Asian Journal of Computer Science and Technology (AJCST)
Vol.2.No.2 2014 pp 19-24.
available at: www.goniv.com
Paper Received :05-03-2014
Paper Published:28-03-2014
Paper Reviewed by: 1. John Arhter 2. Hendry Goyal
Editor : Prof. P.Muthukumar

# AN EVALUATION OF COMPRESSION EFFECTS ON MRI BRAIN IMAGES USING LOSSY AND LOSSLESS CODING

**Shanmugapriya B, Suresh S, Archana K S**
Pallavaram, chennai.
shanmupriya616@gmail.com, sureshsundaram2k5@gmail.com, ksarchanaan@gmail.com

## ABSTRACT

The Project proposes the region based Image compression technique based on clustering model and hybrid compression technique. The primary and secondary region of interest will be selected automatically by clustering algorithm. The lifting based discrete wavelet and Curvelet is used to decorrelate the pixels into fine as well as redundant or noisy data and edge details. The regions are encoded by lossless and lossy technique to increase the compression ratio and preserve the image quality. These methods are useful to compress data for transmission and telemedicine application.

**IndexTerms**—segmentation,spatial information,spatial fuzzyclustering algorithm,Curvelet,image processing techniques, morphological filtering, Compression etc.,

## 1. INTRODUCTION

With the advances in imaging technology, diagnostic imaging has become an indispensable tool in medicine today. X-ray angiography (XRA), magnetic resonance angiography (MRA), magnetic resonance imaging (MRI), computed tomography (CT), and other imaging modalities are heavily used in clinical practice. Such images provide complementary information about the patient. While increased size and volume in medical images required the automation of the diagnosis process the latest advances in computer technology and reduced costs have made it possible to develop such systems.

Brain tumor detection on medical images forms an essential step in solving several practical applications such as diagnosis of the tumors and registration of patient images obtained at different times. Segmentation algorithms form the essence of medical image applications such as radiological diagnostic systems, multimodal image registration, creating Anatomical atlases, visualization, and computer-aided surgery. Tumor segmentation algorithms are the key components of automated radiological diagnostic systems. Segmentation methods vary depending on the imaging modality, application domain, method being automatic or semi-automatic, and other specific factors. There is no single segmentation method that can extract vasculature from every medical image modality.

While some methods employ pure intensity-based pattern recognition techniques such as thresholding followed by connected component analysis, some other methods apply explicit tumor models to extract the tumor contours. Depending on the image quality and the general image artifacts such as noise, some segmentation methods may require image preprocessing prior to the segmentation algorithm. On the other hand, some methods apply post-processing to overcome the problems arising from over segmentation.

Medical image segmentation algorithms and techniques can be divided into six main categories, pattern recognition techniques, model-based approaches, tracking-based approaches, artificial intelligence-based approaches, neural network-based approaches, and miscellaneous tube-like object detection approaches. Pattern recognition techniques are further divided into seven categories, multi-scale approaches, skeleton-based approaches, region growing approaches, ridge-based approaches, differential geometry-based approaches, matching filters approaches, and mathematical morphology schemes.

Clustering analysis plays an important role in scientific research and commercial application. This thesis provides a survey of current tumor segmentation methods using clustering approach and provides both early and recent literature related to tumor segmentation algorithms and techniques.

## 2. BACKGROUND

The segmentation of brain tumor from magnetic resonance (MR) images is a vital process for treatment planning, monitoring of therapy, examining efficacy of radiation and drug treatments, and studying the differences of healthy subjects and subjects with tumor. The process of automatically extracting tumors from MR images is a challenging process. This leads to many different approaches for automatic tumor segmentation.

The usual standard used for validating segmentation results of the automatic methods is the manual segmentation results done by human experts. However, different investigators are likely to employ different image acquisition parameters and different manual segmentation techniques. A compounding issue is that any manual segmentation method suffers from lack of reliability and reproducibility. Even if a rich set of manual segmentations are available, they may not reflect the ground truth and the true gold standard may need to be estimated Furthermore, validation is typically not performed for the segmentations of non-tumor structures since manual segmentations of edema and the healthy brain tissue are very challenging tasks and have a high degree of variability.

**Brain MRI exhibiting tumor is difficult to segment due to a combination of the following factors:**

**1.** The deformation of brain tissue due to tumor mass effect or volume expansion.

**2.** The infiltration of brain tissue by tumor and edema (swelling). Edema appears around tumor mainly in the white matter regions and may also contain infiltrative tumor cells.

**3.** The gradual transition between tumor, edema, and surrounding brain tissue. This results in the ambiguity of the structural boundaries.

The T1w MRI with contrast enhancement, typically using a gadolinium agent, is the standard modality for identifying tumors. This modality results in active tumor tissue appearing with bright intensity. Unfortunately, blood vessels also appear bright while parts of tumor that are necrotic do not have higher levels of intensity. Therefore, the information provided by the intensities in this modality is not always consistent, and it is generally impossible to segment the tumor by thresholding the intensities in this image modality.

In order to provide objective assessments of segmentation performance, there is a need for an objective 3Dground truth with associated MR images that exhibit the same major segmentation challenges as that of common, realistic scans of a tumor patient. A database of real brain tumor MR images, along with their segmentations, may provide the means to measure the performance of an algorithm by comparing the results against the variability of the expert raters' judgments. However, an objective evaluation to systematically compare different methodologies also needs a ground truth with little or no variability. An example of such a ground truth is the synthetic brain MRI database provided by the Montreal Neurological Institute 1 that is currently considered to be the common standard for evaluating the segmentations of healthy brain MR images. For this purpose, a method that generates a realistic looking MR image with the associated ground truth by approximating the brain tumor generation process is proposed.

## 3.METHODOLOGIES

Methodologies are used to process and implement the Segmentation, Classification and Compression of MRI brain tumor for medical application. The Implementation process includes three methodologies as follows.

### 3.1 Preprocessing

***Image restoration***is the operation of taking a corrupted/noisy image and estimating the clean original image. Corruption may come in many forms such as motion blur, noise, and camera miscues. *Image restoration is different from image enhancement* in that the latter is designed to emphasize features of the image that make the image more pleasing to the observer, but not necessarily to produce realistic data from a scientific point of view. Image enhancement techniques (like contrast stretching or de-blurring by a nearest neighbor procedure) provided by "Imaging packages" use no a priori model of the process that created the image. In a Fluorescence Microscope resolution in the z-direction is bad as it is. More advanced image processing techniques must be applied to recover the object. De-Convolution is an example of image restoration method. It is capable of: Increasing resolution, especially in the axial direction removing noise increasing contrast.

### 3.1.1 Input Image

**Purpose:**

An Input image which might consist of some noise like Gaussian noise, Salt and Pepper noise, Speckle noise etc.

**Description:**

The Input MR image with noise added provides complementary information about the patient. It leads to wrong treatment for normal tissue as well as the abnormal tissue in such images

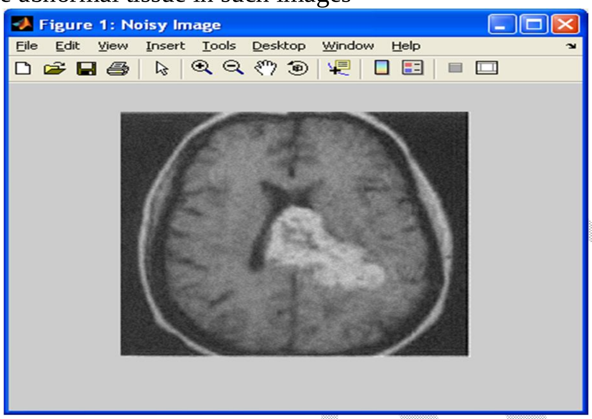



*Fig 3.1: Noisy Image*

### 3.1.2Restored Image

**Purpose:**

The Noisyregions are removed also the Abnormal regions areextracted after an Input image was selected.

**Description:**

The Noise part at the Fine Edge is removed using the ***Neighboring node values***thenenhancing part of the tumor and highlighting the region with help of level set method Preprocessing and Morphological Filtering. These Filters uses the *Shrinkage and Wrapping Rule* to remove the Curve Edge noisy part. It will give us the Denoised Image with Fine Edge cut.

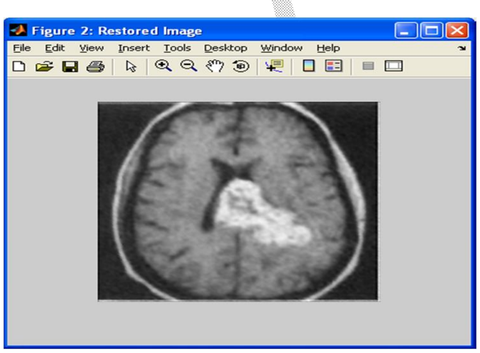



*Fig 3.1.1Denoised Image*

### 3.2 CLUSTERING MODEL

Clustering can be considered the most important ***unsupervised learning*** problem, so, it deals with finding a *structure* in a collection of unlabeled data. A *Cluster* is therefore a collection of objects which are "similar" between them and are "dissimilar" to the objects belonging to other clusters.

Curvelets implementations are based on the original construction which uses apre-processing step involving a special partitioning of phase-space followed by the ridge let transform which is applied to blocks of data that are well localized in space and frequency.

In the last two or three years, however, Curvelets have actually been redesigned in a effort to make them easier to use and understand. As a result, the new construction is considerably simpler and totally transparent. What is interesting here is that the new mathematical architecture suggests innovative algorithmic strategies, and provides the opportunity to improve upon earlier implementations. The two new fast discrete Curvelet transforms (FDCTs) which are simpler, faster, and less redundant than existing proposals:

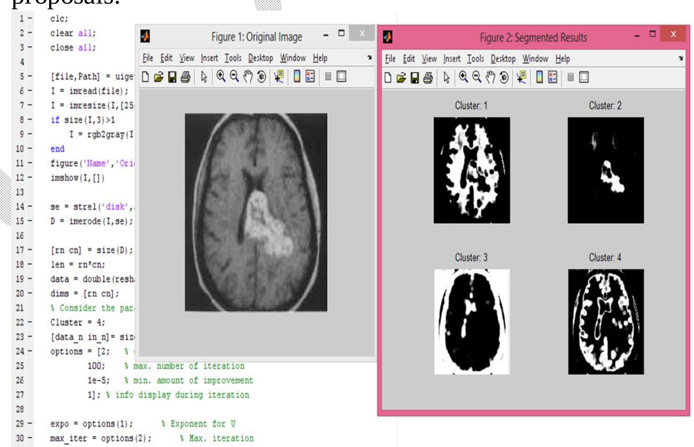



*Fig 3.2Clustering implementation using preprocessed image*

### 3.3SPATIAL FUZZY C MEANS CLUSTERING

Fuzzy clustering plays an important role in solving problems in the areas of pattern recognition and fuzzy model identification. A variety of fuzzy clustering methods have been proposed and most of them are based upon distance criteria [6]. One widely used algorithm is the fuzzy c-means (FCM) algorithm. It uses reciprocal distance to compute fuzzy weights. A more efficient algorithm is the new FCFM. It computes the cluster center using Gaussian weights, uses large initial prototypes, and adds processes of eliminating, clustering and merging. In the following sections we discuss and compare the FCM algorithm and FCFM algorithm.Spatial Fuzzy C Means method incorporates spatial information, and the membership weighting of each cluster is altered after the cluster distribution in the neighborhood is considered.

### 3.3.1Spatial fuzzy C Means Algorithm

**Purpose:**

The Noisy regions are removed. Also, the abnormal regions are extracted after an Input image was denoised and which is segmented using the Spatial Fuzzy Clustering Means algorithm.

**Description**

The Spatial Fuzzy Clustering Means Method is used for Segmenting the Image and which extracts the exact tumor part by eliminating the Curve edge noise among the Pixels. Clustering works with the help comparing the Image's Pixel value against the neighboring values. The Neighboring values are fixed using the Thresholding Function.

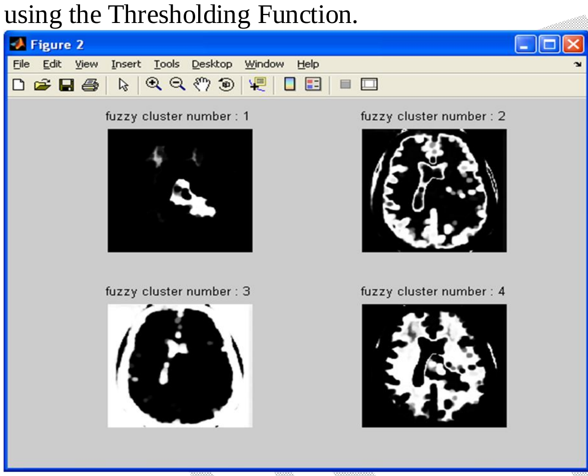



***Fig: Segmentation of an Image Using Spatial Fuzzy Clustering Means***

***The first pass*** is the same as that in standard FCM tocalculate the membership function in the spectral domain.

$$J(w_{qk}, z^{(k)}) = \Sigma_{(k=1,K)} \Sigma_{(k=1,K)} (w_{qk}) \| x^{(q)} - z^{(k)} \|^2 \text{ -- } (1)$$

$$\Sigma_{(k=1,K)} (w_{qk}) = 1 \text{ for each } q \text{ —}(2)$$

$$w_{qk} = (1/(D_{qk})^2)^{1/(p-1)} / \Sigma_{(k=1,K)} (1/(D_{qk})^2)^{1/(p-1)}, \ p > 1\text{—} (3)$$

***In the second pass***, the membership information of each pixel is mapped to the spatial domain and the spatial function is computed from that. The FCM iteration proceeds with the newmembershipthat is incorporated with the spatial function. The iteration is stopped when the maximum difference between cluster centers or membership functions at two successive iterations is less than a least threshold value. The FCM allows each feature vector to belong to every cluster with a fuzzy truth value (between 0 and 1), which is computed using Equation (3). The algorithm assigns a feature vector to a cluster according to the maximum weight of the feature vector over all clusters.

### 3.4 MORPHOLOGICAL FILTERING PROCESS

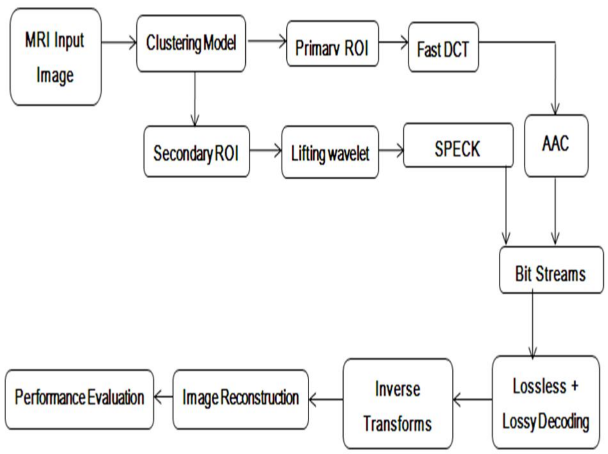
Morphological image processing is a collection of non-linear operations related to the shape or morphology of features in an image. Morphological operations are processed only on the relative ordering of *pixel values*, not on their *numerical values*, and therefore are especially suited to the processing of binary images.

Morphological operations can also be applied to grey scale images such that their light transfer functions are unknown and therefore their absolute pixel values are of no or minor interest. Morphological techniques probe an image with a small shape or template called a **structuring element**. ***The structuring element*** is positioned at all possible locations in the image and it is compared with the corresponding neighbourhood of pixels. Some operations test whether the element "***fits***" within the neighbourhood, while others test whether it "***hits***" or intersects the neighbourhood

## 4. REGION BASED HYBRID IMAGE COMPRESSION THROUGH,

- ***Clustering model for region selection***
- ***Lifting wavelet with SPECK Coding for Lossy compression***
- ***Parameter Analysis(MSE, PSNR, CR, Correlation and Elapsed Time)***
- ***Discrete Curvelet transform***
- ***Entropy coder-Adaptive arithmetic coder(AAC)***

### 4.1 Block Diagram




**4.1.1 CLUSTERING MODEL:**

The segmentation refers to the process of partitioning a digital image into multiple segments.Thegoal is to select the tumor region automatically by pixel classification using cluster centroids.The segmentation is performed by using K means clustering algorithm.It is an unsupervised clustering algorithm that classifies the input data points into multiple classes based on their inherent distance from each other. The algorithm assumes that the data features form a vector space and tries to find natural clustering in them.

**4.1.2 LIFTING WAVELET TRANSFORM:**

LWT decomposes the image into different sub band images, namely, LL, LH, HL, and HH for getting pixel coefficients of images. An LL sub band contains the significant part of the spatial domain image. High-frequency sub band contains the edge information of input image.Integer wavelet transform can be obtained through lifting scheme. Lifting scheme is a technique to convert DWT coefficients to Integer coefficients without losing information. This will be used to provide unique values for quantization and encoding process.

**4.1.3SPECK CODING:**

Set partitioning in embedded coder is based on multiscale 2D DWT and exploits the self-similarity across scales by using set partitioning.After transformation, the coefficients are ordered into a tree structure, called spatial orientation tree (SOT). The SOT is defined by each wavelet coefficient (parent) in a certain decomposition scale has either no child (i.e., tree leave) or four children in the next finer scale and the coefficients in the low-frequency sub band are the tree roots.The coefficients are quantized by partitioning them into different set likes significant information and insignificant information and performs the priority based transmission.

**4.1.4 DISCRETE CURVLET TRANSFORM:**

The Curvelet transform is a higher dimensional generalization of the Wavelet transform designed to represent images at different scales and different angles. In wavelets, point discontinuities affect only a limited number of coefficients. Hence the WT handles point discontinuities well.Discontinuities across a simple curve affect all the wavelets coefficients on the curve. Hence the WT doesn’t handle curves discontinuities well.Curvelets are designed to handle curve discontinuities well.

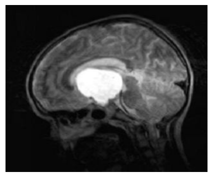
**4.1.5 ARITHMETIC CODING:**

It assigns a sequence of bits to a message, a sting of symbols. It can treat the whole symbols in a list or in a message as one unit The number of bits used to encode each symbol varies according to the probability assigned to that symbol. Low probability symbols use many bit, high probability symbols use fewer bits. The main idea is to assign each symbol an interval. Starting with the interval [0...1), each interval is divided in several subinterval, which its sizes are proportional to the current probability of the corresponding symbols. The subinterval from the coded symbol is then taken as the interval for the next symbol. The output is the interval of the last symbol.

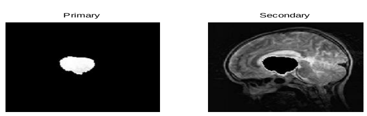
**5. CONCLUSIO**N

This section describes a hybrid compression system for lossless compression of ROI (Region of Interest) in MR Image Diagnostic Analysis. The region that undergoes diagnostic analysis is considered as the primary region and other region are secondary and background.

Lossless compression is applied over primary region and secondary and background undergoes lossy/lossless compression. The Edges are also detected and preserved here. It has an efficient combination with error protection and good image quality with the compression effects on medical image will be evaluated with following metrics,*Compression ratio, Root mean square Error, Peak Signal to Noise Ratio, Correlation measurement.*We applied our ROI based hybrid compression method to three datasets of 20 slices each. 8 by 8 and 16 by 16blocksizes were used. Observe that ROI compression with 8 by 8 blocks produces not only a better RMSE (Root Mean Square Error), but also better compression rate compared to ROI compression with 16 by 16 blocks.



REAL IMAGE




5.0 IMAGE SPLIT INTO PRIMARY &SECONDARY

## REFERENCES

[1] Ardizzone.E, Pirrone.R, and Orazio.O.G, "Fuzzy C-Means Segmentation on Brain MR Slices Corrupted by RF-Inhomogeneity," In Proc. The 7th international workshop on Fuzzy Logic and Applications: Applications of Fuzzy Sets Theory, WILF '07, Springer- Verlag, pp: 378-384, 2007.

[2] Bianrgi.P.M, Ashtiyani.M, and Asadi.S, "MRI Segmentation Using Fuzzy C-means Clustering Algorithm Basis Neural Network," In Proc. ICTT A 3rdInternationai Conference on Information and Communication Technologies: From Theory to Applications, pp: 1-5, 2008.

[3] M. Prastawa, E. Bullitt, S. Ho, and G. Gerig, “A brain tumor segmentation framework based on outlier detection,” *Med. Image Anal., vol.* 8, no. 3, pp. 275–283, 2004.

[4] Xiao.K, Ho.S.H, and Bargiela.B, "Automatic Brain MRI Segmentation Scheme Based on Feature Weighting Factors Selection on Fuzzy C means Clustering Algorithms with Gaussian Smoothing," International Journal of Computational Intelligence in Bioinformatics and Systems Biology(3):316-331,2009.

[5] V. SubbiahBharathi, L. Ganesan, "Orthogonal moments based texture analysis of CT liver images", Pattern Recognition Letters, Vol, 29, pp, I 868-1872, 2008

[6] Pan, Zhigeng; Lu, Jianfeng;;"A Bayes-Based Region-Growing Algorithm for Medical Image Segmentation" Computing in Science & Engineering, Volume 9, Issue 4, July-Aug. 2007 Page(s):32 – 38

[7] Maglogiannis, I., Kormentzas, G.: ‘Wavelet-based compression with ROI coding support for mobile access to DICOM images over heterogeneous radio networks’, Trans. Inf. Technol. Biomed., 2009, 13, (4), pp. 458–466

[8] Doukas, C., Maglogiannis, I.: ‘Region of interest coding techniques for medical image compression’, IEEE Eng. Med. Biol. Mag., 2007, 26, (5), pp. 29–35

[9] Zhang, Q., Xiaio, X.: ‘Extracting regions of interest in biomedical images’. Int. Seminar on Future Biomedical Information Engineering, 2008, pp. 3–6

[10] Yu, Y., Wang, B.: ‘Saliency based compressive sampling for image signals’, IEEE Signal Process. Lett., 2010, 17, (11), pp. 973–976

[11] Calderbank, A.R., Daubechies, I., Sweldens, W., Yeo, B.L.: ‘Wavelet transforms that map integers to integers’, Appl. Computer. Harmon. Anal., 1998, 5, pp. 332–369