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Compression of Medical Images Based on 2D-Discrete Cosine Transform and Vector Quantization Algorithms

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Abstract: In this paper, two types of Medical images which were collected from CT scan and Ultrasound system in order to reduce the number of bits needed to represent a medical image with preservation of image quality. Medical imaging has a great impact on diagnosis of diseases and preparation to surgery. On the other hand, the storage and transmission is an important issue due to massive size of medical image data. For example, each slice of CT images is 512 by 512, and the data set consists of 200 to 400 images leading to 150 MB of data in average .An efficient compression of the medical data can solve the storage and transmission problem. Medical images are compressed using proposed algorithm that includes two techniques which are discrete cosine transform DCT and Vector Quantization VQ. The paper started from collecting Medical images, and developing compression algorithms by DCT-QV using MATLAB and evaluate the performance of these techniques by measuring the difference between the original image and compressed images using Peak Signal to Noise Ratio PSNR, mean square error MSE, compression ratio CR, and bit per pixel BPP and. Experimental results show that proposed algorithm produces a high quality for compressed images with acceptable compression rate in terms quantization level is more than 30%.

Keywords: (PSNR, JPEG, DCT, Compression Ratio, CT)

Introduction

With the improvement of medical imaging facilities, a growing amount of data is brought out in the modern image processing, and it leads to an increasingly heavy burden for data storage and transmission. Image compression is a technique of reducing the redundancies in image and represents it in shorter manner, which can allow more cost-effective utilization of network bandwidth and storage capacity. Therefore, the medical image compression plays an important role in many applications. In the past decades, numerous and diverse image compression methods have been proposed to compress the digital images [1]. Digital image are generally characterized by three types of redundancies: spatial redundancy, coding redundancy and psych visual redundancy. The compression algorithms exploit these redundancies to compress image. Spatial redundancy represents a fact that grey value of one pixel may be partially calculated by values of other pixels. The coding redundancy also called statistical redundancy refers to the use of variable length code to match the statistics of the original image. Psych visual redundancy is based on the human perception of the image information. Removing psych visual redundancy introduces distortion in uncompressed images, so this step is skipped during lossless image compression. Image compression can be classified as lossy and lossless. In lossy compression scheme, there is loss of information. And encoding is achieved with an acceptable degree of deterioration in the reconstructed image, with a high compression ratio, such as JPEG, JPEG2000. But lossless scheme is reversible and this represents an image signed with the smallest possible number of bits without loss of any information, and the compression ratio achieved is low JPEG2000. Applications like satellite image compression, medical image compression where any loss in data may lead to incorrect prediction or diagnosis, lossless compression methods are used. Lossy compression methods are used for compressing general purpose digital images where minor loss of data is no hindrance. Here we proposed compression method based on a frequency transform that is able to compress Medical image which is DCT-VQ. This transform contains unique features which allow for the creation of an efficient image compression. The main edge of image transformation using DCT-VQ is the elimination of redundancy between neighbour pixels. Efficiency or performance of the transformation scheme can be directly measured by its ability to array input data into as few coefficients as possible [1, 2].

Transform Coding

In transform coding, a reversible linear transform is used to map the image into a set of transform coefficients, which are then quantized and coded. The decoder is just reverse of the encoder. A typical transform coding system has four steps which are Decomposition of image into sub-images, forward transformation, quantization, and coding. An N x N image is subdivided into sub images of size n x n (mostly 8 x 8), which are then transformed; so as to collect as much information into a smaller number of transform coefficients. The quantization then quantizes the coefficients that contain the least information. The encoding process ends with the coding of the transformed coefficients. The most famous transform coding systems are Discrete Cosine Transform (DCT) .Transform Coding are preferred over all the transform coding techniques as it involves less number of calculations. The standard presently accepted, created by the Joint Photographic Experts Group (JPEG) for lossy compression of images uses DCT as the transformation

JPEG Image Compression

Joint Photographic Expert Group (JPEG) image compression is an accepted technology. JPEG is a modern lossy/loss-less compression technique for colour or grey scale static images. In a case where there are neighbouring similar coloured pixels, this compression works well on continuous tone images. JPEG utilizes many parameters to in order to enable the users to manipulate the amount of information lost (and in this way likewise the compression ratio) over a very wide range.

DCT Computation

DCT is a computationally intensive algorithm which takes several electronic applications. DCT is a mathematical transformation that converts the data in the space or time domains to the frequency domain providing a close version of the signals with fast transmission, memory saves and many more. This algorithm is known to be exactly efficient due to its regularity and simple ability. Several DCT coefficients which are located in the frequency domain is a converted version of a DCT-2D pixel values a spatial image in the region. The image data inside the storage is distributed into some blocks MCU (minimum code units) before compression. Each block comprises of 8x8 pixels [2]. Some of the compression processes plus DCT-2D inside it will be carried out on every block. Each pixel value in the 2-D matrix is a value in the range of 0 to 255 for the intensity or luminance values and the range of -128 to + 127 for the chrominance values. Before DCT is computed, all the values are moved to the range of -128 to +127. The average of every (64) values in the matrix is [DC] coefficient and the value are in the transformed matrix location F[0,0] while the remaining values(63) are known as the AC coefficients which contains a frequency coefficient associated with them. Furthermore, spatial frequency coefficients increment as it move amongst left and right (on a level plane) or between start to finish (vertically). Low spatial frequencies are grouped in the left top corner. Moreover, DC coefficient and the lower spatial frequency coefficients and the DC coefficient are responded to by the human eye. Besides, the eye will not detect the frequencies if a higher frequency coefficient magnitude reaches a certain low threshold.

The two dimensional DCT can be expressed as the following equation which is F (u,v) .

$$\frac{4}{N^2}\alpha(u)\alpha(v)\sum_{x=0}^{N-1}\sum_{y=0}^{N-1} f(u,v).\cos\left(\frac{(2x+1)u\pi}{2N}\right).\cos\left(\frac{(2y+1)u\pi}{2N}\right) \quad (1)$$

The two dimensional inverse DCT is given by *f(x,y)*

$$\sum_{u=0}^{N-1}\sum_{v=0}^{N-1}\alpha(u)\alpha(v)\,F(u,v).\cos\left(\frac{(2x+1)u\pi}{2N}\right).\cos\left(\frac{(2y+1)u\pi}{2N}\right) \quad (2)$$

Where:

*F(u,v)*and *F*: coefficient values in the transform domain.

*f(x,y)*and *f*: coefficient values in the spatial domain.

x,y: spatial coordinates in the pixel domain.

u,v: coordinates in the transform domain.

$$\alpha(u),\alpha(v)=\begin{cases}1/\sqrt{2} & \text{for } u,v=0\\ 1 & \text{for } u,v=1,2,\ldots,N-1\end{cases} \quad (3)$$

Equation (1) shows that the two dimensional DCT is derived by multiplying the horizontal one dimensional basis function with the vertical one dimensional basis function. Both one and two dimensional DCT works in similar approach [3].

Vector Quantization

Quantization is the manner by which visual data are carefully disposed without a major lack in the visible effect. Quantization helps to decrease the number of bits that is used to represent an integer value for the purpose of reducing the precision of the integer. Every component of the DCT is divided by different quantization coefficient also gathered together to an entire whole integer value step in the JPEG compression algorithm to evacuate a lot of data, this however lessens the entropy of the info streams of data. Quantization helps the compression process because of it lossy compression technique. Each nonzero AC coefficient in the intermediate symbol sequence is denoted by combining with the "run - length" (succeeding number) of zero-valued AC coefficients that go before it in the zigzag sequence [2]. Image compression contains standard quantization matrices that changes in every stage and quality that allows the user to determine on the level of quality that ranges between 1 to 100, where the lowest image quality is 1 and maximum compression 100 gives the finest quality and lowest compression. Due to this reason, quality/compression ratio can be designed according to purpose or requirement. From fig.1. It is good to note that quantization matrix that has a quality level 50 can produce a very good compression and tremendous decompressed image quality.

$$Q50 = \begin{bmatrix} 16 & 11 & 10 & 16 & 24 & 40 & 51 & 61 \\ 12 & 12 & 14 & 19 & 26 & 58 & 60 & 55 \\ 14 & 13 & 16 & 24 & 40 & 57 & 69 & 56 \\ 14 & 17 & 22 & 29 & 51 & 87 & 80 & 62 \\ 18 & 22 & 37 & 56 & 68 & 109 & 103 & 77 \\ 24 & 35 & 55 & 64 & 81 & 104 & 113 & 92 \\ 49 & 64 & 78 & 87 & 103 & 121 & 120 & 101 \\ 72 & 92 & 95 & 98 & 112 & 100 & 103 & 99 \end{bmatrix}$$

Fig. 1:Quantization Matrix

Zigzag Scan

The sequential zeros that occurs within each and every block are exploited with zigzag pattern. It normally start increasing from low-frequency to high frequency terms and the quantization will probably remove high frequency term in the quantization stage. This process will generally produce a more compressed output by positioning entropy for more order. The lower frequency components depict the steady luminance variations and are essential to the human visual system than the high frequency changes since human eye cannot note changes in higher frequency components. More zeros are expected to run after the quantization process where the important coefficients in the order of 8x8 blocks can be expected towards the end of the 8x8 block to enable more compression in the entropy [4]. Figure.2 displays the zigzag pattern. Data of 64 addresses that are organized in a zigzag pattern.

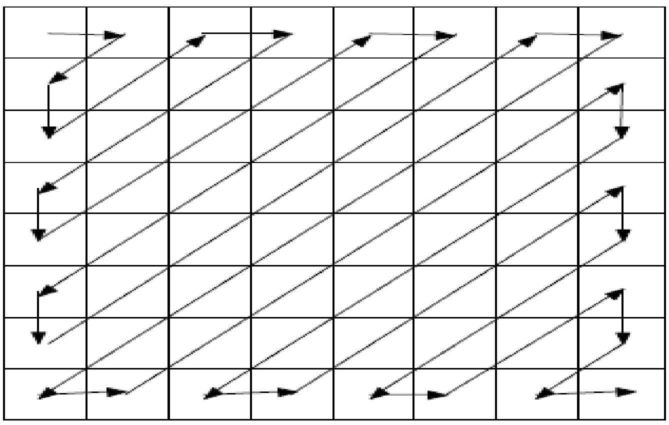


Fig. 2: Zigzag-sequence

Run Length Encoding RLE

RLE is used to encode the zero values contained in the AC coefficients by retaining the omitted value and this are the number of zeros and the next non-zero component.

Experimental Procedures

The Compression algorithm for medical image compression based on the DCT-VQ implemented using MATLAB is given in the following steps as the figure

1. Load the original image into MATLAB.
2. split the image into 8x8 blocks of pixels.
3. Process a DCT on every pixel block from left to right, Top to bottom
4. Then quantize each block of DCT coefficients using weighting functions in order to optimize for the human eye.
5. Differentiate the DC and AC coefficient.
6. Encode the resulting AC coefficients (image data) of Zig-Zag Scan using a RLE Encoding

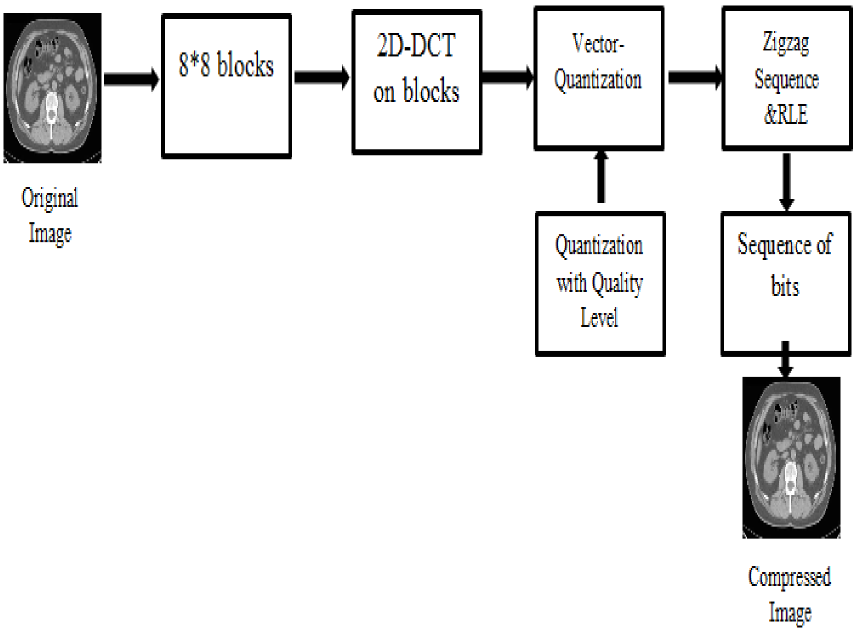


Fig. 3: The proposed algorithm of medical image compression

Implementation of Algorithm

Firstly the proposed algorithm is modelled and verified using MATLAB code as shown in the figure 4. Compression and reconstruction is performed and the performance is measured using several standard measurements for compression algorithm such as PSNR, MSE, CR, and BBP which are introduced in next topic.

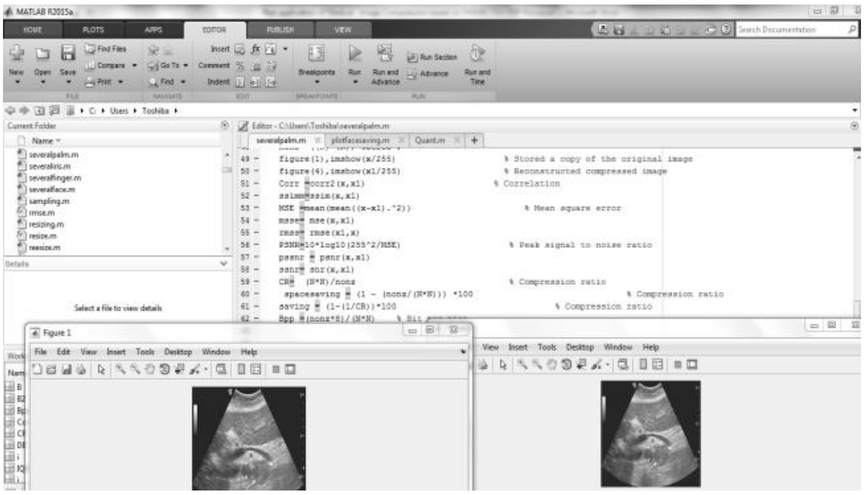


Fig. 4: Implementation proposed algorithm on MATLAB environment

Image Quality Assessment Methods

Objectively, four most significant similarity measures are employed to compare the image that reconstructed after the process of compression algorithm with the actual image. It starts with the measure of PSNR and the next step is the measure of MSE whiles the third step and fourth step are the BBP and compression rate.

1. **Peak Signal to Noise Ratio**

PSNR measures the estimates of the quality of reconstructed image compared with the original image and is a standard Way to measure image fidelity. The PSNR can be evaluated as:

$$PSNR = 20log_{10}\frac{255}{RMSE} \qquad (4)$$

2. **Mean Square Error**

The MSE is the cumulative squared error between the compressed and the original image. This metric is applied as:

$$MSE = \frac{1}{NM}\sum_{i=1}^{N}\sum_{j=1}^{M}\left(I_o(i,j) - I_{rec}(i,j)\right)^2 \qquad (5)$$

$I_{original}$ is the original image before the compression process and $I_{reconstructed}$ is the image after applying DCT algorithms and MxN is size of image , A lower value of MSE signifies lesser error in the reconstructed image.

3. **Compression measures**

The basic measure of the performance of a compression algorithm is the compression ratio *(Cr)* and is defined by equation.

$$\text{Cr} = \frac{\text{original data size}}{\text{reconstrucated data size}} \qquad (6)$$

The higher the value of the compression rate will be worst image quality and vice versa.

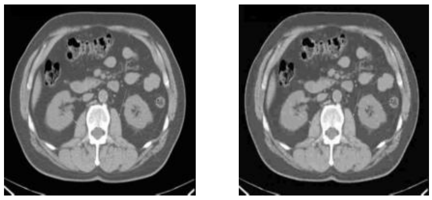
4. **Bit Per Pixel**

The image quality is represented by the number of bits per pixel in the compressed image *(BBP)* which is defined as the total number of bits in the compressed image divided by the number of pixels. Moreover, bit per pixel BPP Can be calculated as 8 bit divided by compression ratio

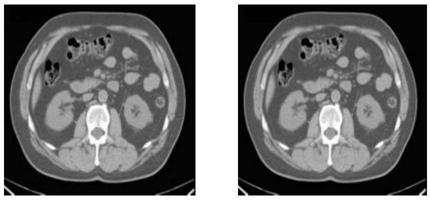
$$BBP = \frac{\text{bits in the compressed image}}{\text{number of pixel}} \quad (7)$$

Results and Discussion

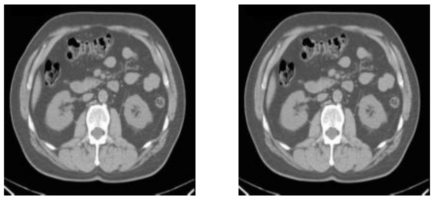
In this analysis, the proposed compression algorithm is conducted on CT scan and ultrasound images with different quality levels. These quality levels are from 10 to 90 scales. PSNR, MSE, CR, and BBP are used to evaluate the differenc between the original image and reconstructed image. In this paper , medical image compression quality was performed with five quality levels. These quality levels indicate that perfect reconstructed images is related with high quality level. However, inferior image quality came with low quality level due to colour depth is reduced and the detail of sections of the image are removed. Figure 5&8 illustrate the original image of CT scan and Ultrasound images with reconstructed images with different quality respectivly. Table 1&2 show that, if quality level is high the error measurements for reconstructed images were excellent and if quality level is low , image quality was inferior. The best value for PSNR at quality level 90. This parameter indicates that reconstructed image had no perceptual difference from the original. On the other hand, as shown in table 1&2 when quality level is decreased the error measurements start getting worse until a point is reached where it is easy to note perceptual difference from the original image. Table 1&2 illustrate that there is inverse relationship between PSNR and MSE because higher value of PSNR is good because it means that the ratio of signal to noise is higher. Here, the signal is the original image, and the noise is the error in reconstruction. If compression scheme have a lower MSE and a high PSNR, you can recognize that it is a better. Figures 7&10 illustrate that there are proportional relationship between bit per pixel and PSNR. Because of bit per pixel indicates how much data can be recorded for each pixel. A high number of bits per pixel records more subtle gradations in colour so images are more accuracy and closer to original images. There are inverse relationship between bit per pixel and MSE, and proportional relationship between bit per pixel and PSNR. Because of bit per pixel indicates how much data can be recorded for each pixel.



(a) Original Image (b) Quality level 10



(c) Quality level 30 (d) Quality level 50



(e) Quality level 70 (f) Quality level 90

Fig. 5 : Original & Reconstructed CT Scan images with different Quality levels

Table 1: The Proposed Algorithm compression of CT Scan Image

CT scan Images				
Q	**PSNR**	**MSE**	**CR**	**BPP**
10	32.08	40.25	3.73	2.14
30	38.08	9.7	2.05	3.88
50	40.77	5.44	1.74	4.57
70	43.26	3.06	1.54	5.07
90	48.6	1.02	1.42	5.60

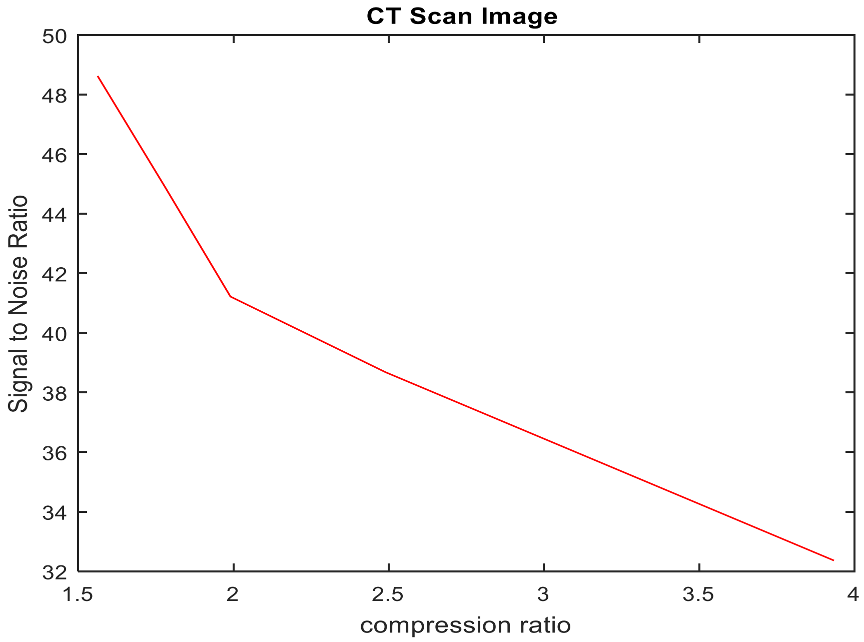


Fig. 6: The relationship between CR & SNR of CT scan

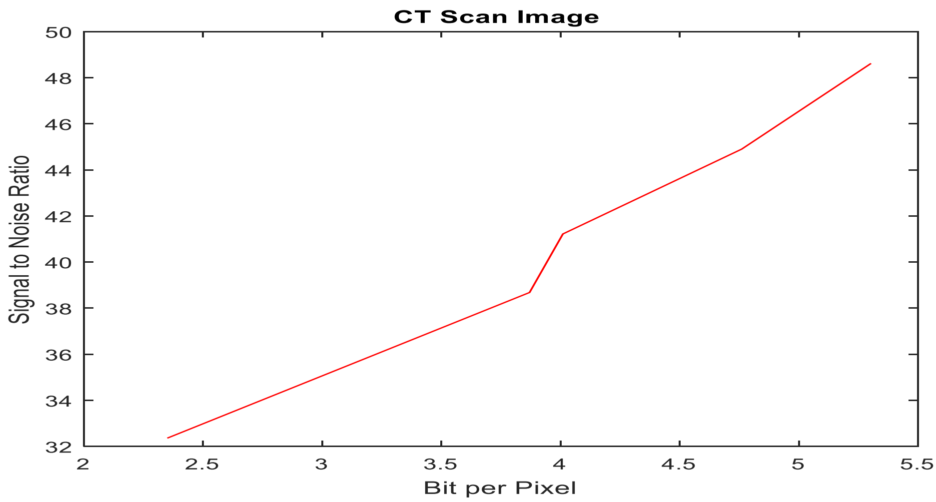
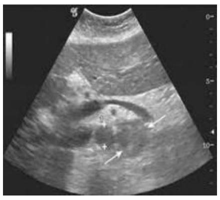


Fig. 7: The relationship between BPP &SNR of CT scan Scan Image

a)Original Image

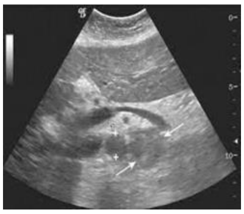
(b) Quality level 10

(c) Quality level 30



(d) Quality level 50

(e) Quality level 70



(f) Quality level 90

Fig. 8: original & reconstructed Ultrasound Images with different quality level

Table 2: The Proposed Algorithm compression of Ultrasound Image

Ultrasound Images				
Q	**PSNR**	**MSE**	**CR**	**BPP**
10	32.7	34.7	3.77	2.11
30	38.5	9.17	1.97	4.04
50	41.08	5.06	1.73	4.62
70	43.59	2.84	1.59	5.01
90	48. 8	0.86	1.4	5.70

Fig. 9: The relationship between CR & SNR of Ultrasound Scan Image

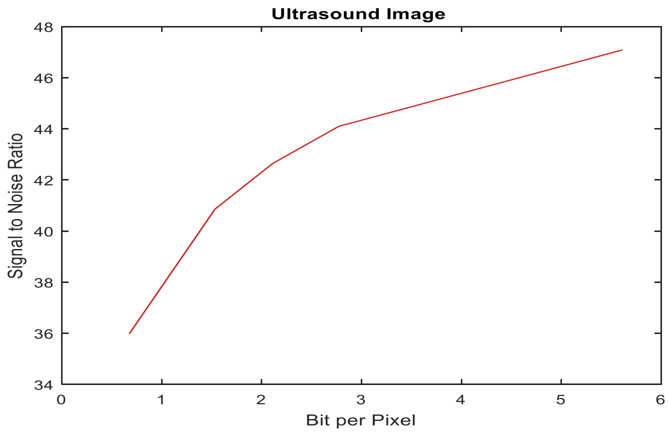


Fig. 10: The relationship between BBP & SNR of Ultrasound Scan Image

Conclusions

A successful algorithm has been applied for compressing of medical images. This paper was successfully compressed medical images using DCT and VQ techniques. These techniques were applied on two medical images as CT scan, and Ultrasound images. Compression of medical images was performed with five different quality levels. The performance of compression process was successfully using the proposed techniques namely as MSE, PSNR, BBP, and CR. From the experimental and mathematical results it can be deduced that the proposed algorithm produces a high PSNR with different quality levels.

References

Mohta, J. (2015). Image Compression and Gamma Correction using DCT. T International Conference on Futuristic Trend in Computational Analysis and Knowledge Management (ABLAZE- 2015, 1(1).

Kusuma, E. D., & Widodo, T. S. (2010). FPGA Implementation of Pipelined 2D-DCT and Quantization Architecture for JPEG Image Compression. IEEE.

Trang, & Bihn, D. N. (2010). A High-Accuracy and High-Speed 2-D 8x8 Discrete Cosine Transform Design. Proceedings of ICGCRCICT, 1, 135–138.

Jain, N., & Mishra, B. (2015). DCT and CORDIC on a Novel Configurable Hardware. 2015 IEEE Asia Pacific Conference on Postgraduate Research in Microelectronics and Electronics (PrimeAsia) DCT, 51–56.

Wang, Y. L., Liao, C. Te, Su, A. W. Y., & Lai, S. H. (2010). Fingerprint compression: An adaptive and fast DCT-based approach. Proceedings - International Conference on Image Processing,ICIP,3109–3112.

Zheng, W., & Liu, Y. (2011). Research in a fast DCT algorithm based on JPEG. 2011 International Conference on Consumer Electronics, Communications and Networks, CECNet2011-Proceedings,551–553.

An, S., & Wang, C. (2009). A computation structure for 2-D DCT watermarking. Midwest Symposium on Circuits and Systems, (1), 577–580. https://doi.org/10.1109/MWSCAS.2009.5236026

Li, Z., Sun, X., Du, C., & Ding, Q. (2013). JPEG algorithm analysis and application in image compression encryption of digital chaos. Proceedings - 3rd International Conference on Instrumentation and Measurement, Computer, Communication and Control, IMCCC 2013, 185–189.