Hybridization of Lossless and Lossy Compression for Medical Images

Prof. Vijaya S M
Dept. of Electronics and Communication
Rajarajeswari College of Engineering
Bangalore, India

Dr Suresh K
Dept. of Electronics and Communication
SDMIT
Ujire, India

B Deekshitha
Dept. of Electronics and Communication
Rajarajeswari College of Engineering
Bangalore, India

Bindu R
Dept. of Electronics and Communication
Rajarajeswari College of Engineering
Bangalore, India

Chandana G
Dept. of Electronics and Communication
Rajarajeswari College of Engineering
Bangalore, India

Gnanamanjari S
Dept. of Electronics and Communication
Rajarajeswari College of Engineering
Bangalore, India

***Abstract*— Hybrid compression techniques are adopted to get efficient compression for medical images. This paper proposes an efficient method for the digital medical images in DICOM format. Medical images such as MRI images are broadly classified into Region of interest (ROI) and Non Region of interest (NON-ROI).The ROI consists of diagnostically important areas such as tumour region in MRI. The NON-ROI consists the remaining part of the medical image. The image is segmented using Fuzzy c-Means (FCM) algorithm and its accuracy is evaluated in terms of contrast, correlation, energy and homogeneity. For ROI lossless compression coding is applied so that the quality of the image is preserved and is encoded using Huffman coding, for NON-ROI lossy compression coding is applied using SPIHT compression algorithm. The hybrid method is evaluated in terms of Compression ratio (CR), Peak signal to Noise Ratio (PSNR), Structural Similarity Index (SSIM) and Mean Square Error (MSE) for various Brain MRI images.**

Keywords— Hybrid Compression, ROI, Huffman Coding, SPIHT, CR, PSNR, SSIM, MSE

I. INTRODUCTION

Digital image processing is the most important areas of research from few decades, the use of computer software's to build up algorithms to perform processing on digital images is the major application of digital image processing. It allows a much wider range of algorithms to be applied to the input data and can easily avoid problems such as noise and signal distortion during processing. We are considering the medical images, which is one of the most important applications in digital image processing and it is used to represent the interior of human body in visual manner. The images are defined over two dimensions digital image processing may be modeled in the form of multidimensional systems, the normal size of an image ranges from 512x512x8 bit up to 1024x1024x12 bit for X-ray and for 16 bit MRI images the typical size of a standard MRI image can be of size 5-6MB.Such large sized images are difficult to store and hence require high bandwidth for transmission of the images. Hence for convenient access and economical storage hybrid technique is applied. By using the hybrid technique the storage capacity can be reduced.

A. *Image Compression:*

Image compression techniques are employed to resolve the problem of bandwidth required for transmission of an image. Since the data base of the patients have to be maintained for longer duration efficient storage is required. There are numerous techniques and algorithms which are developed to obtain the efficient image compression and also to obtain the high quality of the decompressed image even then there is a tradeoff between the compression ratio obtained and the quality of the reconstructed image. The compression can be done either by Lossy compression or Lossless compression techniques. In lossless compression technique the reconstructed image is a reasonably close or replica of the original image. Typically lossless compression is necessary for medical applications. The compression ratio for this will be lower. In lossy compression techniques the compressed image is not identical to the original image but reasonably closer image can be obtained, and compression ratio obtained in lossy compression will be higher than the compression ratio obtained in the lossless compression technique.

B. *Region Based Compression:*

Medical images are divided into ROI and NON-ROI based on the selective process. The image is classified based on their diagnostically important region. The ROI is located over small region in an image and represents the affected part in an medical image, the region excluding the ROI region rest of the part is considered as NON-ROI as show in the figure1.

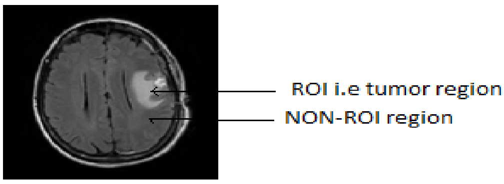

Figure1 Brain MRI image showing different regions.

In order to have a balance between high quality of the reconstructed image and low use of memory, a region of interest based compression is being used. This type of region based compression is known as the Hybrid technique. Hybrid compression combines both lossy and lossless techniques and gives the combined output of the image. The lossy and lossless techniques are combined to achieve good compression ratio at visually acceptable image quality.

The remaining paper is organized as follows: section 2 discusses various related work which have been implemented earlier. The proposed hybrid technique and its detailed process is explained in section 3. Analysis of experiment is done in section 4. Section 5 concludes the paper. The acknowledgement is the section 6.

II. RELATED WORK

Lossless data compression in which runs of data are stored as a single data value and count, rather than as the original run [11]. The sequence of repeating pixel in an RLE it is replaced by a two number. The first number is replaced by a value of pixel and second number is replaced by the number of times it is repeated [12]. The coding sequence increases as the pixel varies. Entropy coding is a type of lossless coding to compress digital data by representing frequently occurring patterns with few bits and rarely occurring patterns with many bits by this in second stage coding redundancy is removed. Huffman coding, Lempel-Ziv-Welch coding and arithmetic coding are the commonly used entropy coding techniques.

The output from Huffman's algorithm can be viewed as a variable-length code table for encoding a source symbol which is used for image compression. Each symbol's probability of occurrence, image sequence and symbols are required for the Huffman algorithm. By referring the code book, the symbols can be obtained from the encoded bits and without any loss the reconstructed image sequence can be obtained [13].

In an image spatial redundancy can be addressed by dictionary-based coding called LZW. Static or dynamic dictionary based coding. For encoding and decoding processes, it is fixed in static dictionary. The dictionary is updated on fly in dynamic dictionary coding. In both lossless and lossy data compression algorithms we use commonly arithmetic coding algorithm. Arithmetic coding is an entropy encoding technique, in which the frequently seen symbols are encoded with fewer bits than rarely seen symbols. For first iteration, we consider 0 and 1 to calculate the range as the difference between lower and upper values [14].

The source encoder, quantizer and entropy are the three closely connected components of lossy image compression. To enhance or stretch, colour differences found in each pixel of an image i.e. de-correlate the image data linear transform is applied from this compression is succeed in doing. The transform co-efficient results are quantized, and quantized values are done with entropy coding [7].

Pixels are converted from original image to frequency domain co-efficient by various transform techniques such as DFT, DWT, DCT to accomplish source coding. In only few of the significant transformed co-efficient the energy of the original data is concentrated. For further quantization and entropy encoding these few significant co-efficient are considered. For any further processing blocking effect of DCT technique should be resolved [4]. Corresponding to the various frequency bands, an image can be decomposing into a set of different resolution sub images. This results the representation of image with localization in both spatial and frequency domain in multi resolution. In wavelet-based compression algorithm EZW and SPIHT are the commonly used algorithms. In EZW algorithm the SPIHT algorithm is a highly refined version. For a wide variety of images for a given compression ratio SPHIT algorithm produces higher PSNR values. In image compression SPIHT wavelet -based algorithm is most widely used [15]. Bit synchronization before transmission is the only limitation of SPIHT algorithm it can be resolved by performing arithmetic coding on the encoded data [16].

III. METHODOLOGY

The proposed procedure for hybrid image compression is shown in figure2 and figure3. The methodology consists of following parts:

Figure 2 General procedure of the proposed method.

A. Image Pre-Processing

The pre-processing of an image is done to make the further processing of the image easier. The steps involved in pre-processing are noise removal from an input MRI image by using median filter which is widely used in image processing to remove the salt and pepper noise and also to preserve the edges of the image. The main idea of using median filter is to run through image entry by entry, replacing each entry with the median of neighbouring entries. The pattern of neighbours is called the "window", which slides, entry by entry, over the entire image.This is followed by the image enhancement process; enhancement increases the perception of the information in images for the human viewers. The enhanced image is segmented using the Fuzzy c-Means algorithm.

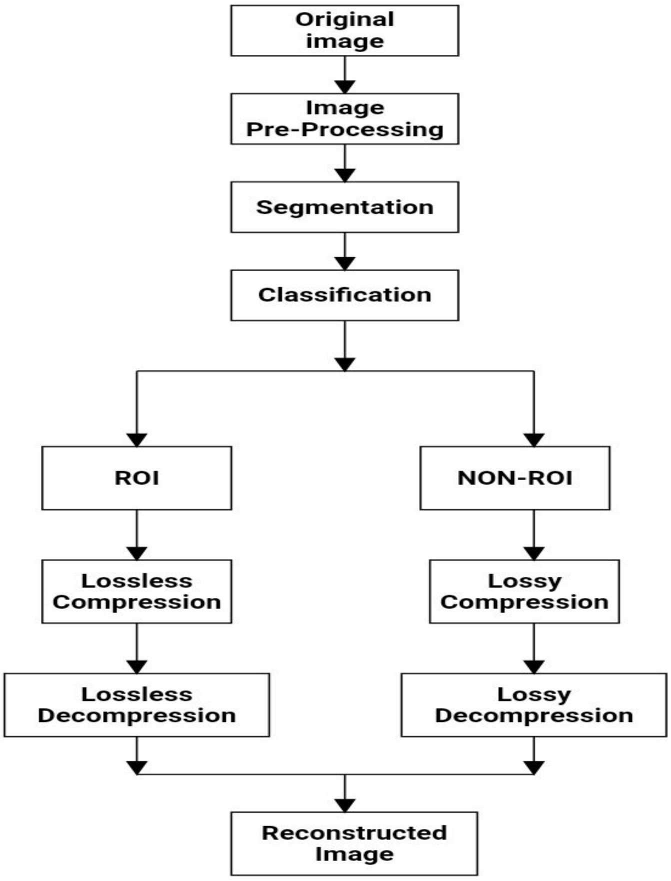

Figure 3 Flow chart of the proposed methodology.

B. *Segmentation*

Segmentation process is applied for an MRI image to locate the tumor region. Segmentation is the process of partitioning a digital image into set of multiple segments so that it gives the meaningful, similar and non-overlapping region of similar parameters like intensity, texture or depth which is very helpful for further processing. The ROI and NON-ROI regions are extracted from the medical image. The ROI and NON-ROI regions are extracted from the MRI of the brain using FCM clustering based algorithm for the segmentation. In Fuzzy c-Means algorithm each item may belong to more than one group hence the word Fuzzy. The degree of membership for each item is given by the probability distribution over the clusters. The clustering is done by calculating the euclidean distance from the pixel considered to the centroid of the considered clusters. The accuracy of the segmentation process is measured with the parameters like contrast, correlation, homogeneity and energy.

Contrast gives the intensity variation between a pixel and its neighbor over the whole image. Correlation gives a measure of how correlated a pixel is to its neighbor over the whole image. Homogeneity measures the closeness of the distribution of elements in the Gray Level Co-occurrence Matrix (GLCM) to the GLCM diagonal. Energy is the amount of information present in an image. All the above-mentioned parameters range between [0,1] except the correlation. Correlation ranges between [-1,1].

A. *Huffman Coding*

The Huffman coding is a popular lossless variable length coding. It was developed by David A. Huffman.
There are few principles involved in Huffman coding as follows

Shorter code words are assigned to more probable symbols and longer code words are assigned to less probable symbols. No code word of a symbol should be a prefix of another code word. Every source symbol must have a unique code word assigned to it.

The steps involved in development of Huffman Coding and decoding algorithm involves, Reading the ROI segmented image from the database. Call a function which finds the symbols. (i.e. pixel value which is not repeated) Call a function which will compute the probability of each symbol. Arrange the symbols in the decreasing order of their probabilities. Combine the lowest probability symbols into a single compound symbol that replaces them in the next source reduction. Continue the source reductions until left with only two symbols. Huffman encoding is performed i.e. mapping of code words to the corresponding symbols will in compressed data.

Decompression is done using Huffman decoding. Then match the code words with code dictionary to get the reconstructed image. The original image is reconstructed.

B. *SPIHT Algorithm*

Set Partition In Hierarchical Tree algorithm was developed by Said and Pearlman. It is the most popular lossy compression technique. The image is first decomposed into number of sub bands with the help of hierarchical wavelet decomposition. These bands are called as spatial-orientation trees. The co-efficient in the spatial-orientation trees are then encoded. SPIHT is a multistage encoding algorithm therefore it employs three lists. The list of insignificant pixels (LIP) it contains unique coefficients which have magnitude lesser than the threshold. The list of insignificant sets (LIS) it contains sets of wavelet coefficients that are defined by tree structures that have magnitudes lesser than the threshold. They should have at least four elements. The list of significant pixels (LSP) these pixels have the magnitudes greater than threshold values.

The coding is done by applying two types of iterations. The first one is the sorting pass where it searches the LIP and moves the significant coefficients to LSP and outputs its sign. Then it searches LIS and executes the significant information.

The second process is the refinement pass that browses the coefficients in LSP and outputs a single bit based on the new threshold. After the completion of two passes the threshold is divided by 2 and the two passes are repeated recursively until the desired number of output bits are obtained.

C. Performance Evaluation Metrics

The hybrid compression technique is evaluated in terms of Peak signal to noise ratio (PSNR). Mean square error (MSE), Structural similarity index (SSIM) and Compression ratio (CR).

1. Mean Square Error (MSE)

Mean square error is the distortion between the reconstructed image and the original image.

$$MSE = 1/MXN \sum_{i=0}^{MXN} ((\mathrm{Xi} - \mathrm{Yi})(\mathrm{Xi} - \mathrm{Yi}))\mathrm{dB} \quad \textbf{(1)}$$

Where, MXN is the size of the image

2. Peak Signal to Noise Ratio (PSNR)

Peak signal to noise ratio is an expression for the ratio between the maximum values of power from a signal to the power of the distorting noise which is affecting the quality of the image representation. Higher the PSNR value better is the quality of the image.

$$\mathrm{PSNR} = 10\log(255^2/\mathrm{MSE}) \quad \textbf{(2)}$$

3. Structural Similarity Index (SSIM)

Structural similarity index is a comparison parameter which requires two images and checks the similarity between the original image and the reconstructed image. It is developed by considering
three different factors such as local luminance similarity, local contrast sensitivity, and local structure similarity.

$$\mathrm{SSIM} = \frac{(2\mu x\mu y + C1)(2\sigma xy + C2)}{(\mu x2 + \mu y2 + C1)(\sigma x2 + \sigma y2 + C2)} \quad \textbf{(3)}$$

Where, µx, µy are the mean values of local luminance, and σx, σy are the standard deviations of the luminance similarity for original image and reconstructed image. C1 and C2 are the local contrast sensitivity of the original image and reconstructed image.

4. Compression Ratio (CR)

Compression ratio is used to measure the ability of data compression by comparing the size of the image being compressed to the size of the original image.

$$\mathrm{CR} = \frac{\textit{input image size}}{\textit{compressed output image size}} \quad \textbf{(4)}$$

I. SIMULATION RESULTS

The simulation tool being used is MATLAB. The experimental results obtained from the evaluation of hybrid technique by using Huffman coding and SPIHT is represented. All the performance parameters have been evaluated on gray scale brain MRI images as shown in Figure 4.

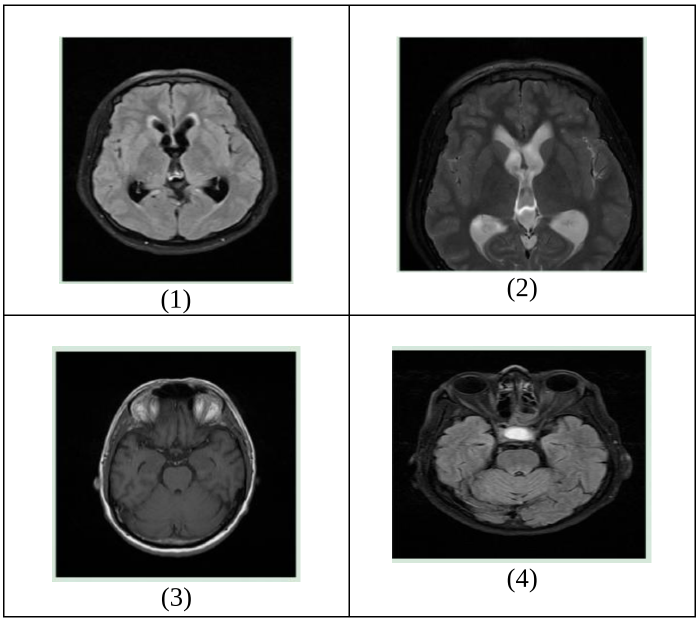

Figure4. Different images used for simulation purpose

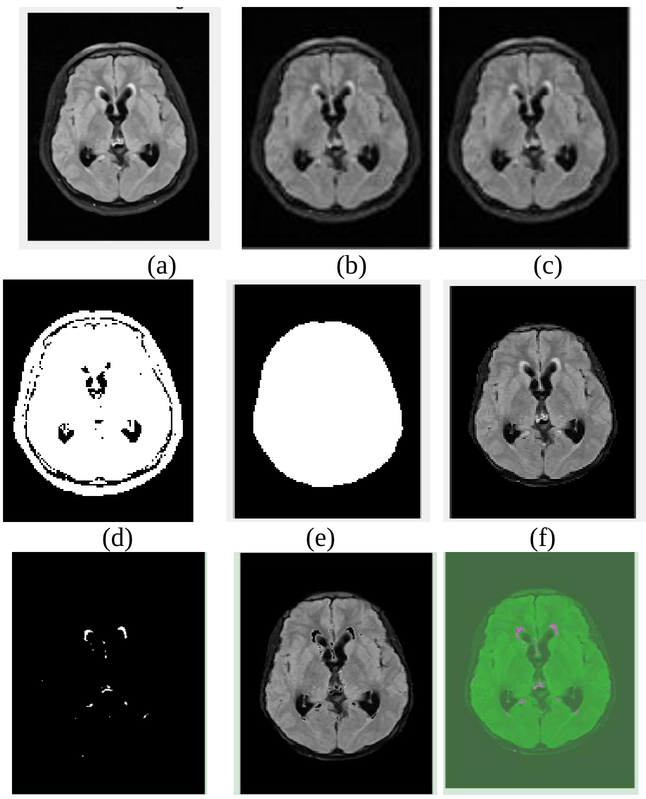

Figure5. Simulation Results (a)Original image (b)Median filtered image (c)Enhanced image (d) Binary masked image (e) Eroded image (f) Skull stripped image (g) ROI (h) NON-ROI (i) Reconstructed image

Table1: Compression Ratios of various MRI images

IMAGES	COMPRESSION RATIO
Image 1	1.2378
Image 2	1.4591
Image 3	1.2891
Image 4	1.16 4

It is observed form table1 that the compression ratio of the proposed hybrid technique depends upon the area to which extent the tumor is spread. The obtained compression ratio is more in case of image 2 in which the tumor is small sized whereas the image is less compressed in image 4.

Table 2: Hybrid technique evaluation parameters

IMAGES	PSNR		SSIM		MSE	
	ROI	NON-ROI	ROI	NON-ROI	ROI	NON-ROI
Image 1	31.08	26.25	0.955	0.901	50.670	154.017
Image 2	33.09	24.91	0.977	0.887	31.909	209.553
Image 3	32.68	24.59	0.969	0.915	35.075	225.493
Image 4	35.22	24.29	0.989	0.905	19.507	241.665

From table2 it is observed that the PSNR ranges between 5.36dB to 10.98dB. The PSNR varies with the compression ratio even the PSNR depends on the size of tumor region. Thus, the difference in PSNR is highest in the ROI part of image 2 and image 4.

The SSIM value is almost closer to 1 which indicates that the reconstructed images are almost similar to the original image chosen.

The MSE is the loss of information from the image i.e. where ever there is compression there will be loss of data. The values are lesser for ROI region than NON-ROI hence the data lost is more in NON-ROI than from ROI.

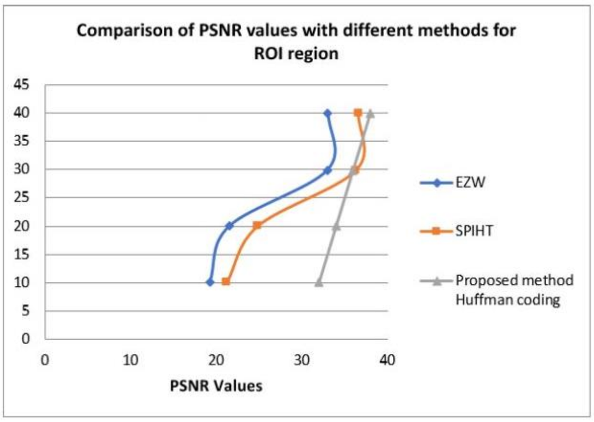

Figure 6 Comparison Table

From figure 6 it is inferred that the calculated PSNR values from EZW and SPIHT method do not give better PSNR values than the proposed method using Huffman coding. Therefore the proposed algorithm is better than the earlier proposed methods.

I. CONCLUSION

This paper has discussed about the various existing techniques of compression for medical images. The hybrid compression technique gives a good compression ratio while preserving the diagnostically important regions. The segmentation procedure efficiently extracts the tumor regions from the brain. The redundant information is eliminated by this technique of segmentation. Hybrid technique is extensively used in telemedicine system especially at rural areas. The proposed method is less complex as compared with other methods. The PSNR output for the ROI part of the proposed system is compared with different technique of EZW and SPIHT and observed that the obtained PSNR value is better than the other two methods.

In future the PSNR value may be still enhanced. This work will be extended for 3D images so that it becomes very easy for the visualizers to identify the tumor region more easily.

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