HYBRID COMPRESSION FOR MEDICAL IMAGES USING SPIHT

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Abstract

Medical imaging techniques produce visual representation of interior of human body in digital form. These techniques are data intensive and compression is required for efficient storage and transmission purpose. Medical images are preferred to be compressed using lossless manner in order to preserve the details and to avoid wrong diagnosis. However, in some areas of medicine, it may be sufficient to maintain high image quality in diagnostically important region i.e. region of interest (ROI). This paper proposes a hybrid compression scheme for medical images using SPIHT. The ROI part is compressed using lossless Huffman and arithmetic coding techniques, while NON-ROI part is compressed using lossy SPIHT. The performance is evaluated in terms of compression ratio and execution time for Huffman encoding and arithmetic encoding techniques.

Index Terms: Huffman coding, Hybrid compression, ROI, SPIHT,

I. INTRODUCTION

A common characteristic of most images is that the neighboring pixels are correlated and therefore contain redundant information. Reduction of this redundant information is the primary objective of image compression [1]. Image compression reduces the data required to represent a digital image by the removal of one or more of the three basic data redundancies: coding redundancy, spatial and temporal redundancy, and irrelevant information [2]. This yields a compact representation of an image, thereby minimizing the storage and transmission requirements.

A. *Lossless v/s Lossy compression:*

The image compression techniques are broadly classified into two categories: lossless compression and lossy compression based on whether or not an exact replica of the original image could be reconstructed using the compressed image. Lossless image compression is a reversible technique in which exact reconstruction of the original image can be achieved [3]. The compression ratio obtained could be as low as 2:1 to 3:1. Lossless compression techniques can be modelled as two stage procedure. The first stage removes spatial and interpixel redundancy using predictive and transform coding. The second stage includes entropy coding for the removal of coding redundancy [4].

Lossy compression schemes are irreversible in nature. The decompressed image is not identical to the original image, but reasonably close. The compression schemes provides high compression ratio as high as 10:1 at the cost of image quality degradation [3].

The rest of the paper is organized as follows: section 2 briefs about the medical image compression and different modalities used for digital imaging. Section 3 details some of recent related work. The proposed methodology is described in section 4. Experimental results are discussed in section 5. Section 6 concludes the paper.

II. MEDICAL IMAGE COMPRESSION

Medical image compression plays a key role as hospitals move towards filmless imaging and go completely digital. Several widespread technologies for digital imaging, such as X-ray, Computed Tomography (CT), and Magnetic Resonance Imaging (MRI) produce three-dimensional images. A typical 12-bit medical X-ray may be 2048 pixels by 2560 pixels in dimension. This translates to a file size of 10,485,760 bytes. A typical 16-bit MRI image may be having a file size of 5-6MB [5]. Storage and transmission are key issues in such platforms, due to the significant image file sizes. Table 1 describes the common resolution of different medical imaging modalities [6].

Table 1 Common Resolution of Digital Images [6]

Image acquisition modality	Image size (No. of pixels)	Pixel Value (No. of bits)
Scanned conventional radiography	2048 × 2048	12
Computerized tomography	512 × 512	16
Magnetic resonance imaging	256 × 256	12
Ultrasound	512 × 512	8
Nuclear medicine	128 × 128	8

The primary objectives of medical image compression are namely to reduced file size and achieve high quality of decompressed image [7]. Reduced file size makes it more suitable for telemedicine applications, while high quality of decompressed image ensures maintenance of relevant information important for diagnosis.

Out of the several proposed techniques, ROI based coding has proved to be a good approach for medical image compression especially in telemedicine application. ROI describes the affected part of the image which is to be analyzed. Fig 1 shows the brain MRI image marked with ROI and NON-ROI regions. ROI-based compression techniques take advantage of both lossy and lossless techniques to compress images. These techniques use lossless compression for abnormal regions that are important for diagnosis and therefore require high quality, while lossy compression is applied on other all regions.

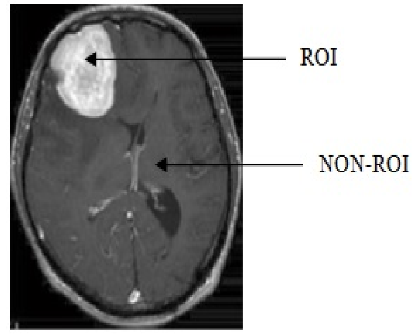


Fig. 1 Brain MRI image showing different regions

III. RELATED WORK

Bharti et al [8] performed a comparative analysis of wavelet based compression techniques based on ROI for medical images. Four different combinations of JPEG2000 and SPIHT algorithms have been implemented for ROI and NON-ROI region. The performance is evaluated for compression metrics such as PSNR, SSIM and correlation parameters. They have concluded that the similarity between the reconstructed image and original image is more when SPIHT/SPIHT hybrid ROI scheme is used.

ROI based compression using JPEG algorithm has been proposed in [7]. They have used active contour method to separate foreground and background region. Lossless JPEG algorithm has been used to compress foreground and lossy JPEG compression for background. The proposed method has been compared with the traditional JPEG algorithm in terms of compression ratio, PSNR and speed of compression.

Soundarya et al [9] have proposed two hybrid coding techniques – Hybrid-A and Hybrid-B, on MRI human brain tumor image datasets. They have compressed ROI part using Integer Wavelet Transform (IWT) in both schemes. DCT has been used for compression of NON-ROI region in scheme A, while scheme B uses fractal compression. The results have been drawn in terms of compression ratio and PSNR. The ROI is extracted using region growing algorithm.

Sophia et al [10] proposed a block based and region of interest (ROI) based compression algorithm for telemedicine application. They have combined three classical compression algorithms such as Run Length Coding (RLE), Huffman coding and arithmetic coding with 1D and 2D quantization. The importance of selective image compression has been analyzed by comparing the proposed algorithm with their block based compression.

Sahu et al. [11] presents a procedure of employing both lossless and lossy compression methods in a manner to achieve effective compression ratio and less error rate. The proposed method employs merging the Huffman encoding technique along with Linear Predictive Coding (LPC) for the enhancement of compression ratio (CR). The results are drawn in terms of CR, PSNR, Mean structural similarity Index (MSSIM), ERMS. Manual region of interest extraction has been used.

A compression scheme focusing on performance analysis of Haar transformed is presented in [12]. The brain MRI image is segmented into ROI and NON-ROI part. The ROI part has been kept uncompressed while the Non-ROI part undergoes compression using Haar wavelet. The selection of pyramid levels for Haar wavelet is user defined. Both ROI and compressed Non-ROI have been combined at a later stage. They have used various parameters such as Mean Square Error (MSE), PSNR to list a few, for quality measurement of the reconstructed image.

Gupta et al [13] combines IWT and SPIHT in the implementation of their proposed ROI based medical image compression. Global thresholding method has been used to separate background from ROI and NON-ROI regions. The ROI and NON- ROI have been separated manually. ROI region has been encoded with IWT with high bpp, and NON-ROI using SPIHT with low bpp. They have used MATLAB simulation for the proposed work.

Dayal have used SPIHT algorithm for ROI compression in [14]. The medical image has been segmented into ROI and NON-ROI using seeded region growing method. They have compressed ROI part with DWT followed by SPIHT, while NON-ROI region with DCT algorithm. The results have been stated in terms of compression ratio, PSNR and MSE.

IV. METHODOLOGY

The general flowchart of the proposed work has been shown in Fig.2. The steps involved in the proposed image compression are as follows:

- Load the brain MRI image.
- Separate the ROI and NON-ROI regions.
- Encode ROI using Huffman and arithmetic coding.
- Encode NON-ROI region using SPIHT.
- Calculate the compression ratio of the compressed image by combining SPIHT with Huffman and arithmetic coding.

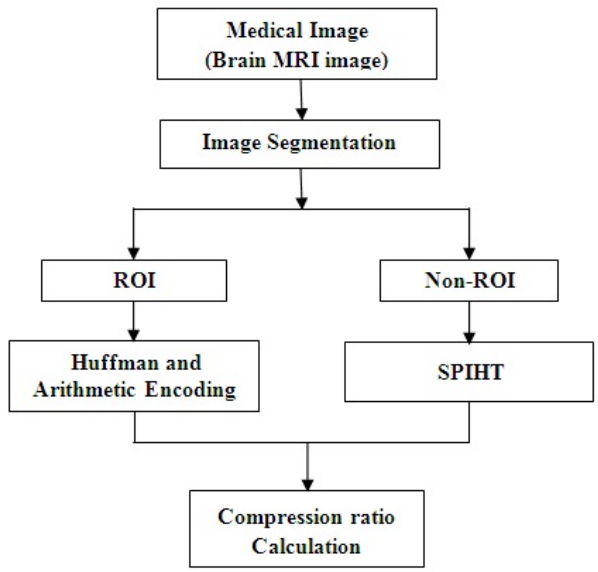
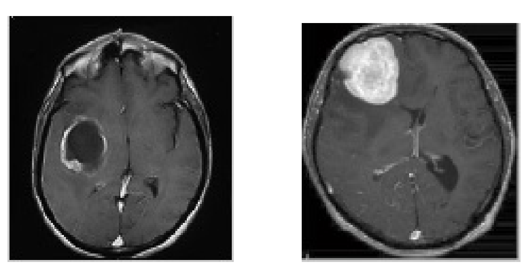


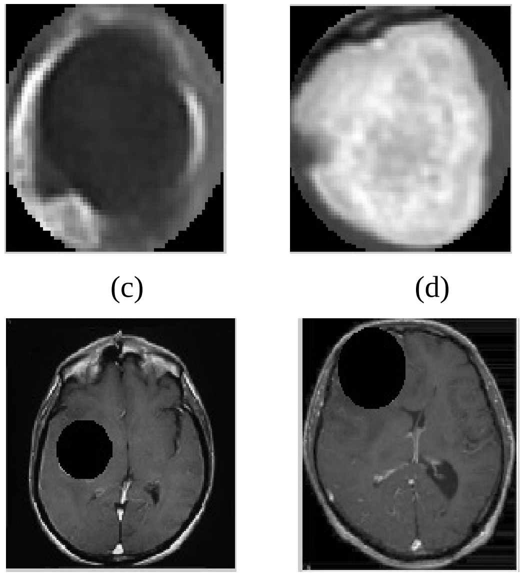
Fig.2 Flowchart of the proposed system

A. *Region of Interest (ROI) Extraction:*

In case of brain MRI images ROI part comprises the tumor while rest of the image forms NON-ROI region. Fig.3 shows ROI extracted for T1 and T2 MRI scans. In case of T1 MRI, the tumor region is hypodense (i.e. darker) than the background while in case of T2 MRI scan, tumor region is hyperdense (i.e. lighter) [15]. The ROI is selected manually using circular window.



(a) (b)



(c) (d)

(e) (f)

Fig.3 (a) T1 MRI scan (b) T2 MRI scan
(c, d) ROI part of T1 and T2 (e, f) NON-ROI part of T1 and T2

B. Huffman Coding:

A Huffman code is an optimal prefix code calculated using the algorithm introduced by David A. Huffman. It is an entropy encoding algorithm. The term refers to the use of a variable length code table for encoding a source symbol. It uses a specific method for choosing the representation for each symbol, resulting in a prefix code that expresses the most common source symbols using shorter strings of bits than are used for less common source symbols [16].

The symbols are coded based on their statistical occurrence frequencies (probabilities). The symbols that occur more frequently are assigned a smaller number of bits, while the symbols that occur less frequently are assigned a relatively larger number of bits. Huffman coding yields the smallest possible number of code symbols per source symbol. The term prefix means that the (binary) code of any symbol is not the prefix of the code of any other symbol [17].

It is also called as a block code because each source symbol is mapped into a fixed sequence of code symbols. It is instantaneous because each code word in a string of a code symbols can be decoded without referring succeeding symbols. It is uniquely decodable because any string of code symbols can be decoded in only one way. Most image coding standards use lossy techniques in the earlier stages of compression and use Huffman coding as the final step [2].

Algorithm for Huffman coding [18]:

- Read the image and get the pixel values.
- Calculate the distinct symbols in the image and number of times they occur.
- Find the probability of the occurrence for each symbol.
- Generate the codebook for the symbols.
- Encode the sequence using the codebook generated in previous step.

C. Arithmetic Coding:

Arithmetic coding is a form of entropy encoding used in lossless data compression. It requires symbols, probability range and image sequence for coding. It encodes data by creating a code string which represents a fractional value on the number line between 0 and 1 according to the probabilities of occurrences of the intensities [19].

Arithmetic coding does not generate individual codes for each symbol but performs arithmetic operations on block of data, based on the probability of next symbol. Using arithmetic coding, it is possible to encode symbols with a fractional number of bits, thus approaching the theoretical optimum.

Algorithm for Arithmetic Coding:

- Read the image and get the pixel values.
- Calculate the distinct symbols in the image and number of times they occur.
- Calculate probability of each symbol
- Calculate the cumulative probability.
- Calculate the sequence of the symbols.
- Encode the data using the sequence and count.

D. SPIHT:

SPIHT algorithm was introduced by Said and Pearlman. It has an embedded coding property which sorts the information on demand and decreases error correction codes from the beginning to the end of the compressed file. SPIHT stand for Set Partitioning in Hierarchical Trees. The term Hierarchical Trees refers to the quad trees. Set Partitioning refers to the way these quad trees are being divided up or partitioned, and the wavelet transform values at a given threshold [20].

SPIHT algorithm has following characteristics [21]:

- The greater part of an image's energy is concentrated in the low-frequency components.
- A decrease in variance is detected from the highest to the lowest levels of the sub band pyramid.
- There is a spatial self-similarity amongst the sub-bands and the coefficients are to be better magnitude-ordered on moving downward in the pyramid along the same spatial orientation.

In general, SPIHT algorithm is based on following concepts:

- Ordered bit plane progressive transmission.
- Set partitioning sorting algorithm.
- Spatial orientation in trees.

SPIHT uses three ordered lists namely LIS, LIP, and LSP. LIS is a list of insignificant sets that contains sets of wavelet coefficients which are defined by tree structures, and which had been found to have magnitude smaller than a threshold (are insignificant). The sets exclude the coefficient corresponding to the tree or all sub tree roots, and have at least four elements. LIP is the list of insignificant pixels which contains individual coefficients that have magnitude smaller than the threshold. LSP is the list of significant pixels which contains pixels found to have magnitude larger that the threshold (are significant) [22].

The coding is done by running two passes. The first, sorting pass, browses the LIP and moves all significant coefficients to LSP and outputs its sign. Then is browses LIS executing the significant information and following the partitioning sorting algorithm.

The second is the refinement pass that browses the coefficients in LSP and outputs a single bit alone based on the current threshold. After the execution of two passes the threshold is divided by 2 and the two passes are repeated. The procedure is recursively applied until the number of output bits reached the desired number.

V. RESULT ANALYSIS

In this section, the results obtained from experimentation to test the performance of hybrid coding scheme of SPIHT with Huffman coding and arithmetic coding are presented. The simulation has been done using MATLAB R2010a. The performance is evaluated on gray scale T1 and T2 MRI scanned images, which have been resized to 256 × 256, in terms of compression ratio (CR) and execution time. The execution time is calculated by using default commands in MATLAB and the compression ratio of the proposed algorithm is calculated as follows:

$$CR = \frac{bytes\, in\ original\ image}{bytes\ in\ compressed\ image}$$

In this paper, various MRI images have been examined. Table 2 shows simulation results for T1 andT2 MRI images

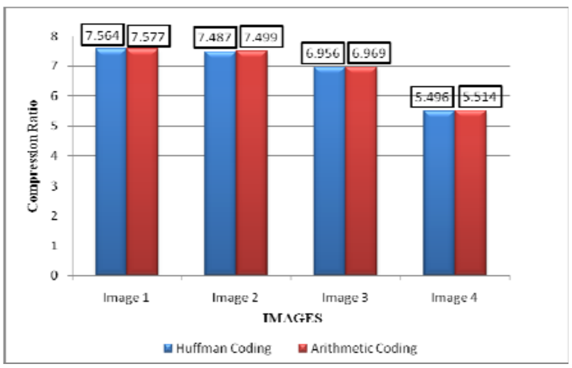
Table 2 Performance of Huffman and arithmetic coding in proposed hybrid image compression algorithm

Size of the original image = 256 × 256					
Image	**Size of ROI**	**Huffman Coding**		**Arithmetic coding**	
		CR	**Execution Time (Sec)**	**CR**	**Execution Time (Sec)**
T1 MRI images					
Image 1	53 × 53	7.564	0.808	7.577	0.627
Image 2	57 × 57	7.487	0.731	7.499	0.666
Image 3	65 × 65	6.956	0.777	6.969	0.721
Image 4	85 × 85	5.496	0.937	5.514	0.979
T2 MRI images					
Image 1	43 × 43	8.271	0.684	8.275	0.587
Image 2	51 × 51	7.658	0.764	7.667	0.604

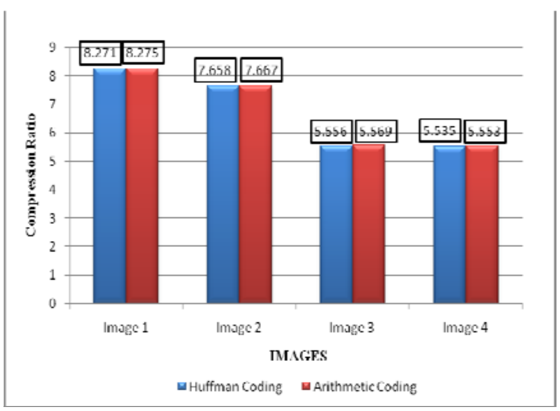
Image 3	79 × 79	5.556	1.299	5.569	0.927
Image 4	85 × 85	5.535	1.344	5.553	0.978

It is observed from table 2 that the compression ratios for both Huffamn and arithmetic compression schems are comparable. In terms of execution time, it is found that arithmetic coding performs better than Huffman coding for small size ROIs.

The graphical comparison of simulation results in terms of compression ratio and execution time for T1 and T2 MRI images is depicted in Fig. 4 and Fig. 5 respectively. From Fig. 4 (a) and (b), it is observed that the compression ratio decreases with increase in size of ROI for both the algorithms.



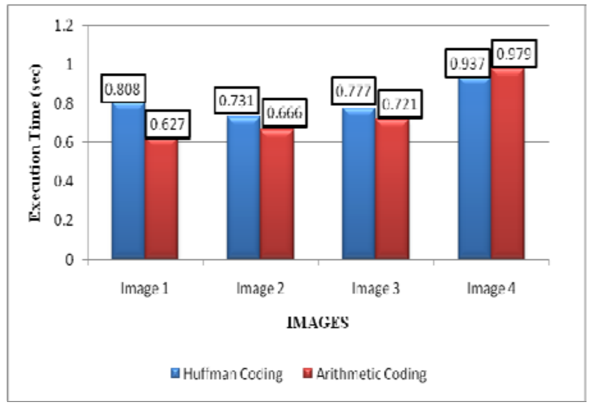
(a)



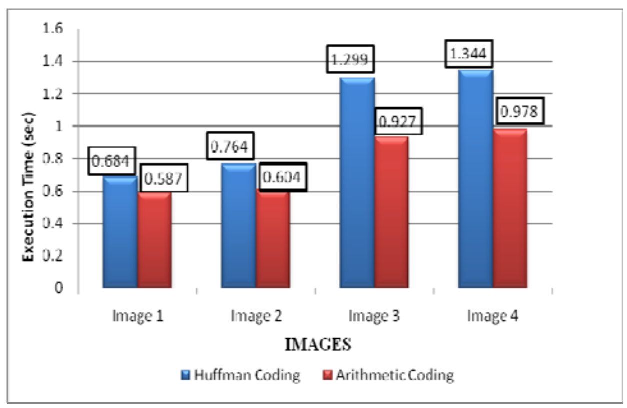
(b)

Fig. 4 Comparison of compression ratio of Huffman and arithmetic coding for (a) T1 MRI and (b) T2 MRI scan Images.

The difference between execution time, for T1 MRI scanned images, decreases with increase in the size of ROI. However, for T2 MRI scanned images, the performance of arithmetic coding in terms of execution time is superior to that of Huffman coding irrespective of size of ROI. It is also observed that the execution times of Huffman and arithmetic coding are comparable if the shape of tumor in near circular. As circular window has been used for extraction of ROI, less background appears for such images. For example, Image 2 and Image 3 from Fig 5 (a) and Image 1 and Image 2 from Fig 5 (b).



(a)



(b)

Fig.5 Comparison of execution time between Huffman and arithmetic coding for (a) T1 MRI and (b) T2 MRI scan Images.

VI. CONCLUSION

Hybrid compression technique provides an intermediate solution for efficient compression of medical images. It combines both lossless and lossy compression schemes and maintains the quality of image near lossless. In the proposed technique, ROI based hybrid compression of brain MRI images is done. A manual segmentation procedure has been employed for separation of ROI and NON-ROI regions.

Huffman and arithmetic coding are used in a combination with lossy SPIHT for the proposed hybrid scheme. Simulation results demonstrate the improvement in compression for the proposed hybrid scheme as compared to lossless compression alone on entire image. The overall compression produced is on an average 50% less than SPIHT on entire image, but the fidelity of ROI is preserved.

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