RESEARCH ARTICLE OPEN ACCESS

ROI Based Hybrid Compression Techniques for Transferring MRI Brain Images

T. Kalaiselvi [1], S. Boopathiraja [2], P. Sriramakrishnan [3]
Department of Computer Science and Applications
Gandhigram Rural Institute-Deemed University, Gandhigram
Tamil Nadu - India

ABSTRACT

Region of interest (ROI) in medical images is diagnostically more important than the other portions. Compression methods for medical images that are delivering higher reconstruction quality in that ROI are very appreciable. ROI based image compression might give the high efficiency of space savings as well as the quality of images remains adorable. In this paper, we propose a ROI based hybrid compression methods that the lossless compression used for ROI portion and the lossy compression for non-ROI portion. Further, the image ID and the coordinate details of those ROI and non-ROI portions are written which might be required during decompression process. We propose two hybrid compression techniques that are Huffman coding with block truncation coding and Huffman coding with discrete wavelet transform. The compression ratio and PSNR values of proposed methods are compared with the existing methods. The decompressed images can achieve the satisfactory level of compression with the desired quality.

***Keywords* :—** Hybrid compression, ROI, Huffman coding, BTC, DWT, Compression ratio, PSNR.

I. INTRODUCTION

This medical imaging has a prominent role in the diagnosis of diseases and surgical planning. It is a computer-aided diagnostic process that is accompanied by the development of new technologies and several imaging modalities. Because of such evolution, high qualities and quantities of medical images can be acquired. In modern hospitals, a large number of medical images are produced, diagnosed and archived in picture archiving and communication systems (PACS) every day. There is a big amount of data that is essential for storing and transmitting medical images. So the compression techniques are introduced to overcome the high complexity of transition and storage processes [1]. Region of interest (ROI) in medical images is diagnostically more important than the other portions. For example tumor is ROI in MRI for brain diagnostics process. Lossless compression is used in medical images, but the accomplished compression ratio is low and while using the lossy compression loss of resolution may affect some of diagnostically important part of the medical image. Hence, there is a need of some hybrid technique which can preserve diagnostically important part (ROI) and also provide high compression ratio. These regions should be encoded with higher quality than the non-ROI or background of an image. In terms of hybrid compression, both lossless and lossy techniques are used. So that the target regions within the image will be preserved while the number of bits needed to code the images is reduced [2].

Douka and Maglogiannis provided an overview of various methods to region of interest compression methods for medical images [3]. They concluded that ROI coding is considered quite important in distributed and networked electronic healthcare. But they suggested the existing algorithms should adopt in order to decrease complexity. Ade and Raghunadh proposed a method for hybrid compression that the ROI is compressed with a lossless technique and the rest of the portions compressed with a near lossless technique [4]. They mainly focused on face detection and acquired best quality in ROI (Face) but also the good compression ratio. A work done by Bairagi and Sapkal for MRI images that partition the image as ROI, non-ROI and background [5]. Coding that regions with lossless and lossy coding and concluded the paper as ROI-based compression provides better compression as compared to other lossless methods, along with preservation of diagnostically important information. A work done by Gokturk et al. proposed a ROI based hybrid compression model for medical images [6]. They applied their method to CT images and ROI portions are compressed with lossless method which implies to greater quality and other regions are compressed with lossy compression method which implies to high compression ratio. They obtained 2.5% compression rate with their approach. Zukoski et al. discussed the overall compression methods for medical images, further they proposed lossless method for clinically relevant portion (i.e. ROI) and lossy method to other than the clinically relevant portion [7]. The results of proposed method compared with the traditional compression methods and gave better result than other methods.

The proposed work introduced two hybrid compression techniques that achieved better quality as well as good compression ratio. Our first proposed method is combination of BTC and Huffman. BTC is lossy compression method used for non-ROI (i.e. non tumor portion). Huffman coding is a lossless compression method for ROI portion. The second proposed method is used DWT for non-ROI compression and Huffman coding for ROI compression. The performance of our proposed methods is evaluated with compression ratio and PSNR. The proposed hybrid compression methods compared with the existing methods like Huffman coding, BTC and DWT alone.

The remaining parts of this paper is organized as sections, Section II describes existing methods such as the Huffman coding, BTC and DWT, Section III includes the methodology of proposed hybrid methods, Section IV contains materials and evaluation parameters used by our proposed method, Section V having the obtained results and the discussions and finally we conclude the paper in section VI.

II. EXISTING METHODS

The following existing methods were used to develop and compare with our proposed hybrid compression methods and their performance.

A. Huffman Coding

In 1951, David Huffman and his MIT information theory classmates proposed a lossless data compression algorithm called Huffman coding. Huffman coding is used on images for efficient compression [8]. The idea of using a frequency-sorted binary tree proved this method the most efficient. Huffman built the tree from the bottom up instead of from the top down. Huffman coding uses variable length encoding of symbols instead of fixed length coding. It exploits the statistical frequency of symbols. It is very efficient when symbol probabilities vary widely. The main consideration of Huffman coding is to use fewer bits to represent frequent symbols and use more bits to represent infrequent symbols. The steps involved in Huffman coding as follows:

Step 1:Compute the probability of symbols from the histogram of an image

Step 2:Order the probabilities (histogram magnitudes) from smallest to largest

Step 3: Merge the symbols that have least probabilities

Step 4:The step 3 is continued until only two probabilities are left and the Huffman tree is generated

Step 5:Based on that tree, codes are assigned to samples where the least two samples have the same code but the last bit is changed

Step 6:A compressed file with samples and corresponding codes are ready

Step 7:In decompression, by traversing the Huffman tree node by node, the prefix codes are separated and the corresponding samples are decoded

B. Block Truncation Coding

Delp and Mithcell in 1979 proposed a novel method called block truncation coding for image compression [9]. The key idea of BTC is perform the moment preserving (MP) quantization for blocks of pixels so that the quality of the image will remain acceptable and at the same the demand for the storage space will decrease. BTC is the simple method of lossy compression. A pixel image is divided into smaller blocks of the pixels and every block is processed separately. The mean value ($\bar{x}$) and standard deviation (σ) are calculated in each block and encoded. The formulae for mean and standard deviation are given in Eqn. (1) and Eqn. (3).

$$\bar{x} = \frac{1}{m} \sum_{i=1}^{m} x_i \tag{1}$$

$$\overline{x^2} = \frac{1}{m} \sum_{i=1}^{m} x_i^2 \tag{2}$$

$$\sigma = \sqrt{\overline{x^2} - \bar{x}^2} \tag{3}$$

where, 'm' stands for number of pixels in a block.

A two level quantization is performed on that image so that the pixel values above the mean value are indicated as 1 otherwise 0. Then the compressed block is considered as a triple ($\bar{x}$, σ, Q) where $\bar{x}$ and σ are the mean and standard deviation values in block and Q denotes the quantized block values instead of original one. In reconstruction process, the pixel values are preserved with the 'a' and 'b' values. These values are considered as a case for the selection of pixel values. Formulae for 'a' and 'b' are given in Eqn. (4) and Eqn. (5).

$$a = \bar{x} - \sigma \sqrt{\frac{q}{m-q}} \tag{4}$$

$$b = \bar{x} + \sigma \sqrt{\frac{m-q}{q}} \tag{5}$$

where, q is the pixel value that greater than the mean $(\bar{x})$.

To reconstruct the image, or create its approximation, elements assigned as 0 are replaced with the 'a' value and elements assigned as 1 are replaced with the 'b' value.

C. Discrete Wavelet Transform

The signals are generally measured in function of time that is most of the signals are time domain signal. A mathematical transformation is applied to raw signals that extract the further unknown information from that signal. After applying the transformation we get the processed signal that means particularly it gives the frequency spectrum of the signal. Fourier transform gives the frequency information of signal such that how much frequency exist in signal but not when in time it exist in signal. Fourier transform is much used for stationary signals (whose frequency does not change in time) but not for non-stationary signals. So we go for wavelet transforms which are also used for non-stationary signal.

A wavelet function $\psi(x)$ is called mother wavelet over a real space. This function is used as a basis function. A translation and dilation can modifies the mother wavelet as,

$$\psi\left(\frac{x-a}{b}\right), (a,b) \in R^{+} \times R \tag{6}$$

where, $a = 2^j$ and $b = k.2^j$ with k and j are integers.

The choosing of a and b are known as critical sampling and it yields a sparse matrix. This sparse matrix contains the wavelet coefficients which are used to reconstruct original image while applying the inverse DWT. Wavelet is reversible transform and it provides time-frequency representation. It adopted multi resolution analysis (MRA) which means that signals in different frequency with different resolution [10]. It analyzes the signals with wavelet function that is wavelet transformation decomposes the signal into set of basis function [11]. Discrete wavelet transform (DWT) transforms a discrete time signal to a discrete wavelet representation. The DWT is an efficient decomposition of signals into lower resolution and details. The Fig.1 illustrates the compression scheme by using DWT.

The steps includes in DWT compression method are:

Step 1: Decompose the image into a given n level with given wavelet function

Step 2: Apply thresholding to wavelet coefficients and encode it

Step 3: Reconstruct the image with the decoded wavelet coefficients

Haar wavelet

In our proposed method 2, we use Haar wavelet as a basis function. Haar wavelet is a step function that is compactly supported, orthogonal and symmetric. Compactly supported wavelets are functions defined over a finite interval and having an average value of zero and symmetric filters are preferred because of minimizing the edge effects in the wavelet representation of a function.

The Haar wavelet is defined as

$$\psi(x) = \begin{cases} 1 & 0 \le x < \frac{1}{2} \\ -1 & \frac{1}{2} \le x < 1 \\ 0 & Otherwise \end{cases} \qquad (7)$$

III. PROPOSED METHOD

The proposed method is to focus the space complexity of vast amount of images. The method contains both lossless and lossy schemes that are used on MRI brain images. While working with the MRI sequences the tumor part is more important than the other. So we exploit the Region of interest (ROI) based method that apply the lossless compression for ROI and apply the lossy compression for non-ROI portions. The flow chart of our proposed methods for a communication channel is shown in Fig.2.

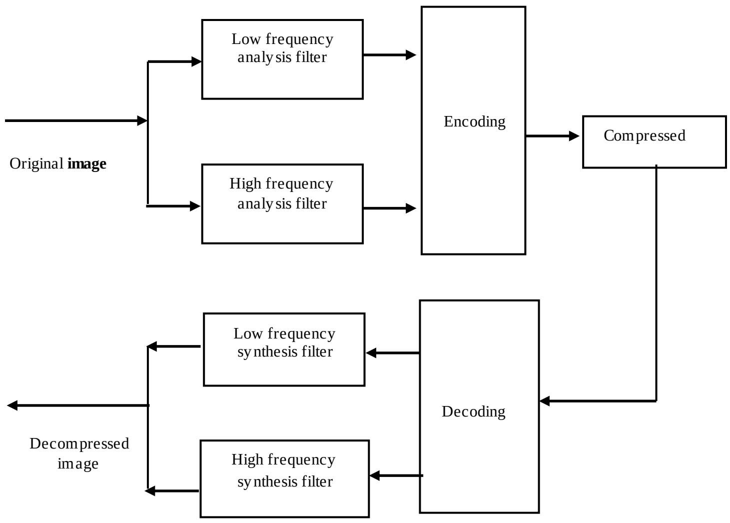


Fig. 1 Compression flow of DWT

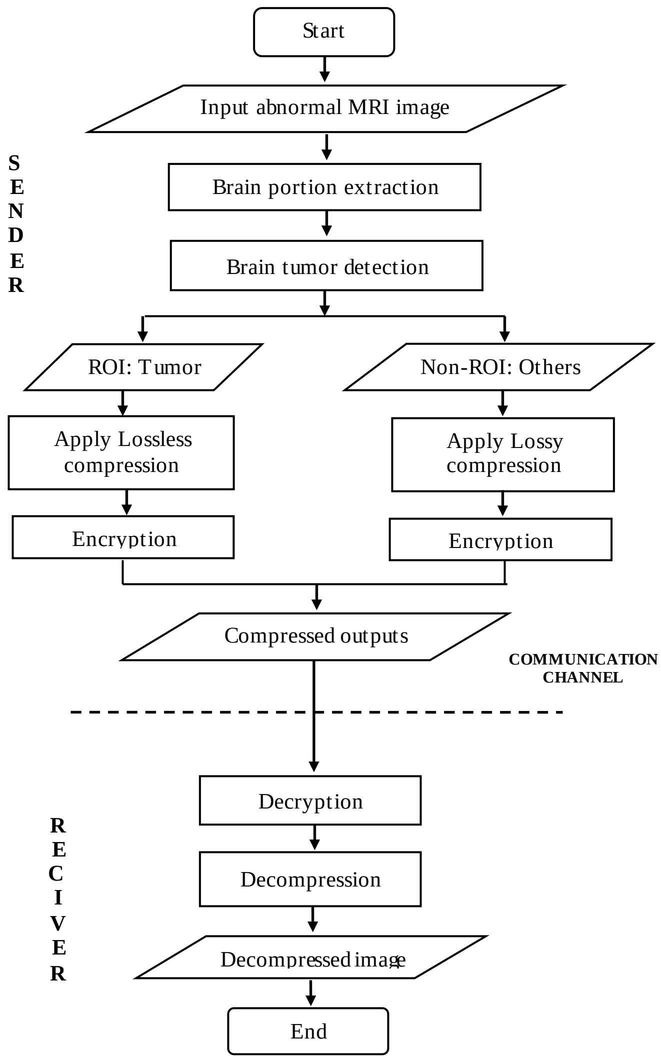


Fig. 2 Flow chart of proposed method

The input to the proposed method is MRI abnormal slices. The Slice is processed by the following two methods for separating ROI and non-ROI regions. Brain extraction algorithm (BEA) method is used for brain portion extraction. Watershed segmentation algorithm is an efficient tool for detecting the tumor part from brain images [12]. Those methods are used to detect the bounding boxes of tumor portion (ROI) and non-ROI of given input images. The steps involved in the proposed method are given below:

INPUT: MRI abnormal slice

Step 1: Extracting the brain portion using BEA method

Step 2: Tumor detection using Watershed algorithm

Step 3: Detecting ROI and non-ROI portions using bounding boxes

Step 4: Applying lossless compression on ROI portion

Step 5: Applying lossy compression on non-ROI portion

Step 6: Encrypt the image ID and coordinate details of bounding boxes to the compression files

Step 7: Transmission through communication channel

Step 8: At the receiver end, does the decryption and decompression processes

In this paper we propose two different hybrid compression methods such as Huffman coding (lossless) with BTC (lossy) compression method and Huffman coding (lossless) with DWT (lossy) compression. They are names as Huffman with BTC and Huffman with DWT respectively.

The methodology of the proposed method is explained below.

1) Brain portion extraction

This process referred as brain extraction or skull stripping and is a preliminary step for several quantitative morphometric studies of MR images [13]. Somasundaram and Kalaiselvi proposed two brain extraction algorithms (BEA) named as 2D-BEA and 3D-BEA to extract brain portion from T2-weighted MRI head scans automatically [14]. The T2-weighted image is first filtered with a low pass filter (LPF) to remove or subdue the background noise. Then the brain boundaries enhanced using anisotropic diffusion and threshold value obtained using Ridler's method. The brain mask is generated from morphological operations and the largest connected component (LCC) analysis. This method uses only 2D information of slices and is named as 2D-BEA and LCC failed in few slices. To overcome this problem, 3D information available in adjacent slices is used which resulted in 3D-BEA. Experimental results on 20 MRI data sets show that the proposed 3D-BEA gave excellent results. The performance of this 3D-BEA is better than 2D-BEA and other popular methods, brain extraction tool (BET) and brain surface extractor (BSE). The sample image with brain extraction is shown in Fig. 3 (a) and Fig. 3 (b).

2) Tumor detection

The next step of the proposed method is to extract the brain tumor region for ROI detection. For that watershed algorithm is used for segmenting the tumor region. Watershed is a region-based segmentation and a gradient- based technique. A gradient in an image is a directional change in the intensity value. Region edges correspond to high watersheds and low-gradient region interiors correspond to catchment basins. An image has homogenous regions that are usually have low gradient values. The general steps involved in watershed segmentation are:

Step 1: Calculate the gradient values

Step 2: Apply watershed transform on gradient image

Step 3: A binary image acquired with the segmented region as white

Thus this method can be effectively used and the proper detection of the ROI can be achieved. The extracted tumor portion for the sample image is given in Fig.3 (c).

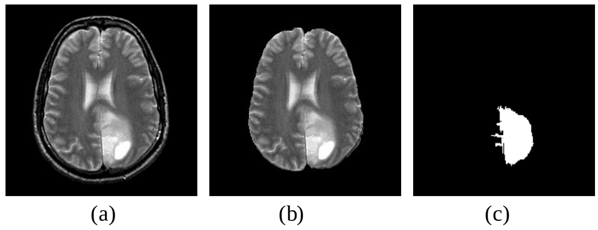


Fig. 3 Brain and tumor extraction (a) Sample image (b) Brain extraction using BEM (c) Tumor detecttion using watershed algorithm

3) Detecting ROI and non-ROI portions

At first we need to separate the brain portion from the whole image because most of the background pixels are black i.e. pixels with zero intensity. So excluded those pixels are also helpful to reduce the amount of bits during transmission and used for reasonable compression ratio. Bounding box is a technique used to separate the brain portion from background. Bounding box is also used to extract the ROI produced by watershed algorithm. ROI is selected using bounding box is shown in Fig. 4(b). The extracted brain portion from the whole image is selected as non-ROI portion and is shown in Fig. 4(c).

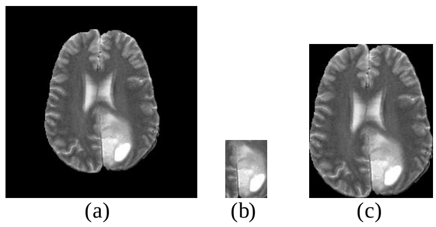


Fig. 4 ROI and non-ROI portions (a) Sample (b) ROI (c) Non-ROI

4) Applying compression methods to ROI and non-ROI

Here we propose two hybrid methods. First one is Huffman coding with BTC and the second one is Huffman coding with DWT.

4.1 Proposed *method 1 (Huffman with BTC):*

Region of interest of an input image is successfully identified. After that the ROI portion is compressed with Huffman coding method. Huffman tree is generated and then the compressed file with symbols and corresponding code is preserved. This compressed file is used to reconstruct the actual ROI portion while executing the decompression process.

A unique key is generated in the compressed file which is necessary when the ROI portion get reconstructed in decompression process.

The 2×2 block size is selected for BTC lossy compression on non-ROI portion. The BTC algorithm is normally executed with 4×4 block size on images for preserving perfect compression ratio. In the case of medical images, quality of decompressed images is much important. Hence, 2×2 block is selected. Calculate the mean and standard deviation values on each block of that portion and two level quantization block matrix is generated as a compressed file. This compressed file is used to send over transmission.

4.2 Proposed method 2 (Huffman with DWT)

The ROI portion is applied with the Huffman coding method. The non-ROI portion is applied with the discrete wavelet transform (DWT). The haar wavelet is used as a basis function with the 4-level decomposition of that non-ROI portion. At last the encoded process gives the sparse matrix that contains the wavelet coefficients for decompressing that portion.

5) Encryption

Two compressed output files are generated by our proposed method. One is from lossless and another from lossy compression. The encryption process writes image ID and coordinates details of both ROI and non-ROI into the compressed files. Image ID is used for match the ROI with corresponding non-ROI while decompress after transmission. The diagonal coordinate values are used to reconstruct the original size while decompression.

6) Decryption

The coordinate details of ROI and non-ROI is necessary to reconstruct the image in decompression process. So the details should decrypt before starting the decompression process. Image ID mapped with two compressed files, coordinates of ROI and corresponding non-ROI are identified. Coordinate values are used to construct corresponding regions of both ROI and non-ROI.

7) Decompression

In decompression process, the inverse processes of the operations done in compression are performed.

7.1 Proposed method 1 (Huffman with BTC)

The keys and objects in compressed file are used to decompress the Huffman coding and BTC individually. ROI portion is decompressed with the compressed file that contains symbols and corresponding coding. Similarly, the non-ROI portion is decompressed by manipulating the ‘a’ and ‘b’ values along with the triple of mean, standard deviation and binary block values.

7.2 Proposed method 2 (Huffman with DWT)

The ROI portion is decompressed separately with the help of image ID and corresponding details. The non-ROI portion is decompressed by the wavelet coefficients in the sparse matrix. It took those wavelet coefficients and inverse wavelet transform is performed to reconstruct the original image. At last we get the decompressed non-ROI portion as well as ROI portion. The final step in decompression is carried out that combine the ROI, non-ROI and the background portion to get the final decompressed image.

IV. MATERIALS AND EVALUATION PARAMETERS

The image data collected from brain tumor image repository (BTIR) maintained by our research team. We used some sample tumor slices from our repositories. The evaluation parameters acquired for compression are compression ratio (CR) and peak signal to noise ratio (PSNR) [15].

Compression ratio is defined as the ratio of an original image Size to the compressed image Size

$$CR = \frac{n_1}{n_2} \tag{8}$$

where, n_1, n_2 represent the number of bits required for original and compressed image respectively.

The PSNR is the ratio between the maximum possible powers of a signal to the power of corrupting noise that affects the fidelity of its MSE. The PSNR (in db) is given in Eqn. (9).

$$\text{PSNR} = 10 \,.\, log_{10}\left(\frac{MAX_I^2}{MSE}\right) \tag{9}$$

where, MAX_I is maximum fluctuation in an image and

$$MSE = \frac{1}{MN}\sum_{y=1}^{M}\sum_{x=1}^{N}[I(x,y)-I'(x,y)]^2 \tag{10}$$

where, I(x, y) is the original image, I'(x, y) is the approximated version (which is actually the decompressed image) and M, N are the dimensions of the image.

Logically, a 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.

V. RESULTS AND DISCUSSION

The existing methods results are given in Table I, Table II and Table III. From Table I, the Huffman coding is a lossless compression method and original image is decompressed without loss of any information. But very low compression ratio only achieved. Results of BTC are given in Table II. BTC gives low compression ratio as well as low PSNR values using 2×2 block are shown in Table II. The BTC algorithm executed with 4×4 block size on images gave better compression ratio. But when we use medical images, quality of decompressed images is more important. Hence, 2×2 block is selected. Table III has shown DWT give good compression ratio but the quality in consideration of ROI is very low (i.e. loss of information). In our proposed method 1 (Huffman with BTC) 2×2 block size is selected for BTC to the entire images.

TABLE I
Huffman coding results

Image ID	CR	C_PER (%)	Computation Time (Sec)
001	2.54	60.70	4.85
002	2.45	59.14	5.32
003	2.47	59.56	5.02
004	2.18	54.22	3.11
005	2.02	50.54	3.99
Average	2.33	56.83	4.45

TABLE II
BTC Results (2×2 block size)

Image ID	CR	C_PER (%)	PSNR (db)	Computation Time (Sec)
001	1.6	37.5	23.55	0.63
002	1.6	37.5	23.09	0.70
003	1.6	37.5	22.94	0.63
004	1.6	37.5	21.32	0.66
005	1.6	37.5	20.34	0.40
Average	1.6	37.5	22.24	0.60

TABLE III
DWT Results (level 4)

Image ID	CR	C_PER (%)	PSNR (db)	Computation Time (Sec)
001	10.34	90.33	50.62	0.05
002	9.06	88.96	49.69	0.04
003	9.61	89.6	49.93	0.05
004	9.69	89.68	49.21	0.03
005	8.46	88.18	48.51	0.03
Average	9.43	89.35	49.59	0.04

The hybrid compression methods are applied to the five sample images and the resultant images are shown in Fig.5. Column 1 given the image ID, Column 2 shown the sample image, Column 3 shown the tumor detection using watershed segmentation, Column 4 shown the ROI extraction using bounding box, Column 5 given non-ROI extraction using bounding box, Column 6 given decompressed image using proposed method 1 (Huffman with BTC), Column 7 given the decompressed image using proposed method 2 (Huffman with DWT). The performance comparison of proposed methods is shown in Fig. 6.

Table. IV shows the compression ratio, PSNR value and computation time for our proposed method1 (Huffman with BTC) and Table V shows the compression ratio, PSNR value and computation time for our proposed method2 (Huffman with DWT).

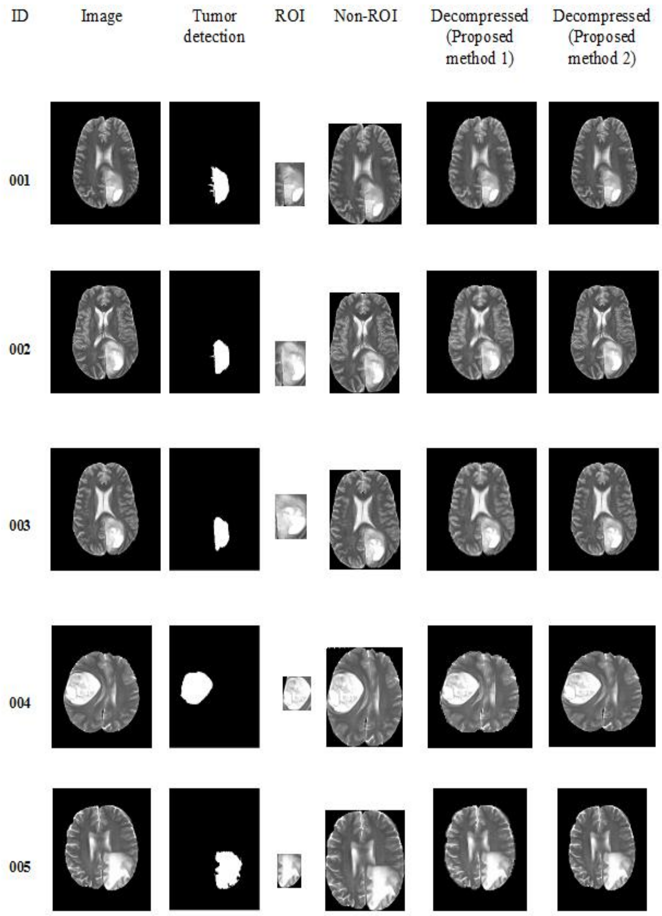


Fig. 5 Resultant images of proposed method. Column 1: Image ID, Column 2: Sample image, Column 3: Tumor detection using watershed segmentation, Column 4: ROI extraction using bounding box, Column 5: non-ROI extraction using bounding box, Column 6: Decompressed image using proposed method 1 (Huffman with BTC), Column 7: Decompressed image using proposed method 2 (Huffman with DWT).

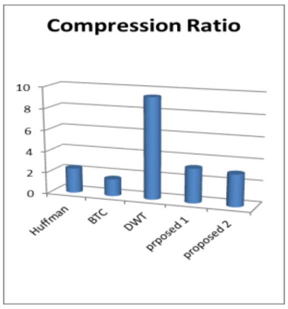
TABLE IV
Results of proposed method1 (Huffman with BTC)

Image ID	CR	C_PER (%)	PSNR (db)	Computation Time (Sec)
001	3.39	70.48	23.92	1.96
002	3.37	70.33	22.71	1.86
003	3.42	70.75	23.02	2.14
004	3.07	67.43	22.61	1.67
005	2.93	65.83	20.98	1.69
Average	3.23	68.96	22.65	1.86

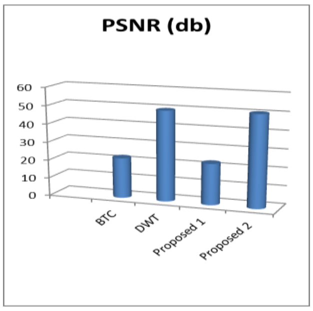
From the Table IV and Table V our proposed method1 (Huffman with BTC) yields 3.23 compression ratio and 69% of space savings and proposed method2 (Huffman with DWT) yields 3.01 compression ratio and 67% of space savings. Our two proposed methods gave better quality and compression ratio than the existing methods value while compared with the corresponding existing methods with better ROI preservation.

TABLE V
Results of proposed method2 (Huffman with DWT)

Image ID	CR	C_PER (%)	PSNR (db)	Computation Time (Sec)
image_1	3.08	67.54	50.84	2.27
image_2	3.00	66.71	50.51	2.26
image_3	3.40	70.59	50.38	2.10
image_4	2.89	65.45	50.34	2.00
image_5	2.71	63.04	50.36	1.93
Average	3.01	66.66	50.48	2.11



(a)



(b)

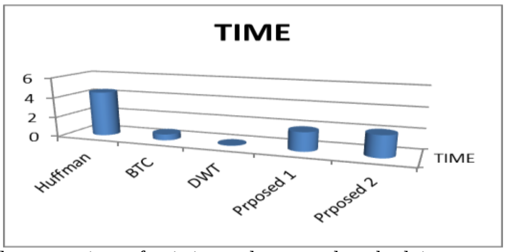


Fig. 6 Result comparison of existing and proposed methods in terms of (a) Compression Ratio (b) PSNR (c) Computation Time.

As shown in Fig. 6(a), proposed method1 (Huffman with BTC) gave the compression ratio two times higher than BTC with 2×2 blocks and 1.4 times higher than the traditional Huffman coding. The high compression rate is achieved by excluding background pixels and applying lossy compression on non-ROI portion. Our proposed method 2 (Huffman with DWT) gives the compression ratio 1.2 times higher than Huffman and three times lesser than the traditional DWT. This is because we exclude the background and applied DWT only on non-ROI portion (less number of low intensity pixels is in non-ROI). In the case of medical images, we mostly care about the quality of the image rather than the compression. While comparing the proposed methods alone both gave almost same compression ratio.

The PSNR values of existing and proposed methods are shown in Fig. 6(b). Our Proposed method 1 yields high PSNR value than the traditional BTC. On the other side, the PSNR value of proposed method 2 (Huffman with DWT) is higher than the traditional DWT and also two times higher than the proposed method 1 (Huffman with BTC). Obviously the computation time for Huffman coding is too high while comparing with the other existing lossy methods. Our proposed methods have little more computation time than the BTC and DWT but less time than the Huffman coding method that are shown in Fig.6(c).

VI. CONCLUSION

In the field of medical imaging, non-ROI portions are also little quit important in diagnostics process as such locating ROI portion accurately. Compression ratio and Peak signal to noise ratio (PSNR) are the metrics used for assess the performance. ROI based hybrid image compression yields better compression than the other existing methods. And also we preserve the ROI and better quality of images. The image ID coordinates of ROI and non-ROI are encrypt and preserved for further processing. The encrypted details do not affect the compression performance and has no loss of information in decryption process as well. The coordinate details are used to reconstruct image in decompression process. The removal of background is assist to achieve better compression. The two proposed methods achieve good quality as well compression ratio while preserving the ROI tumor portion.

REFERENCES

[1] K. Sayood, “Introduction to Data Compression”, 3rd edition Academic Press, Morgain Kaufmann Publishers, 2006.
[2] J. Strom and P.C. Cosman, “Medical Image Compression with Lossless Regions of Interest”, Signal processing, vol. 59, no. 2, pp. 155-171, June 1997.
[3] C. Douka and I. Maglogiannis, “Region of Interest Coding Techniques for Medical Image Compression”, IEEE Engineering in Medicine and Biology Magazine, pp. 29-35, October 2007.
[4] K.K. Ade and M.V. Raghunadh, “ROI Based Near Lossless Hybrid Image Compression Technique”, IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT), pp. 1-5, 2015.
[5] V.K. Bairagi and A.M. Sapkal, "Automated region-based Hybrid Compression for Digital Imaging and Communications in Medicine Magnetic Resonance Imaging Images for Telemedicine Applications”, IET Science, Measurement & Technology, vol. 6, no 4, pp. 247-253, 2012.
[6] S.B. Gokturk, C.Tomasi, B. Girod and C. Beaulieu, ”Medical Image Compression Based on Region of Interest, with Application to Colon CT Images”, IEEE International Conference on Engineering in Medicine and Biology Society, vol. 3, 2001.
[7] M.J. Zukoski, T. Boult and T. Iyriboz, “A novel approach to medical image compression”, International Journal of Bioinformatics Research and Applications, vol. 2, no. 1, pp. 89-103, 2006.
[8] J.H. Pujar and L.M. Kadlaskar, “A new Lossless method of Image Compression and Decompression using Huffman Coding Techniques”, Journal of Theoretical and Applied Information Technology, vol. 15, pp. 18-23, 2010.

[9] E.J. Delp and O.R. Mitchell, "Image Compression using Block Truncation Coding", IEEE Transactions on Communications, vol. 27, pp. 1335–1342, 1979.

[10] M.S. Song, "Wavelet Image Compression", Operator Theory, Operator Algebras and Applications, Contemporary Mathematics, vol. 414, American Mathematical Society, Providence 2006.

[11] R.A. Devore, B. Jawerth and, B.J. Lucier, "Image Compression through Wavelet Transforms Coding" IEEE, vol. 38, no.2, pp. 719-746, 1992.

[12] S. Zin and A. S. Khaing, "Brain tumor Detection and Segmentation using Watershed Segmentation and Morphological Operation" International Journal of Research in Engineering and Technology (IJRET), vol. 3, no. 03, 2014.

[13] K. Somasundaram and T. Kalaiselvi, "Brain Extraction Method for T1 Magnetic Resonance Scans", IEEE sponsored International Conference on Signal Processing and Communication, 2010.

[14] K. Somasundaram and T. Kalaiselvi, "Fully Automatic Brain Extraction Algorithm for Axial T2-Weighted Magnetic Resonance Images", Computers in Biology and Medicine, vol. 40, no. 10, pp. 811-822, 2010.

[15] P.C. Cosman, R.M. Gray and R.A. Olshen, "Evaluating Quality of Compressed Medical Images: SNR, Subjective Rating, and Diagnostic Accuracy", Proceedings of the IEEE, vol. 82, no. 6, pp. 919-931, 1997.