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Performance Analysis of Hybrid Lossless Compression for MRI Brain Images

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Abstract: Medical image compression plays a vital role in the medical field where the high quality medical images require extensive storage capacity. Researchers propose an efficient method for storing MRI brain images with a reduced storage capacity at a lesser execution time. Researchers propose a new lossless compression scheme based on Spatial Fuzzy C-Mean algorithm. The MRI brain image after skull stripping is denoised using curvelet transform and segmented into white, gray and Cerebro-Spinal Fluid (CSF) regions using spatial fuzzy. Each segmented region is then compressed using the proposed compression technique. The proposed method achieved a high compression ratio (78%) and also provides an enhanced image quality after decompression.

Key words: Medical diagnostic imaging, lossless image compression, medical images, JPEG-LS, JPEG2000, lossless hybrid, near-lossless medical image compression, data compression

INTRODUCTION

Compression is a type of datatransform which reduces the amount of data preserving more or less information carried by the data. Data compression techniques can be classified into two categories: Lossless techniques (called also entropy coding schemes) and lossy techniques. In lossless methods, the exact original data can be recovered while in lossy schemes only a close approximation of the original datacan be obtained. Lossless methods are used in specialized applications such as medical imaging and satellite photography. Standard Image Compression algorithms exploit the fact that the human visual system is unable to detect some spectral components but still, lossless image compression techniques are required in many practical cases. Forexample, space and aerial images are expensive to acquireand may contain valuable data undetectable by human eye. Digital medical images are usually written with higher bit depths than natural images. In some countries, there are legal constraints about lossy compression of medical images because they may lose their diagnostic value.

Lossless Compression algorithms were generally designed and optimized to process natural 8 bit images with later extension to higher bit depth images. Many types of high bit depth images are expensive to acquire.

The design of lossless compression of medical images is important and the rapid development of telemedicine and demands for preservation of diagnostic value are to be considered. The compression efficiency that can be obtained on an image depends mainly on the image characteristics. Hence, image compression schemes are generally designed to exploit the presence of such characteristics. Further, implementation aspects such as the image partitioning strategy, block size, area of search space, etc., influence on the compression efficiency as well as the computational complexity. An algorithm will achieve the best possible compression efficiency if it exploits all the characteristics that contribute to the compression and employs efficient implementation strategies.

A medical image contains both useful and useless information, the latter being noise as aresult of the experimental acquisition process and it can be eliminated without degrading the image. A compression method which is able to compress and reconstruct a medical image by rejecting noise information or eliminating redundancies has to be considered lossless because it maintains useful information. A compression algorithm for the reduction of image size is explained in the study.

Literature review: A Lossless and Near-Lossless Compression Method was introduced by Sepehrband *et al.* (2011). This method is more efficient

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due to its high compression ratio and simplicity. This method consists of a new transformation method called Enhanced DPCM Transformation (EDT) which has a good energy compaction and an appropriate huffman encoding. The compression is done and then it is applied to different test cases and the results wereestimated.

Xiong *et al*. (2003) introduced a general 3D integer wavelet packet transform structure that allows implicit bit shifting of wavelet coefficients to approximate a 3D unitary transformation. They developed on context modeling for an efficient arithmetic coding of wavelet coefficients. The video coding techniques, namely, 3D set partitioning in hierarchical treesand 3D embedded sub-band coding with optimal truncation were modified and employed for the compression of data. They accomplished the best performance in terms of lossy and lossless compression.

Nijim *et al*. (1996) proposed a scheme for the compression of 8 bit medical images and its compression values were compared with those obtained using the linear predictor and the lossless JPEG standard. As stated by them, in the differentiation technique, the coefficients of the differentiator are known by the encoder and the decoder which eliminates the need to compute these coefficients and the computational complexity is greatly reduced compared with linear predictor method.

Das and Burgett (1993) presented a method for lossless predictive coding of medical images using 2D multiplicative autoregressive models for both single-resolution and multi-resolution images. The performances of the proposed schemes were compared with some of the existing methods. The experimental results proved that the proposed scheme achieved higher compression compared to other lossless image coding techniques.

Das and Lin (1996) introduced a Hierarchical Auto Regressive (HAR) Model for the lossless medical image compressio n. The 2D HAR Models are considered as modified versions of 1-Dimensional Hierarchical Auto Regressive (1-D HAR) Signal Models. The first layer of a 1D HAR consists of a conventional AR Model for the data whereas each subsequent layer attempts to model the auto regressive coefficients of the preceding layer using a new AR Model. The main advantage of this method is that the transmission of blockwise model coefficients is not needed. The performance of the proposed technique is compared with two existing alternative techniques, namely, Hierarchical Interpolation (HINT) and fixed Differential Pulse Code Modulation (DPCM).

Sepehrband *et al*. (2010) has presented an efficient medical image transformation method for lossless compression by considering real time applications. It has provided low quality medical images due to its variability.

Zhang and Wu (2006) proposed a novel lossless compression of color mosaic images for high level of medical compression and its quality for recovery of medical images.

Calderbank *et al*. (1997) presented lossless image compression using integer to integer wavelet transforms and provided various multi resolution coefficients.

Al-Otum (2003) presented qualitative and quantitative image quality assessment of vector quantization for medical images in real time environment.

Proposed pattern: Among the brain MRI regions, the white matter and gray matter are the most important, since most of the tumors occur in these regions. Researchers propose a matrix based lossless compression for white matter and gray matter regions and SFALIC compression scheme for the Cerebro-Spinal Fluid (CSF) region. The overall block diagram of the proposed system is illustrated in Fig. 1.

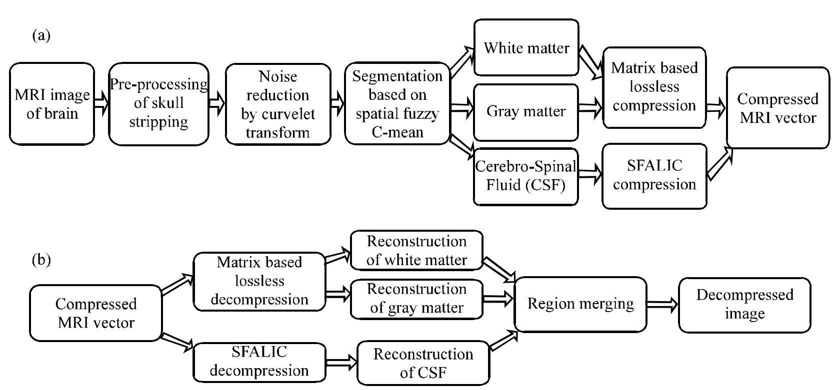

Fig. 1: a) Block diagram of lossless medical MRI brain image encoder and b) lossless medical MRI brain image decoder

MATERIALS AND METHODS

Pre-processing of skull stripping: In this study, two methods of skull stripping are considered, namely, Mathematical Morphology and Region Growing. The initial phase of the process deals with the problem of identifying the threshold value used in performing skull stripping using mathematical morphology. The process flow of the proposed algorithm is shown in Fig. 2. The second phase of the process compares the performance of skull stripping by Region Growing Method with that of Mathematical Morphology Method. Similar, data sets are used for both the methods and both qualitative and quantitative measurements are carried outand their performances are compared.

Data collections: Two dimensional MRI data sets are collected from the web source: www.brainweb.org. A total of 90 MRI brain images for all image sequences are utilized as the test images. The data sets were obtained from adults aged between 18 and 60 years. The details of image sequences used in the experimentare:

- T1-weighted of axial orientation (30 images)
- T2-weighted of axial orientation (30 images)
- Fluid Attenuated Inversion Recovery (FLAIR) of axial orientation (30 images)

Otsu's Thresholding algorithm: Otsu's Thresholding Method is employed for skull stripping using mathematical morphology. In thismethod, the robust threshold values are discovered and the non-cerebral tissues are removed from the brain MRI images. Figure 3 illustrates the non-cerebral tissues (skull, cerebro-spinal fluid, meninges) to be extracted.

Otsu (1979)'s algorithm is very simple and it utilizes only the zeroth-order and the first-order cumulative moments of the gray-level histogram (P_i). It is represented as:

$$P_i = \frac{n_i}{N},\ P_i \geq 0,\ \sum\nolimits_{i-1}^{L} P_i = 1 \tag{1}$$

Where:
n_i = The number of similar pixels
N = The total number of cumulative pixels
L = The integer value 255

To find the optimal threshold value, the separability of the resultant classes in gray levels is maximized. This thresholding method is based on selecting the lowest point between two classes of gray levels. Therefore, the optimal threshold $\sigma_B{}^2(k^*)$ is defined in Eq. 2:

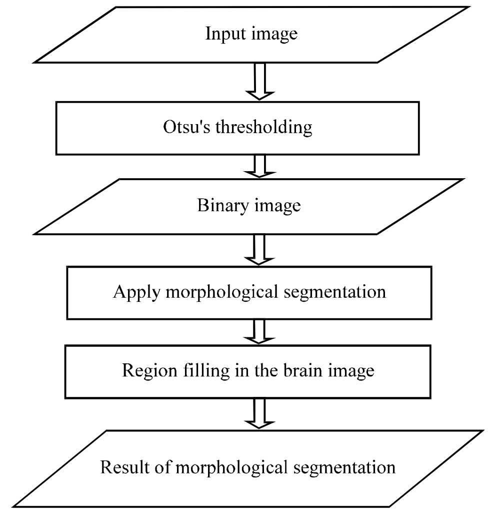

Fig. 2: The process flow of the proposed algorithm

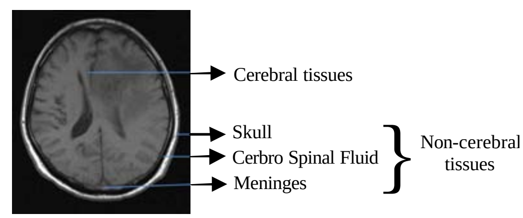

Fig. 3: Cerebral and non-cerebral tissues in brain MRI

$$\sigma_B^2(k^*) = \max_{1\leq k\leq L} \sigma_B^2(k) \tag{2}$$

and the range of k over the maximum islimited to:

$$S^* = \{k;\ \omega\omega_0 = \omega(k)(1-\omega(k) > 0 \ \text{ or } \ 0 \leq \omega(k) \leq 1\} \tag{3}$$

In Eq. 3, ω(k) represents the width of the image pixels taken.

Mathematical morphology segmentation: The mathematical morphology operations such as erosion, dilation and region filling are applied to the binary image to remove the non-cerebral tissues. The binary image is convolved with a structuring element to produce the skull-stripped image. The structuring element is a disk-shaped structure as shown in Fig. 4 which matches the oval-shaped brain.

Erosion is used to remove the pixels at the boundaries of the MRI brain image thus removing the non-brain regions such as skull, Cerebro Spinal Fluid (CSF) and meninges. As described by Gonzalez *et al*. (2004) erosion of a binary image 'A' using a structuring element 'B' can be denoted as:

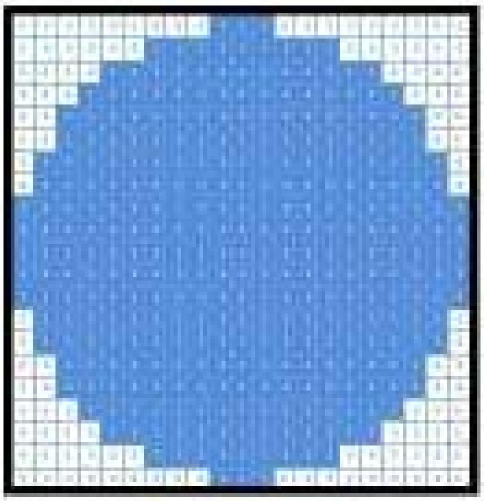

Fig. 4: Disk-shape structuring element used for skull stripping

$$A \ominus B = \{z | (b)_z \subseteq A\} \quad (4)$$

Equation 4 indicates that the erosion of A by B is the set of all points z such that B, translated by z is contained in A. In the Proposed algorithm, the morphological dilation is applied to enhance and interconnect all the intra-cranial tissues within the brain image. Mathematical morphology dilation (Gonzalez *et al*., 2004) of a binary image 'A' using the structuring element 'B' in Fig. 4 but with a different size can be denoted as:

$$A \oplus B = \left\{ z \middle| (\hat{B})_z \cap A \neq \phi \right\} \quad (5)$$

where, ϕ is the empty set. Equation 5 is based on obtaining the reflection of B about its origin and shifting this reflection by z. Thus, mathematical morphology dilation of A by B, denotes the set of all displacements, z such that and A overlap by at least one element.

Region growing: Region growing is a method by which the pixels are grouped into larger regions based on a predefined criterion, i.e., the seed point is selected and the region starts to grow based on the pixel value of the seed point. The segmentation by region growing method is described as follows:

Seed point selection: The seed point is selected by choosing the centre point of the maximum region area within the brain image. Figure 5 shows the seed point of the image encircled in red color.

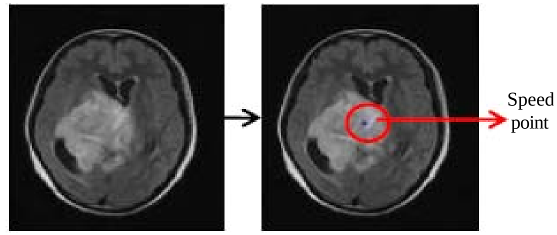

Fig. 5: Selection of seed point

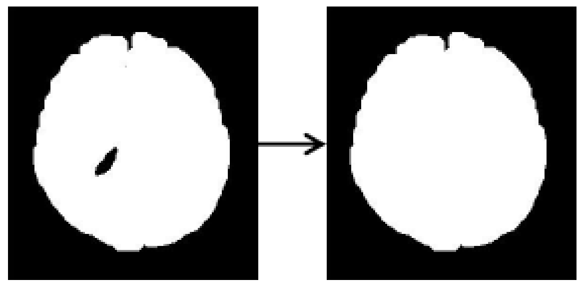

Fig. 6: Region filling process

Growing and stopping of predicates: The region starts to grow by comparing the values of all 8-neighbouring pixels of the original image with the seed point which is within the range of defined threshold values. The region stops growing if the neighboring pixels are outside the range of the threshold values. The region filling process is depicted in Fig. 6.

Noise reduction using curvelet transform: The noises in the brain MRI image are eliminated by using curvelet transforms. The curvelet transform is used to represent the edges and other singularities along curves more efficiently than traditional transforms, i.e., using fewer coefficients. Noises like Random noise, Gaussian noise and Poisson noise are added to the image and denoised using the Curvelet Transform algorithm. The performance of the Curvelet Transform algorithm is evaluated and the results are obtained:

$$X_{i,j} = f(i, j) + \sigma z\_(i, j)$$

Where:
f = The image to be recovered
z = The white Gaussian noise

Algorithm steps to denoise the MRI image: The following steps are followed in the denoising algorithm of Curvelet Transform:

- Step 1: compute all the thresholds for curvelet
- Step 2: compute the norm of curvelet
- Step 3: apply curvelet transform to the noisyimage

- Step 4: apply hard thresholding to the curvelet coefficients
- Step 5: apply inverse curvelet transform to theresult of step 4

Spatial fuzzy C-mean: After noise removal, the Fuzzy C-Mean (FCM) Clustering algorithm is used to create a fuzzy partition. One of the significant uniqueness of an image is that neighboring pixels are extremely correlated. In other terms, the neighboring pixels have similar feature values and the probability that they belong to the same cluster is much more. This spatial relationship is essential in clustering but it is not considered in a standard FCM algorithm. A spatial function to develop the spatial information is defined as:

$$h_{ij} = \sum_{k \in NB(x_j)} U_{ik} \tag{6}$$

Where:

$NB(x_j)$ = A 3×3 square window centered on pixel x_j in the spatial domain

h_{ij} = The probability that pixel x_j belongs to ith cluster

The value of spatial function of a pixel for a cluster is much great if many of its neighborhoods belong to the same cluster. The spatial functionis included into membership function as follows:

$$U'_{ij} = \frac{U_{ij}^p h_{ij}^q}{\sum_{k=1}^{C} U_{kj}^p h_{kj}^q} \tag{7}$$

where, p and q are parameters to control the relative importance of both functions. In a homogenous region, the spatial function of the cluster remains unchanged. But for a noisy pixel, this formula reduces the weighting of a noisy cluster by the labels of its neighboring pixels. Accordingly, the misclassified pixels from noisy regions can be easily corrected.

Matrix based lossless compression: The motion vectors obtained from the first stage lossless compression technique are further compressed in the second stage. The second stage compression is based only on two matrices; binary matrix and grayscale matrix. The steps followed in the proposed algorithm are as follows:

- Step 1: read the source Image matrix [I].
- Step 2: construct the Binary Matrix [BB] and Grayscale Matrix [GM]

$$BB = 0; \quad \text{if } [I]_{ij} = [I]_{i,\ j+1} \tag{8}$$

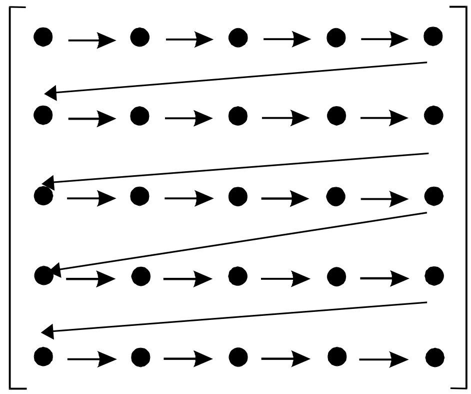

Fig. 7: Original image pixels comparison using Raster-Scan Method

$$BB = 1; \text{otherwise} \tag{9}$$

$$GM = \text{null}; \quad \text{if } [I]_{ij} = [I]_{i,\ j+1} \tag{10}$$

$$GM = [I]_{ij}; \quad \text{otherwise} \tag{11}$$

- Step 3: compare each pixel in the matrix [I] with the previous pixel in the same matrix as shown in Fig. 7
- Step 4: the binary matrix elements are calculated
- Step 5: first element in [GM] is set to be equal to the value of the first pixel of [I]
- Step 6: the rest of the elements of [GM] are calculated
- Step 7: the original image can be reconstructed using Eq. 11

Simple Fast and Adaptive Lossless Image Compression algorithm (SFALIC): This method compresses the continuous tone gray-scale images. The image is processed in a Raster-scan mode. It uses 9 set predictors. The 8 mode predictors are the same with lossless JPEG. The last predictor mode is a bit more complex that actually returns an average of mode 4 and 7. Predictors are calculated using integer arithmetic. The presented predictive and adaptive lossless image compression algorithm was designed to achieve high compression speed. The prediction errors obtained using simple linear predictor are encoded using codes adaptively selected from the modified golomb-rice code family. As opposed to the unmodified golomb-rice codes, this family limits the codeword length and allows coding of incompressible data without expansion. Code selection is performed using a simple data model based on the model known from FELICS algorithm. Since, updating the data model, although fast as compared to many other modeling methods is the most complex element of the algorithm, they apply the reduced model update frequency method that increases the compression speed by a couple of 100% at the cost of worsening the compression ratio.

This method could probably be used for improving speed of other algorithms in which data modeling is a considerable factor in the overall algorithm time complexity. The main purpose of this method is to reduce time complexity of other predictive methods such as FELICS, inconsequence less performance than previous methods.

RESULTS AND DISCUSSION

The simulation results are given as follows. The original image used for the experimentation is shown in Fig. 8. The ground truth images as predicted by a physician and the segmented images using the proposed method are shown in Fig. 9 and 10, respectively. The performance comparisons of various parameters of proposed and existing methods are done and their values are plotted graphically in Fig. 11.

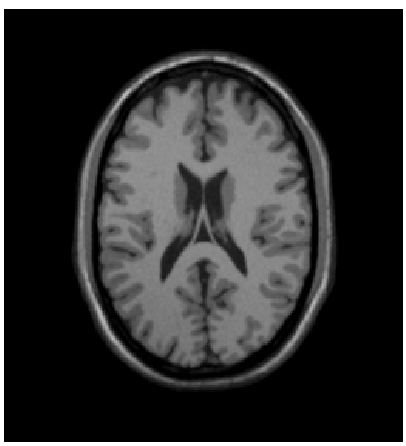

Fig. 8: Original brain MRI image with noise

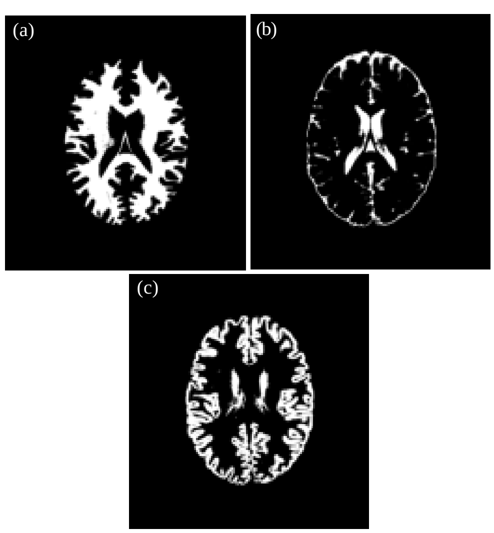

Fig. 9: Ground truth images of brain MRI showing the; a) white matter; b) gray matter and c) CSF

Researchers also evaluate the compression ratios and PSNR values of the proposed method and compare it with the existing method. Also, the same parameters are

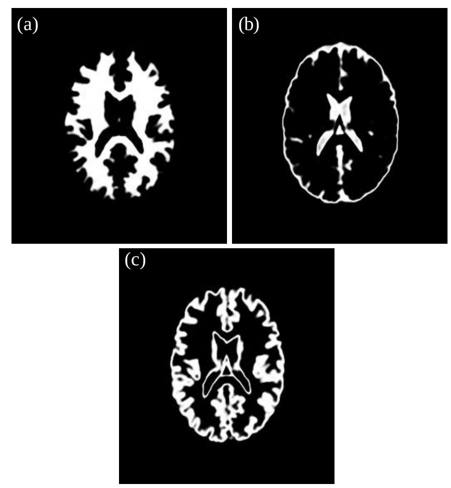

Fig. 10: Segmented brain MRI images using proposed technique showing a) the white matter; b) gray matter and c) CSF

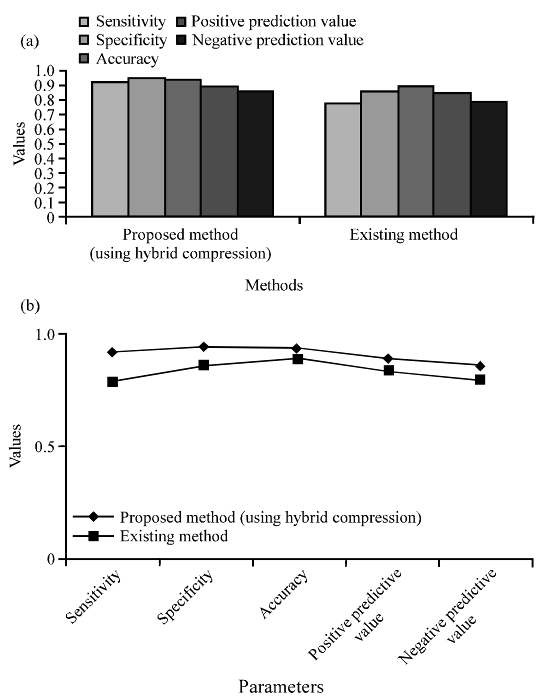

Fig. 11: Performance comparison of proposed method with existing method

Table 1: Comparison of compression ratio and PSNR values

Methodology	Compression ratio (%)	PSNR (dB)
Proposed method (using hybrid compression)	78	82
Existing method	65	74

Table 2: Performance evaluation of various regions of brain MRI image

Segmentation region	Compression ratio (%)	PSNR (dB)
GM and WM region	76	80
CSF region	79	78

evaluated for the segmented regions (white matter, gray matter and CSF) individually and are compared with the existing method. These results are clearly tabulated in Table 1 and 2.

CONCLUSION

In this research, researchers proposed a hybrid lossless compression scheme using Spatial Fuzzy C-Means algorithm. The curvelet transform is used here to remove the noises from brain MRI images. The various important brain image regions such as white matter, gray matter and CSF are segmented and then compressed individually. The proposed method achieved a high compression ratio (78%) and also provides an enhanced image quality after decompression.

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