IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

IMPECCABLE MRI IMAGE COMPRESSION WITH NON-UNIFORM PARTITION AND U-SYSTEM

[1] Sr.J. Rani, [2] Dr.T. Brindha, [3] Dr.G. Glorindal [4] Dr. Ignatius A Herman4

[1] Research scholar, [2] Nooral Islam Center for Higher Education, India, [3] DMI St. John the Baptist University, Malawi
[4] Director of Education, DMI Group of Institutions, Africa

Abstract: In MRI digital images have multivariate texture complexities, there is a need for a compression algorithm that is effective in the compression of such images with improved quality of the compressed image and successfully reduced blocking artifacts. This paper gives an efficient algorithm that compresses an MRI image by dividing the image into 8×8 high texture image blocks then 16×16 low texture image blocks using image texture adaptive non-uniform rectangular partition and a transform coding blocking of different sizes which finally uses a flexible adaptive quantization scheme while considering human visual system (HSV). The algorithm discussed in this paper is more efficient than the DCT algorithm and is more tolerant to low bit rate images create the compressed image to a high quality and conquer all the potential blocking artifacts that develop with DCT algorithm image compression.

1. INTRODUCTION

In general compression concept has proven to be very important for a number of years in the 21st century which makes issues to do with storage easier rather than complicating; for example the use of mnemonics during memorization in monks which helped them to memorize a litany of prayers and chants with a technique of minimizing what they directly take in and thanks to a very specific capacity of human mentation namely, association which uses computationally weighted probabilities as a way of relating acquired data and relating it with already existing data and generating short codes which are decoded during recalling hence reconstructing the original strings of text with minimal error and giving them the capability of storing a lot of information.

Compression in problem domains dealing with data can either be lossy or lossless. Lossy compression has a noticeable amount of data is removed or discarded while reducing the size of the given data and lossless compression involves reducing the size of data while making sure that the original data and the compressed data is as identical as possible in terms of its attributes.

Since the origin of computers an increased necessity for reducing space of files stored in computers was an inevitable, complex and an intractable challenge that was to be solved until computer scientists turned back to the once forsaken compression techniques, only that this time they were more formal including being syntactically and semantically coherent due to the usage of mathematics which is logical in nature. This has been an issue in multimedia and a lot of wonderful solutions have been developed while ostracizing the medical field which suffers greatly from unnecessary storage consumption if the data is stored in a softcopy format. Due to the vast field of medical technology this paper only concentrates on MRI images which is mentioned above, DICOM files are used, and they occupy spaces a large as 65MBs hence image compression is a necessity. A facsimile in principle of MRI image compression need is photo shooting in which there is a need of identifying regions of interest hence preserving information on the areas of interesting which discarding other information on other areas. Medicine being a very critical field, errors cannot be tolerated henceforth thorough research should be conducted to make sure that no important information is left out and to make the system more reliable. Given the number of abbreviated terminologies used, below is a table that shows the abbreviations and there corresponding meaning:

Abbreviation	**Meaning**
APDT	All-phase digital filter
CR	Compression Ratio
DCT	Discrete Cosine Transforms
DICOM	Digital Imaging and Communications in Medicine
HVS	Human Visual System
ITANRP	Image Texture Adaptive Non-Rectangular Partition
JPEG	Joint Photographic Expert Group
MRI	Magnetic Resonance Imaging
MSE	Mean Square Error
PSNR	Peak Signal to Noise Ratio
RMSE	Root Mean Square Error
SSIM	Structural Similarity Index Measure

Table 1: Abbreviations and corresponding meaning.

2. LITERATURE SURVEY

Technologically in today's world to get going, people use computers and reliance of computers, continue to increase as much as the population is increasing, causing our need for efficiently storing humongous amounts of data increase because the storage space consumption of data and bandwidth is very high which creates a need to increase the storage consumption of data before transmission and storage is done because the world is interconnected and computational storage devices have become inevitable for individuals and organizations to be owned [1]. For example, someone with a website or an online catalog that uses a lot of images will be more than likely to use some image compression technique to store the respective images because the required amount of space for storage will take a little amount of time to be exhausted and images can be intolerably large with respect to cost. Several methods of the compression of images are available today [2]. They are two general categories namely: lossless and lossy image compression techniques. Compression reduces the fidelity of an image, especially when the image compression happens at lower bit rates. The reconstructed images have degraded quality and loss of some artifacts if the compression ratio is high [3].

When there is a need to have a good compression together with a high-quality reconstructed image DCT is the right technique to use. A discrete cosine transforms (DCT) expression of a sequence of finite multiple data points consisting of a sum of cosine functions which are oscillating at different frequencies [4]. The JPEG process is widely used since compression that centers on the Discrete Cosine Transform is very efficient in lossy image compression whereby. DCT and Fourier transforms involves the conversion of images into decor relate pixels from frequency domain [5]. Reversibility is one of the properties of DCT due to separating images into parts of differing frequencies which have the capability of being reconstructed again [6]. From the step called quantization, compression occurs such that less important frequencies are gotten rid of, hence the use of the term lossy and the most important frequencies only remain in use in order to be converted into the next possible larger power of two, including the size of arrays that are consequently initialized. Haar wavelet transform which separates an image into either high or Low frequency parts or components. In the first cycle, the transformation algorithm is first run along the ROW whilst the second cycle, transformation algorithm runs along the columns such that the individual results are combined to make a compressed image.

According to V. Mishra et Al [7], bi-orthogonal wavelet is a type of orthogonal wavelet transform that has a property of symmetry in its filter making functions used in the transform to be easier and the calculation algorithms to be maintained. Every part of an image that falls out of the segment is zero in value making the information on that region falling out of the segment to be lost. Biorthogonal wavelet transform has two different scaling function that might generate different multiresolution analysis result depending on an image and at the same time generating two different wavelet functions.

In this paper a method that deals with hybridized image compression algorithm that uses Image Texture Adaptive Rectangular Non-Uniform Partition (ITANRP) and flexibly use a coding system based on U-system and all-phase digital filter.

3. SYSTEM IMPLEMENTATION

3.1 PROPOSED WORK

The objective of this paper is to improve the quality of compressed images and suppress blocking artifacts by improving the JPEG image compression model at low bit rates. First, the image texture adaptive non-uniform rectangular partition (ITANRP) algorithm is proposed which partitions the image into 8×8 size image blocks with high texture complexity and 16×16 size image blocks with low texture complexity. Then, a new transform coding based on the complete orthogonal U-system and all-phase digital filter (APDF) is proposed for coding image blocks with different sizes. Next, a flexible adaptive quantization scheme is designed to quantize image blocks with different sizes by considering the sensitivity of the human visual system (HVS) to different texture complexities.

Finally, combining the above method with the JPEG model, a novel image compression algorithm model with low algorithm complexity is proposed to solve the problem in JPEG. The experimental results demonstrate that the performance of our algorithm model outperforms the JPEG image compression algorithms, the quality of the compressed image is greatly improved, and the blocking artifacts are also significantly suppressed.

3.2 SYSTEM ARCHITECTURE

The diagram below shows the complete system of how the ITANRP algorithm works during the compression of an MRI image:

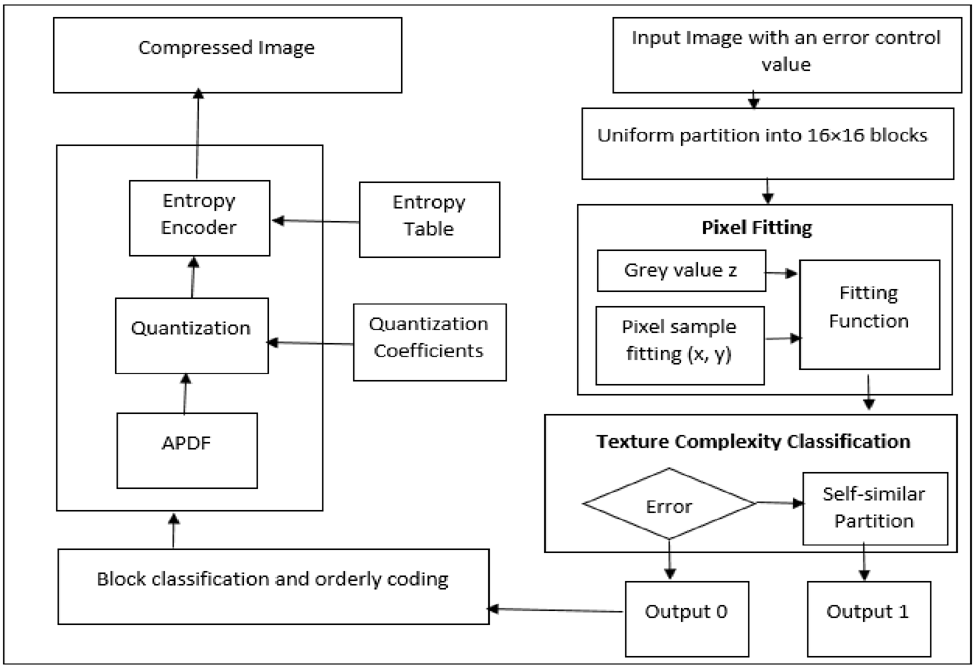

Figure 1: Image compression using ITANRP and APDF in MRI images

3.3 SYSTEM DEVELOPMENT

3.3.1 SYSTEM FLOW DIAGRAM

This given a generalized sequence of how the system will function from one module to the other, and conditions included during the process of MRI digital image compression.

Give this input image:

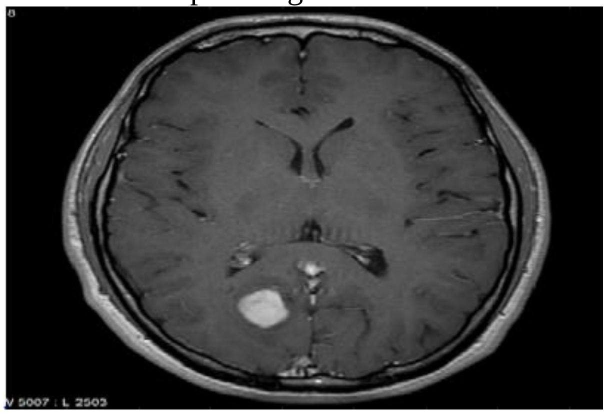

Figure 2: Input Brain MRI Image

The data flow diagram is given below:

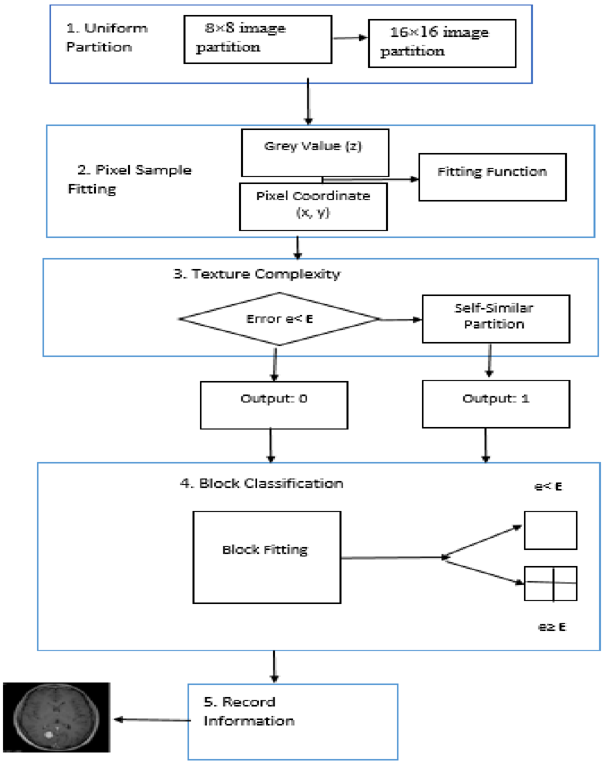

Figure 3: Data flow diagram

3.4 ALGORITHMS

3.4.1 **UNIFORM RECTANGULAR PARTITION:** An original image serves as an input from which is partitioned into 8×8 high texture non-overlapping image blocks then 16×16 low texture non-overlapping image blocks using image texture adaptive non-uniform rectangular partition (ITANRP).

3.4.2 **PIXEL SAMPLE FITTING:** Analysis of an image block at a time recursively is done on a generated 16×16 image and a gray scale (Z), a set of rows (X) and a set of columns (Y) and below are the sets:

$$X = \{\chi_0, \chi_1, \chi_2, \dots \chi_{k-1}, \}$$

$$Y = \{y_0, y_1, y_2, \dots y_{k-1}, \}$$

$Z = \{z_{0,}\ z_{1,} z_{2,}\ \dots z_{k-1,}\}$

The fitting data X, Y, Z sets and the polynomial regression function is the fitting function which is algebraically represented as z= ax + by + c which is directly associated with a set of coefficients A. Finally, a root mean square error (RMSE) is calculated using least-squares method (LSM).

3.4.3 **TEXTURE COMPLEXITY CLASSIFICATION:** Error control value ε together with the root mean square error (e) to calculate the texture complexity, such that, when e is less than ε the block is of low texture denoted by 0 while if e is great than ε the block is of a high texture complexity denoted by 1.

Below are the equations associated with the processes above:

$$z = ax + by + c$$

$$Z = \begin{bmatrix} z_0 \\ z_1 \\ \dots \\ z_{k-2} \\ z_{k-1} \end{bmatrix},\ G = \begin{bmatrix} x_0 & y_0 & 1 \\ x_1 & y_1 & 1 \\ \dots & \dots & \dots \\ x_{k-1} & y_{k-1} & 1 \end{bmatrix}$$

$$A = [abc]^T$$

$$e = RSME = \frac{1}{k}\sqrt{\sum_{p=0}^{k-1}[z_p - z_p]^2}$$

3.4.4 **BLOCK CLASSIFICATION AND ORDERLY CODING:** The low texture blocks and high texture blocks are combined in a series of bits, 0 for low texture and 1 for high texture and they are ordered from left topmost block through the right bottom most block.

3.4.5 **ALL-PHASE DIGITAL FILTER:** Specifically, this digital filter is called all phase U of degree 3 (APUBT3) which is an adaptive flexible coding technique used instead of DCT for transform coding of non-uniform rectangular partitions using four polynomial piece wise functions which are of the first function. The Walsh function which is the all phase U function of degree 0 and the functions are used iteratively to analyze the blocks of data and in order to suppress all the high frequency parts which results in the suppressing of all blocking artifacts using a quantization coefficient.

3.4.6 **ENTROPY ENCODING:** all the high frequency blocks (high texture complexity) of the image are further partitioned into smaller blocks hence generating low frequency image blocks. Then the blocks are compressed and connected to reconstruct a fully compressed image.

3.5 SYSTEM DEVELOPMENT

3.5.1 INPUT IMAGE:

This involves clicking the select image button to select an image of a chosen file format but if the format is not in the specified formats an error message is given to the user as a popup notification. An image that is selected, is displayed on the user interface waiting for the next user to specify decomposition and threshold. In total 120 sample MRI brain images were used.

3.5.2 PROCESS OF IMAGE:

During processing, a path of choice of a compression technique is chosen remotely and automatically by the system, this is the ITANRP technique after clicking the link compress button whereby the image is divided into non-uniform regular partitions after 16×16 uniform partition and later transform coding of an image using all-phase digital filter in order to get a compressed image.

3.5.3 **DISPLAY OF IMAGE:**

When an image is displayed it involves expanding the compressed image in increasing the scale by a factor of 4. When the image is expanded it is diminished either visually or through the use of parameters that are displayed on the screen and the parameters include: PSNR, CR and MSE.

4. RESULT AND DISCUSSION

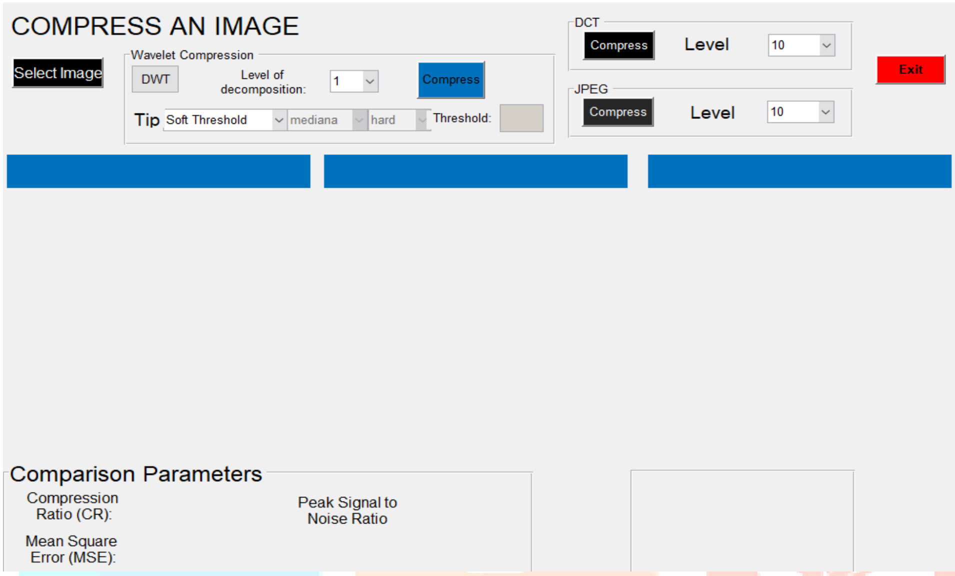

Figure 3: The Matlab interface of a software for the MRI image compression after just opening the software

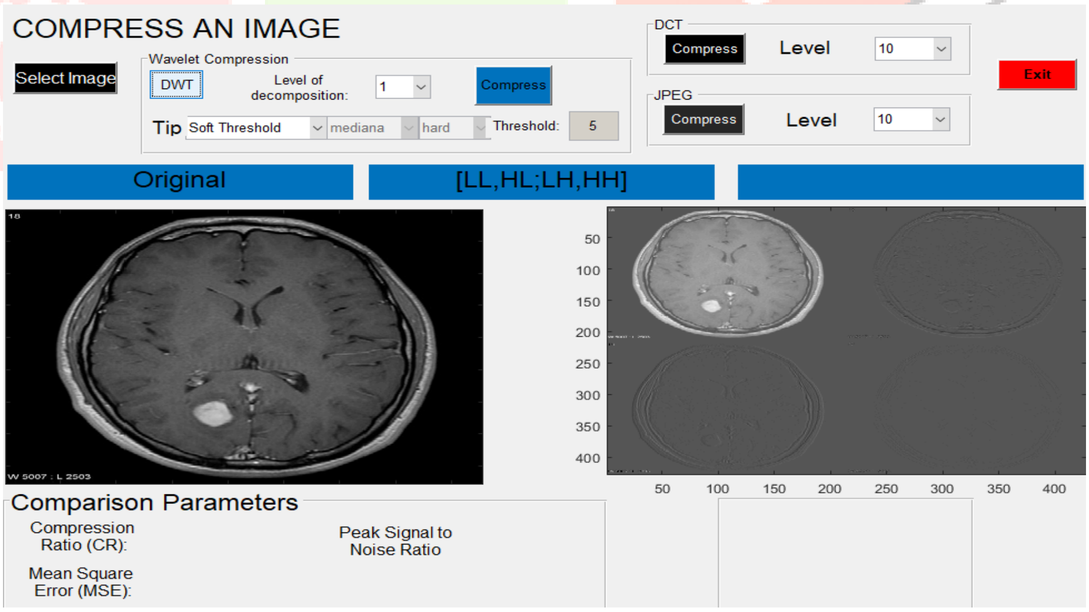

Figure 4: The Matlab interface of a software for the MRI image compression after selecting an image and choosing the compression algorithm

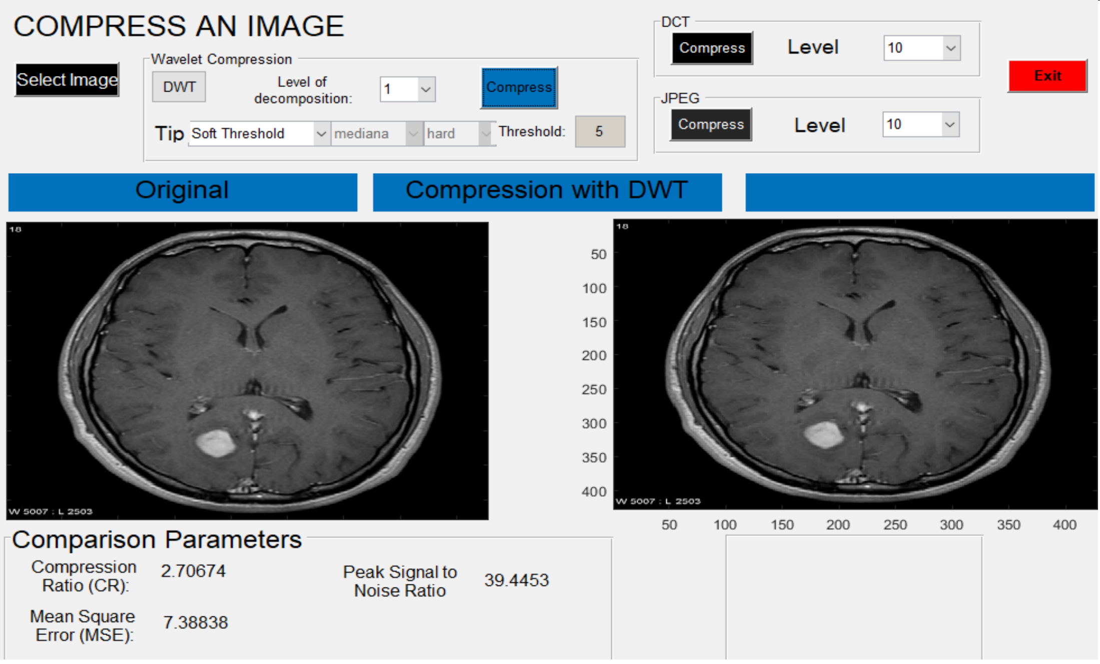

Figure 5: The Matlab interface of a software for the MRI image compression

TABLE 1 FOR COMPUTATIONAL TIME FOR ITANRP ALGORITHM GIVEN A PREDEFINED ERROR CONTROL VALUE

Error control value (ε)	MRI Brain Images	
	MRI Brain image with tumor (Seconds)	MRI Brain image without tumor(seconds)
0.4	0.0320	0.0338
0.6	0.0307	0.0325
1.0	0.0326	0.0344
1.5	0.0350	0.0311
2.5	0.0328	0.0322

98 brain MRI images dataset was collected from https://www.kaggle.com/navoneel/brain-mri-images-for-brain-tumor-detection of 209 ×212pixel dimensions and one image from each of the sub datasets with and without tumors were selected because the overall image texture complexity differs. From the experiment the computation time for the images differed due to the error control value and inherent overall difference in texture complexities of the images. From the table above the following graph is extrapolated:

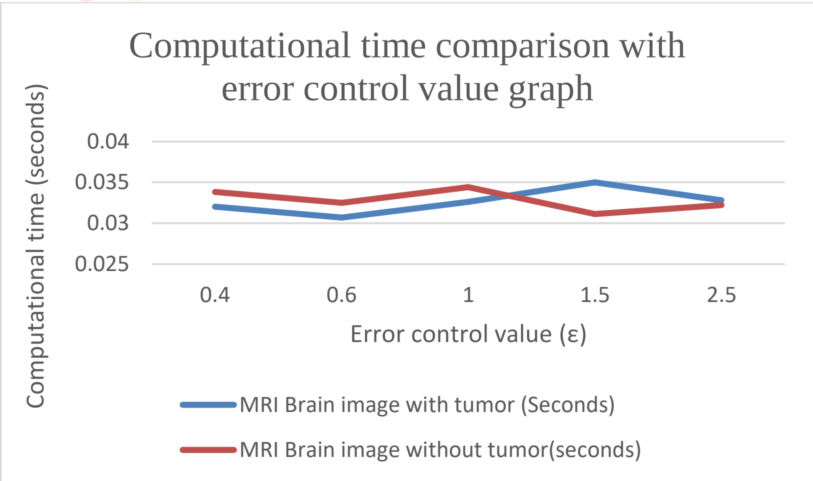

Figure 6: Graph showing computational time comparison with error control value graph

The figure 6 above shows the relationship between computational time and error control value of MRI images with or without a tumor. MRI brain images with a tumor have a low overall texture complexity as compared to MRI brain images with a tumor.

MRI images with a tumor project the ITANRP algorithm to take more time in computation when the error control value is high and less time when the error control value is low because the higher the error control value the more accurate an image is to be compressed to preserve most of the features on the image.
On the contrary when the error control value is low, ITANRP algorithm take a very small time in partitioning the image because there is no need for the image features to be preserved hence reducing the computational time for execution.

TABLE 2 FOR SAMPLE RESULTS AND PARAMETER COMPARISON

ALGORITHM	DCT				ITANRP			
Bit rate (bpp)	CR	MSE	PSNR	SSIM	CR	MSE	PSNR	SSIM
0.2881	6.3	9.2461	31.6661	0.8615	5.1	6.7771	31.6283	0.863
0.2337	6.7	2.8346	30.309	0.8301	5.3	1.7999	30.3678	0.8336
0.1947	7.1	0.0692	28.8885	0.7882	5.6	0.0052	29.0987	0.7997
0.1561	7.3	3.3836	26.7859	0.7232	5.8	2.2212	27.5358	0.7514
0.1407	7.5	9.9099	25.4773	0.6961	5.9	6.37	26.5003	0.7125

Table 2: Parameter comparison between DCT and ITANRP

GRAPHS OF COMPARISON BETWEEN ITANRP AND DCT ALGORITHM

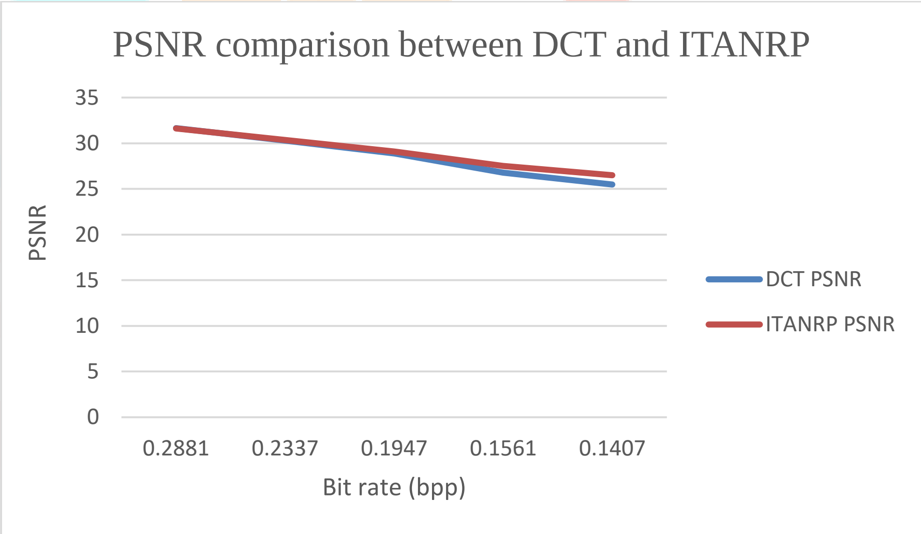

Figure 7: Graph showing comparison of PSNR between DCT and ITANRP algorithms

The figure above (Figure 7), the graph shows that the more the noise the less the PSNR in ITANRP hence reducing blocking artifacts hence making it better than DCT due to the slight variations in the values showing that the ITANRP algorithm has a higher PSNR values despite have closer to similar values at higher bit rate values and big differences are noted in areas of low bit rate images (which are images of a low quality). From this graph it shows that the importance of ITANRP algorithm over DCT images when the bit rate of images is lower

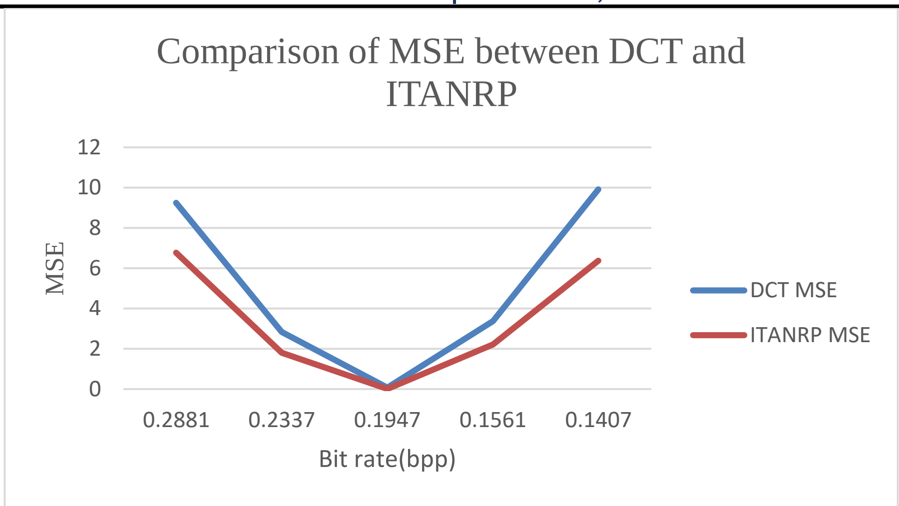

Figure 8: Graph showing comparison of MSE between DCT and ITANRP algorithm

Figure 8 shows the difference for Mean Square Error (MSE) from the ITANRP algorithm and the DCT algorithm have a parabolic graphical representation of the information making the Mean Square Error have minimum and maximum MSE values which according to the figure ranging from 0 to 10. From the figure 6 the DCT algorithm graph is higher than that of ITANRP algorithm, making ITANRP algorithm is better and highly performing the tasks of image compression with minimal errors as compared to DCT algorithm.

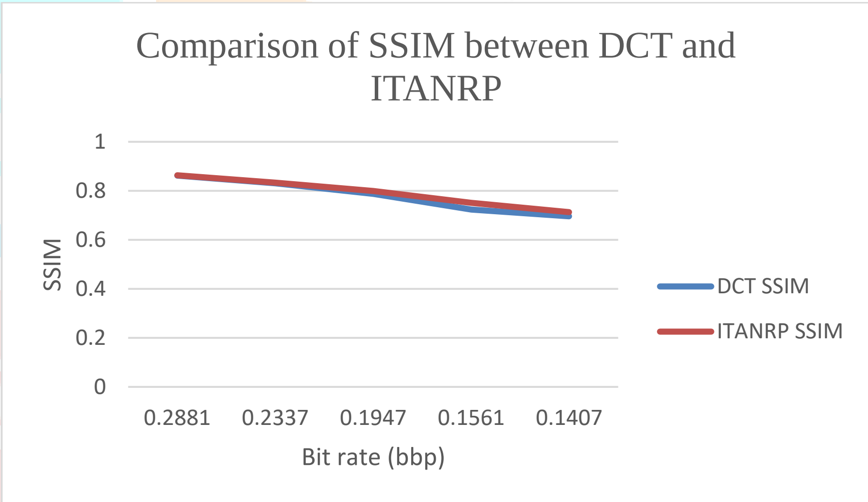

Figure 9: Graph showing comparison of SSID between DCT and ITANRP algorithms

Structural Similarity Index Measurement (SSIM) is compared between ITANRP algorithm and the DCT algorithm. From the original image the ITANRP algorithm has higher SSIM values than DCT algorithm hence making the compression effect only noted with the decrease in size of the image but not with the Human Visual System (HVS).

MRI brain image dataset description

The MRI brain image dataset was used in the testing of the algorithm and the results were very consistent with the theoretical and hypothetical analysis with a very small degree of variation since other high-quality image did not have a high compression ratio since they had a low texture complexity. The ITANRP has a low CR as compares to the DCT because it does a good job in non-regular partitioning of both high texture and low texture blocks on an image thus the degree of decomposition of an original image is not distributed evenly across the blocks hence reducing blocking artifacts which could have been produced in DCT image compression.

From the datasets that were used and there was some skewness in the graphs causing some variation of the values of the parameters between ITANRP algorithm and DCT algorithm when the bit rate of the original image is low but when the bit rate is high variation is very low.

Properties of the dataset:

a. **Bit rate:**
The images are grouped in three main bit rate. Image groups were presented using a range of bit rate values and the groups involve: High bit rate images which have the bit rate greater than 2.0bpp (bits per pixel), moderate bit rate ranging from 1.9bpp to 1.6bpp and finally the low bit rate images which are less than 1.6bpp.

b. **Texture Complexity:**
The images also had the texture complexity property with two main types which are high texture complexity images (MRI brain images without tumor) and low texture complexity images (MRI brain images with tumor).

c. **Grey Scale Images:**
All the images are gray scale in nature because no contrasting is needed and since when an image is compressed the resulting image is grey scale.

d. **Image format:**
There are three main formats of the image that were used and these involved PNG, JPEG and SVG images.

5. CONCLUSION

Given the problems associated with compression of MRI images to ensuring preservation of areas of interest the image texture adaptive non-uniform rectangular partition is used to increase the quality of the compressed image while reducing blocking artifacts hence achieving the higher quality of the images when it comes to doctors having the capability of diagnosis of MRI brain images. This project achieves the higher results by partitioning higher texture images from lower texture images and quantifying the blocks using all-phase digital filter hence achieving a higher quality compressed image with without blocking artifacts.

6. FUTURE ENHANCEMENT

The purpose of making the strongest algorithm, the ITANRP algorithm will be combined with DCT algorithm so as to have two advantages combined, since the DCT algorithm is good at compressing images of a high bit rate while the ITANRP algorithm is good at compressing images of a lower bit rate hence making the algorithm high performing than most of the existing algorithms while maintaining the quantifying algorithm as the APDT.

7. REFERENCES

1 Hermina Alajbegović, 2009“Image Compression Using the Haar Wavelet Transform”.
2 S.S.Tamboli, 2013 "Image Compression Using Haar Wavelet Transform".
3 P.Raviraj, 2007 “ The Modified 2D-Haar Wavelet Transformation in Image Compression”.
4 Colm Mulcahy, 2007 "Image compression using the Haar wavelet transform".
5 Kamrul Hasan Talukder, 2007"Haar Wavelet Based Approach for Image Compression and Quality Assessment of Compressed Image".
6 Telagarapu P., Jagan N.V. 2011 “Image Compression Using DCT and Wavelet Transformations”.
7 Rajesh K. Yadav, S.P.Gangwar, 2012“Study and analysis of wavelet based image compression techniques”.
8 Sonja Grogic, 2001 "Performance Analysis of Image Compression Using Wavelets".
9 S.M.Ramesh and Dr.A.Shanmugam “Medical Image Compression using WaveletDecomposition for Prediction Method”, IJCSIS, 2010, Pp 262-265.
10 V. Mishra, A. Kumar, A. K. Jaiswal, 2015 “Performance comparison of Daubechies, Biorthogonal and Haar Transform for Grayscale Image Compression”.
11 M. Beladgham, A. Bessaid, A. M. Lakhdar, A. T. Ahmed, 2011, “Improving Image Compression Using Biorthogonal CDF Wavelet Based on Lifting Scheme and SPIHT”.

12 G.Pau: Advanced Wavelets and Space-time Decomposition : Application to Video Coding Scalable, Phdthesis, National School of Telecommunications, Paris, 2006.

13 Savakis, R.Carbone: Discrete Wavelet Transform Core for Image Processing Applications, Real-time ImagingIX, SPIE-IS & T Electronic Imaging, San Jose, CA, USA, SPIE Vol.5671, Jan.2005, pp.142–151.

14 Daubechies, W.Sweldens: Factoring Wavelet Transforms into Lifting Steps, Journal of Fourier Analysis and Applications, Vol.4, No.3, May1998, pp.247–269.

15 P. S. A. Kumar: Implementation of Image Compression Algorithm using Verilog with Area, Power and Timing Constraints, Master Thesis, National Institute of Technology, Rourkela, India, 2009.

16 Z. Wang, A. C. Bovik., H. R. Sheikh, E. P. Simoncelli: Image Quality Assessment: From Error Visibility to Structural Similarity, IEEE Transactions on Image Processing, Vol.13, No.4, April 2004, pp.600–612.