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Comparison of Hybrid Codes for MRI Brain Image Compression

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Abstract - **Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) scanning techniques produce human body pictures in digital form, which are prohibitive in nature. Hence compression is necessary for storage and transmission purposes of such medical images. In general, medical images are compressed in a lossless manner in order to preserve details and to avoid wrong diagnosis. But this leads to a lower compression rate. Hence we consider region of interest (ROI) normally the abnormal region in the image and compress it without loss to achieve high compression ratio in par with maintaining high image quality and the Non-region of interest (Non-ROI) of the image is compressed in a lossy manner. This paper discusses two simple hybrid coding techniques (Hybrid A and Hybrid B) on MRI human brain tumor image datasets. Also we evaluate their performance by comparing them with the standard lossless technique JPEG 2000 in terms of compression ratio (CR) and peak to signal noise ratio (PSNR). Both hybrid codes have resulted in computationally economical scheme producing higher compression ratio than existing JPEG2000 and also meets the legal requirement of medical image archiving. The results obtained prove that our proposed hybrid schemes outperform existing schemes.**

Keywords: **Compression, Segmentation, ROI, Non-ROI, CR, PSNR, Fractal**

I. Introduction

In the diagnosis of diseases and surgical planning, vital role is played by the medical imaging techniques. Such medical images are prohibitive in nature and also they require long-term storage and efficient transmission. The need for data storage capacity and transmission bandwidth continues to exceed the capability of available technologies. The process of obtaining a compact representation of an image while maintaining all the necessary information important for medical diagnosis is referred to as image compression. Image compression can be classified into lossless and lossy compression. Lossy compression is called as irreversible compression, whereas the lossless compression is also called as reversible, as it enables complete recovery of the original image from the compressed image. An important disadvantage of lossless compression scheme is its low compression ratio. Hybrid coding of medical images could be the solution for the above problem. The main idea is to preserve the fine details in the region of interest (ROI) by lossless coding, while allowing lossy coding for the Non- region of interest (NON-ROI).

The proposed method is an effort to obtain higher compression ratio by means of hybrid coding the MRI brain (tumor) images, so that the effectiveness of storage and transmission of such images can be improved. To separate ROI and Non-ROI regions we require the image to be segmented. In our proposed scheme, the MRI human brain image is segmented by using Region Growing algorithm and then coded using the hybrid schemes. Our results prove that the hybrid coding schemes outperform the other existing techniques in compressing the MRI brain images. Figure1 depicts the proposed hybrid scheme.

The paper continues as follows: Section II describes image segmentation and region extraction. Section III explains our hybrid coding scheme A. Section IV explains the hybrid coding scheme B. In section V, the results are discussed. Section VI derives at conclusion and discusses the possible future works.

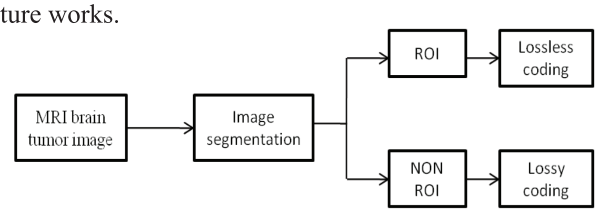


Fig 1 Flow Diagram

II. Image Segmentation and Region Extraction

Image segmentation is required as a preliminary and indispensible stage in the computer aided medical image process, particularly during the clinical analysis of Magnetic Resonance brain images. Segmentation [6] subdivides an image into its constituent regions or objects. The level to which the subdivision is carried depends on the problem being solved. That is, segmentation should stop when the objects of interest in an application have been isolated. Segmentation accuracy determines the eventual success or failure of computerized analysis procedure. For this reason, considerable care should be taken to improve the probability of rugged segmentation.

Image segmentation algorithms generally are based on one of two basic properties of intensity values: discontinuity and similarity. In the first category, the approach is to partition an image based on abrupt changes in intensity, such as edges in an image. The principal approaches in the second category are based on partitioning an image into regions that are similar according to a set of predefined criteria. Thresholding, region growing and region splitting and merging are different methods in this category.

Thresholding is a fundamental approach to segmentation that enjoys a significant degree of popularity, especially in applications where speed is an important factor. Region splitting and merging is a technique in which images is subdivided initially into a set of arbitrary disjointed regions and then merge and/or split the regions in an attempt to satisfy the basic conditions of segmentation. Region growing is a procedure that groups pixels or subregions into larger regions based on predefined criteria. The basic approach is to start with a set of "seed" points and from these grow regions by appending to each seed those neighboring pixels that have properties similar to the seed. Selecting a set of one or more starting points often can be based on the nature of the problem. When a priori information is not available, the procedure is to compute at every pixel the same set of properties that ultimately will be used to assign pixels to regions during the growing process.

Medical image segmentation is a complex and challenging task due to the intrinsic nature of the images. Our segmentation algorithm, Region Growing Algorithm, relies on 3-D extension of mathematical morphology, a branch of science that is built upon set theory with many application areas in image processing. It includes generation of mappings for each pixel according to the pixel's local neighborhood. Many researchers have used this technique to segment biomedical images [2&3].

In figure 2, the flowchart describes the region growing algorithm for segmenting the tumor region from the MRI data set.

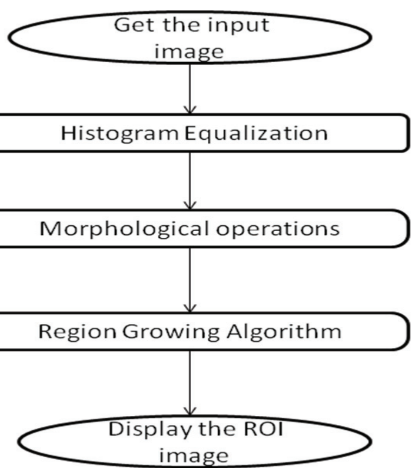


Fig. 2 Segmentation Flowchart

The outputs of the segmentation are depicted in figure 3. Each pixel in the segmented ROI is coded in a lossless manner, while the rest is lossily compressed. Figure 3(e) includes only a little portion of the complete image in figure 3(a) and this brings a considerable amount of compression efficiency.

Region extraction is an algorithmic application of graph theory. Figure 3(f) depicts the extracted region.

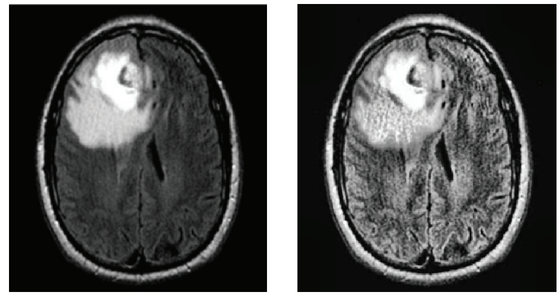
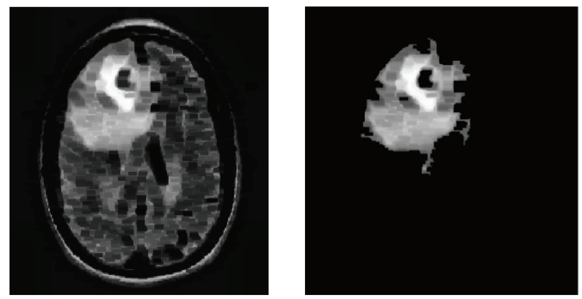
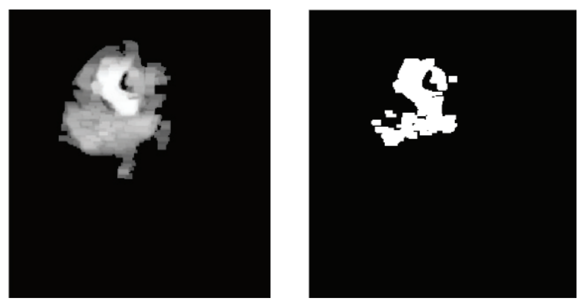


Fig 3 (a) Input image (b) Histogram Equalization



(c) Eroded image (d) Dilated image



(e) Region of Interest (f) Region extraction

III. Hybrid Coding-A

A. Compression of ROI

Once the ROI is segmented, it is compressed using Integer Wavelet Transform(IWT)[4]. IWT is an invertible integer-to integer wavelet analysis algorithm. Compared with Continuous Wavelet Transform and Discrete Wavelet Transform, the IWT is not only computationally faster and more memory efficient but also more suitable in lossless image compression applications. IWT of an image provides the decomposition of the original image into a set of integer coefficients, from which by making use of the inverse IWT the original image can be recovered without any loss. The problem of encoding the original image can therefore be transferred to encoding the wavelet coefficients, which provide a time-frequency description of the original image. Encoding of wavelet coefficients instead of the original image is very attractive, since the separation of the image into a time-frequency representation allows to cope up separately with different image features and events.

We use arithmetic coding to encode the wavelet coefficients.

Unlike Huffman coding, arithmetic coding doesn't use a discrete number of bits for each symbol to compress. It reaches for every source almost the optimum compression in the sense of the Shannon theorem and is well suitable for adaptive models.

B. Compression of Non_ROI

Non_ROI is compressed using Discrete Cosine Transform (DCT) [5]. DCT based image compression relies on two techniques to reduce the data required to represent the image. The first is quantization of the image's DCT coefficients; the second is entropy coding of the quantized coefficients. Quantization is the process of reducing the number of possible values of a quantity, thereby reducing the number of bits needed to represent it. At this stage the basic losses are introduced into compressed image. Larger quantization step (QS) provides larger compression ratio (CR) and simultaneously it leads to larger losses.

Entropy coding is a technique for representing the quantized data as compactly as possible. An entropy encoder further compresses the quantized values losslessly to give better overall compression. DCT exhibits excellent energy compaction for highly correlated images. By inverse DCT, the image can be recovered with minimum loss.

IV. Hybrid Coding-B

A. Compression of ROI

Hybrid coding B also involves compressing the ROI by means of integer wavelet transform as like hybrid coding B. The wavelet transformed coefficients are further encoded by means of arithmetic encoder. Arithmetic coding is a form of variable-length entropy encoding used in lossless data compression.

B. Compression of Non_ROI

Hybrid coding B involves compressing the Non-ROI by using fractal compression [7]. Fractal compression relies on the presence of self-similarity of the image. The image is represented by codes instead of pixels. Although the fractal encoding is computationally expensive, the decoding is simple and quite faster. Fractals are independent of scale and they possess no characteristic size. A general model of fractal image compression system [8] is as shown in figure 4.

Encoding

Decoding

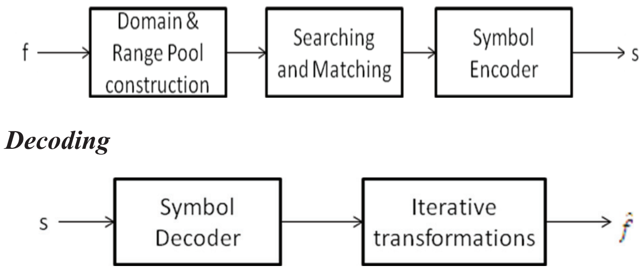


Fig. 4 Generic model of fractal compression

In the encoding phase, an image is partitioned into number of disjoint range blocks of size B*B and a number of domain blocks of size 2B*2B. For each range block, the best matching domain block is searched in the domain pool so that a given metric, say root mean square is minimized. Data compression is achieved by storing only the fractal codes which contains necessary information to reconstruct the image.

Decoding process is performed by iterating the set of transformations on an arbitrary initial image and the quadtree partitioning is used to determine the ranges in the image. For ach range block, the matched domain block size is reduced by two via 2*2 pixel averaging. The pixel values of the reduced domain block are then placed in the location in the range determined by the orientation information after scaling and offsetting. Computing all the range blocks amounts to one iteration.

After several iterations, the reconstructed image (approximated image) will be very close to the original image. Larger range blocks (e.g., 5*5 or above) can result in higher compression ratio and allow good exploitation of redundancy in smooth image areas. But the matching will be less accurate. Therefore smaller range blocks (e.g., 4*4 or below) are preferred to achieve robust coding system. Smoothing the noisy images is another way to improve the fidelity and compression rate, which can be done by clustering.

V. Results

A. Hybrid Code-A

ROI image and its compression using the IWT have been shown in figure 5(a) and 5(b) respectively.

Non_ROI image and its compressed version using the DCT have been shown in figure 5(c) and 5(d) respectively.

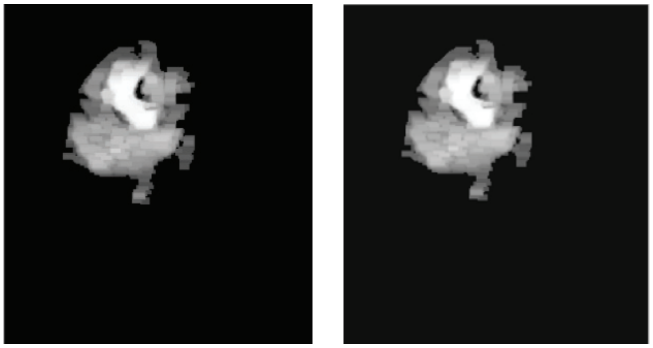
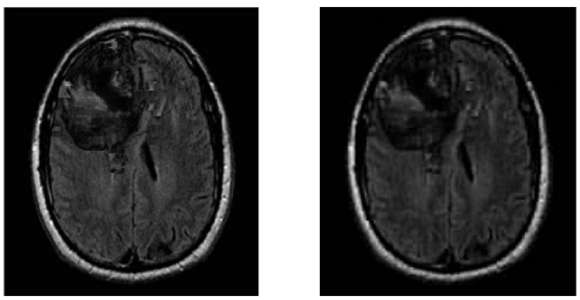


Fig 5. (a) ROI image (b) ROI compressed image using IWT



(c) Non_ROI image (d)Non_ROI compressed image using DCT

Table I shows overall results (Compression Ratio) for hybrid compression scheme A and compare it with JPEG2000 Lossless. If X is compression ratio for ROI of the image and Y is compression ratio for Non_ROI of the image then overall compression ratio (CR overall) [9] is achieved based on

CR overall=X*Y/X+Y

TABLE 1 CR OF HYBRID A AND EXISTING TECHNIQUE

MRI Brain images	Proposed Technique			JPEG2000 Lossless CR
	ROI CR	Non_ROI CR	Overall CR	
Dataset 1	24.02	155.31	20.8	20.3
Dataset 2	31.01	83.25	22.59	17.93
Dataset 3	36.43	83.25	25.34	18.86
Dataset 4	55.39	108.33	36.65	27.7

Table II shows the comparative study of our hybrid scheme A with the JPEG 2000 in terms of Peak to Signal Noise Ratio(PSNR).

TABLE II PSNR OF HYBRID A AND EXISTING TECHNIQUE

MRI brain images	Proposed Technique		JPEG2000 Lossless PSNR(dB)
	ROI PSNR(dB)	Non ROI PSNR(dB)	
Dataset 1	38.59	9.18	21.79
Dataset 2	44.10	10.43	29.48
Dataset 3	49.39	11.16	29.91
Dataset 4	69.5	13.23	35.48

While JPEG2000 is applied directly on original images, the JPEG 2000 is the standard based on wavelet decomposition. It consists of filters that generate integer coefficients; this type is particularly useful when the wavelet decomposition is part of a lossless compression scheme.

B. Hybrid Code-B

Hybrid code B involves the ROI to be compressed by IWT as that of code A. Hence, ROI image and its compression of code B ia same as shown in figure 5 (a) and (b) respectively. Non_ROI image and its compressed version using the fractal compression have been shown in figure 6(a) and (b) respectively.

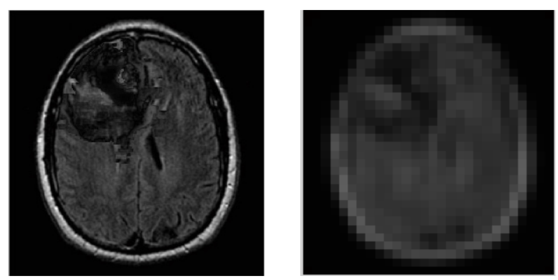


Fig 6 (a) Non-ROI image (b) Non-ROI compressed image using fractal

Table III shows CR for hybrid compression scheme B and compare it with JPEG2000 Lossless.

TABLE III CR OF HYBRID B AND EXISTING TECHNIQUE

MRI Brain images	Proposed Technique			JPEG2000 Lossless CR
	ROI CR	Non_ROI CR	Overall CR	
Dataset 1	24.02	578.55	23.07	20.3
Dataset 2	31.01	69.97	21.48	17.93
Dataset 3	36.43	68.72	23.8	18.86
Dataset 4	55.39	329.34	47.42	27.7

Table IV shows the comparative study of our hybrid scheme B with the JPEG 2000 in terms of PSNR

TABLE IV PSNR OF HYBRID B AND EXISTING TECHNIQUE

MRI brain images	Proposed Technique		JPEG2000 Lossless PSNR(dB)
	ROI PSNR(dB)	Non ROI PSNR(dB)	
Dataset 1	38.59	28.28	21.79
Dataset 2	44.10	28.04	29.48
Dataset 3	49.39	28.05	29.91
Dataset 4	69.5	29.56	35.48

C. Comparison of Hybrid Codes A and B with the JPEG2000

Figure 7 shows the comparison between hybrid codes A, B and JPEG2000 in terms of compression rate.

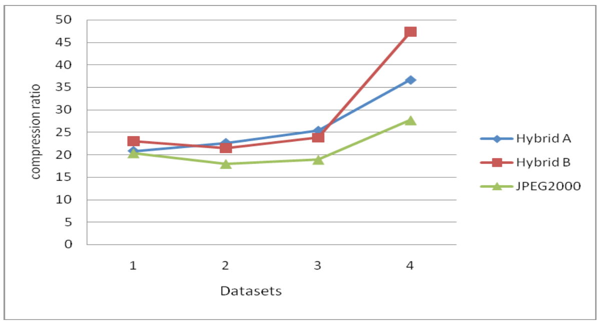


Fig. 7 Comparison in terms of CR

Figure 8 shows the comparison between hybrid compression code A and JPEG2000 in terms of PSNR.

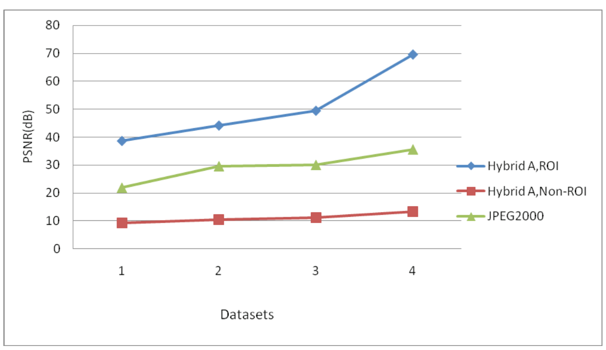


Fig. 8 Comparison of Hybrid A and JPEG 2000 in terms of PSNR

Figure 9 depicts the comparison between hybrid compression code B and JPEG2000 in terms of PSNR.

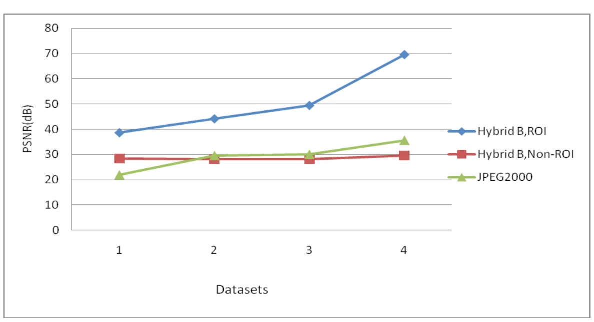


Fig. 9 Comparison of Hybrid B and JPEG 2000 in terms of PSNR

VI. CONCLUSION AND FUTURE WORK

From the analysis we could observe that hybrid compression schemes, can thus achieve higher compression ratios comparable to standard lossless compression technique. Hybrid code B produce higher CR than both hybrid A and JPEG 2000.In Particular, Table 1 and Table 3 shows that lossless compression ratio achieved by JPEG2000 is far less than the proposed hybrid techniques.

There are many possible directions for future investigation. In order to obtain better compression ratio, experiments can be done on different hybrids of lossless and lossy compression techniques.

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