An Assessment of Density Effects on MRI Brain Images Using Lossy and Lossless Coding

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Abstract

The Project proposes the region based Image compression technique based on the clustering model and hybrid compression technique. The primary and secondary region of interest will be selected automatically by the 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.

Index Terms — Segmentation, spatial information, a spatial fuzzy clustering algorithm, Curve let, image processing techniques, Morphological filtering, Compression, etc.…

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 modality is heavily used in clinical practice. Such images provide complementary information about the patient. While increased size and volume in medical images are 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 be extracted 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 before the segmentation algorithm. On the other hand, some functions 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 a main role in scientific research and commercial application. This thesis provides a survey of current tumor segmentation methods using a clustering approach and provides both early and recent literature related to tumor segmentation algorithms and techniques.

Background

The segmentation of brain tumor from magnetic resonance (MR) images is a vital process for treatment planning, monitoring of therapy, examining the efficacy of radiation and drug treatments, and studying the differences of healthy subjects and subjects with a 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 a 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 infiltrations 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. These 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 power. Therefore, the information provided by the intensities in this imaging modality is not always consistent, and it is generally impossible to segment the tumor by thresholding the intensities in this imaging modality.

To provide objective assessments of segmentation performance, there is a need for an objective 3Dground truth with associated MR images that exhibit the same main segmentation challenges as that of general, 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 general 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.

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.

Preprocessing

Image restoration is the operation of taking a corrupted/noisy image and estimating the clean original picture. 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 the 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 dire as it is. More advanced image processing techniques must be applied to recover the object. De-convolution is an example of an image restoration method. It is capable of; increasing resolution, especially in the axial direction removing noise increasing contrast.

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 a normal tissue as well as the abnormal tissue in such images

Restored Image

Purpose

The Noisy regions have removed. Also the Abnormal regions are extracted after an Input image was selected.

Description

The Noise part at the Fine Edge is removed using the Neighboring node values then enhancing part of the tumor and highlighting the region with the 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 Denied Image with Fine Edge cut.

Clustering Model

Clustering can be considered the essential 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 base on the original construction which uses are-processing step involving an unusual partitioning of phase-space followed by the point 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, Curve lets have been redesigned in an effort to make them easier to use and understand. As a result, the new construction is considerably simple and fully 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 cleanly, faster, and less redundant than existing proposal:

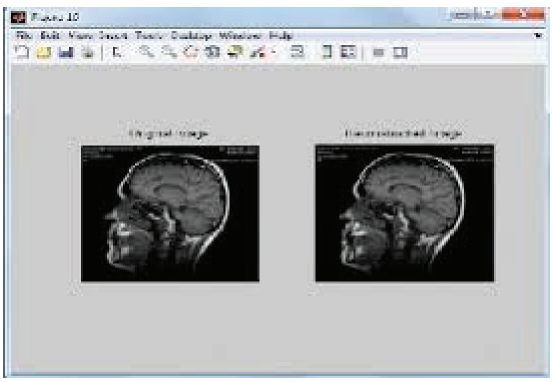
Spatial Fuzzy C Means Clustering

Fuzzy clustering plays a main 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 base on 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.

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 operation is 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 a picture with a small shape or template called a structuring element. The structuring element is position at all possible locations in the image and, it is compared with the corresponding neighborhood of pixels. Some operations test whether the constituent "fits" within the neighborhood, while others test whether it "hits" or intersects the neighborhood.

Region-Based Hybrid Image



Lifting Wavelet Transform

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

Speck Coding

Set partitioning in embedded coder is based on multistage 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 sure decomposition scale has either no child (i.e., tree leave) or four children in the next finer level and the coefficients in the low-frequency are the tree roots. The coefficients are quantizing by partitioning them into different set likes significant information and unimportant information and performs the priority-based transmission.

Discrete Curvelet 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.

Arithmetic Coding

It assigns a sequence of bits to a message, a string of symbols. It can treat the whole symbols in a list or a note 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 bits; high probability symbols use fewer bits. The main idea is to assign each sign an interval. Starting with the period [0...1], each period is divided into several subintervals, which its sizes are proportional to the current probability of the corresponding symbols. The subinterval from the coded symbol is taken as the interval for the next sign. The output is the interval of the last symbol.

Conclusion

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 by the primary region, and other regions are secondary and background.

Lossless compressions are applied over a 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 a 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 16 block sizes will be used. Observe that ROI compression with eight by eight 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.

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