ratio:13.54</p></div>	<div><p>PSNR:42.32 MSE:1.8</p></div>
	<div><p>Kidney Image Compression Ratio: 15.2</p></div>	<div><p>PSNR:41.24 MSE:1.4</p></div>

PET Images	
<div></div> <div>Tumor Image Compression Ratio: 14.3</div>	<div></div> <div>PSNR:43.85 MSE:1.68</div>
<div></div> <div>Leg Melanoma Image Compression Ratio: 21.8</div>	<div></div> <div>PSNR:45.86 MSE:1.45</div>

Ultrasound Images			
			
Embryonic head Image Compression Ratio: 19.89		PSNR:41.55 MSE:1.4	
			
Calcified Knee Image Compression Ratio: 11.87		PSNR:40.84 MSE:1.91	

Xray Images	
 <p>A full-length anteroposterior (P-A) X-ray of a human spine. The image shows the vertebrae from the neck down to the pelvis. A vertical scale is visible on the left side of the image.</p>	 <p>A full-length anteroposterior (P-A) X-ray of a human spine, identical to the one on the left. A vertical scale is visible on the left side of the image.</p>
Long Spine Image Compression Ratio: 21.4	PSNR:43.4 MSE:1.7
 <p>A frontal X-ray of a human skull. A white helmet is visible, covering the top and sides of the head. The text 'R' is in the top left corner, and 'Radiopaedia.org' is in the bottom right corner.</p>	 <p>A frontal X-ray of a human skull, identical to the one on the left. A white helmet is visible, covering the top and sides of the head. The text 'R' is in the top left corner, and 'Radiopaedia.org' is in the bottom right corner.</p>
Helmet stuck on Head Image Compression Ratio :15.21	PSNR:44.65 MSE:2.2

CONCLUSION

The FPGA based realization of FFT based compression approach algorithm for Medical Images using Lookup table and Huffman Coding has been presented. The FFT and its Inverse computation are achieved using real arithmetic operations utilizing the massive parallel and pipeline circuits for RTL realization. The algorithm and architecture are coded using Matlab platform and the rightness of the algorithm approach is verified.

To conforming to the RTL coding the same is coded in Verilog. The performance is measured using the Performance Metrics MSE which is around 2 proving less loss in the resolution of the original image. And the PSNR is found to be

better than 40dB proving that the original image and reconstructed images are indistinguishable. FPGA can be used for the implementation.

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