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Review on: Brain Tumor Detection Techniques from MRI Images and Rough Set Theory

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Abstract - Brain is well protected inside the hard and bony skull that hampers the study of its functions as well as makes the diagnosis of brain diseases more difficult and challenging. In this paper we perform review study on brain tumor detection from Magnetic Resonance Image (MRI). Stages for brain tumor detection using MR image are Pre-processing, Segmentation, Feature Extraction, Classification. The various techniques taking into consideration for study are Hidden Markow Random Field (HMRE), Fuzzy-C-Mean algorithm, Discrete Wavelet Frame Transform (DWFT), Support Vector Machine (SVM), Hoop Field & Feed Forward Neural Network (FFNN), Symmetry Analysis etc. At last we perform short review on brain tumor detection using Rough Set Theory.

***Keywords* - Brain Tumor, MR Images, Segmentation, Rough Set Theory, SVM, FCM.**

1. Introduction

Brain has a very complex structure compared to any other body parts. Nature has tightly safeguarded the brain inside a skull that protects it from normal disease however a common disease by which brain is mostly deflected is brain tumor. Brain Tumor can be found in different regions of brain such as the central spinal canal or inside the cranium. As said earlier brain is well protected inside the hard and bony skull that hampers the study of its functions as well as makes the diagnosis of brain diseases more difficult and challenging. To overcome this problem literature focuses on two different diagnostic methods such as therapeutic applications computed tomography and Magnetic Resonance Imaging (MRI). MRI is a useful method that generally used for human body studies and specifically used for detection and studies of brain cancers. Data obtained from Magnetic Resonance (MR) images is used for detecting tissue deformities such as cancers and injuries. MR is used to identify regions of interest (ROI). This ROI within the brain MRI must be well defined and identified to perform good quantitative studies of brain tumor. There are different types of MR images, from that T1-weighted and T2-weighted images are used to detect tumor. Segmentation of brain MR image is used for extracting meaningful objects from an image. MR image can be segmented into different tissue classes such as white matter (WM), gray matter (GM) and cerebrospinal fluid (CSF). This article has following organisation. Section II provides review on various image segmentation techniques. The main objective of this section is to highlight key advantage and limitation of these techniques. Section III provides an explanation of basic framework of rough set theory. Section IV provides an introduction to rough image processing including rough images, rough representation of region of interest, rough- based medical image applications including object extraction and MRI image segmentation. Finally section V gives conclusion on this article.

2. Review on Image Segmentation Techniques

Zhang et al. [1], Suggest employing the Hidden Markov Random Field (HMRF) model for segmenting Brain MRI by using Expectation-Maximization (EM) algorithm. HMRF model is flexible for modeling as it carries the ability to encode both the statistical and spatial properties of an image. EM algorithm not only offers a good method for parameter estimation, but also provides a comprehensive framework for unsupervised classification. The advantage of HMRF-EM algorithm is that, it produces promising results even with high level of noise, low image quality and large number of classes as compared to EM method. The major limitation in their work is that it does not generate perfect results in case of high invariability of brain MRI, particularly in terms of contrast between brain tissues and intensity ranges. Ahmed et. al. [2] present customised algorithm for estimation of intensity in homogeneity using fuzzy logic that supports fuzzy segmentation of MRI data. This algorithm is work by altering the objective function used in the standard Fuzzy-C-Mean (FCM) algorithm. The alteration of the objective representation function compensates intensity in homogeneities and allows labelling of a pixel (voxel) to be influenced in its immediate neighbourhood. Hence it is effective in segmenting scans corrupted by salt and pepper noise. Major contribution of their work is the introduction of a BCFCM algorithm which is faster to converge to the correct classification. It requires far less iterations to converge as compared to EM & FCM. It also produces the slightly better results than EM due to its capability to cope with salt and paper noise.

This method involves phantom measurement based on global corrections for image non-uniformity. Therefore, further work is needed for localized measurement like impact on tumor boundary or volume determinations. Tolba et. al. [3] proposed a new algorithm which is based on EM algorithm and the multi-resolution analysis of images, namely Gaussian multi-resolution EM algorithm (GMEM). GMEM overcome drawback found in EM algorithm and it is less sensitive to the noise level and can be used for noisy images. Also GMEM algorithm can be used for many other imaging techniques with accurate results. a limitation to this technique is that the GMEM algorithm, when applies to pixel laying on the boundaries between classes or on edges, generates many misclassified pixels because of parent and grandparent images contain only low level frequencies and hence edges rarely appear in these images. Li et al. [4] report that edge detection, image segmentation and matching are not easy to achieve in optical lenses that have long focal lengths. The wavelet function can be improved by applying discrete wavelet frame transform (DWFT) and support vector machine (SVM).

In this paper, authors experimented with five sets of 256-level images. Experimental results show that this technique is efficient and more accurate as it does not get affected by consistency verification and activity level measurements. However, the paper is limited to only one task related to fusion and dynamic ranges are not considered during calculation. J. Sing and K. Basu et al. [5] propose fuzzy adaptive RBS based neural network (FARBS-NN) for MR brain image segmentation. Hidden layer neuron of FARBF-NN neurons has been fuzzifies to reduce noise effect. This asserts that medical image segmentation approach involves combination of texture and boundary information. The authors maintain that geometric algebra can be used to obtain volumetric data using spheres, non- rigid registration of spheres and real time object tracking. Major contribution of the proposed approach is that the use of marching cube algorithm reduces the number of primitives to model volumetric data and uses lesser number of primitives for the registration process, and thus makes registration process faster. Yu et al. [6] state that image segmentation is used for extracting meaningful objects from image. They propose segmenting an image into three parts, including dark, gray and white. Z-function and S-function are used for fuzzy division of the 2D histogram.

Afterwards, QGA is used for finding combination of 12 membership parameters, which have maximum value. This technique is used to enhance image segmentation and significance of their work is that three-level image segmentation is used by following the maximum fuzzy partition of 2D Histograms. QGA is selected for optimal combination of parameters with the fuzzy partition entropy. The proposed method of fuzzy partition entropy of 2D histogram generates better performance than one-dimensional 3-level thresh holding method. Somehow, a large number of possible combinations of 12 parameters in a multi-dimensional fuzzy partition are used, and it is practically not feasible to compute each possible value; therefore, QGA can be used to find the optimal combination. Luts et al. [7] propose a technique to create nosologic brain images based on MRI and MRSI data. This technique uses colour coding scheme for each voxel to differentiate distinctive tissues in a single image. For this purpose, a brain atlas and an abnormal tissue prior is acquired from MRSI data for segmentation.

The detected abnormal tissue is then classified further by employing a supervised pattern recognition method followed by calculating the class probabilities for diverse tissue types. The proposed technique offers a novel way to visualize tumor heterogeneity in a specific image. The study result shows that combining MRI and MRSI features improves classifier's performance. A prior for the abnormal tissue along with a healthy brain atlas further improves the nosologic images. Despite its usefulness, the proposed methodology, however, only provides the one-dimensional image features.

Z. Shi et al. [8] employed neural networks for medical image processing (MRI), including the key features of medical image pre-processing, segmentation and object detection and recognition. The study employed hopfield and feed-forward neural networks. The feed-forward and Hopfield neural networks are simple to use and easy to implement. The advantage of Hopfield neural networks is that it does not require pre-experimental knowledge. The time required to resolve image processing is reduced by using trained neural network. Roy and Bandyopadhyay [9] propose automatic brain tumor detection approach using symmetry analysis. They first detect the tumor, segment it and then find out the area of tumor. One of the important aspects is that after performing the quantitative analysis, we can identify the status of an increase in the disease. They have suggested multi-step and modular approached to solve the complex MRI segmentation problem. Tumor detection is the first step of tumor segmentation. They have obtained good results in complex situations. Padole and Chaudhari [10] proposed an efficient method for brain tumor detection. One of the most important steps in tumor detection is segmentation. Combination of two standard algorithms, first mean shift and second normalized cut is performed to detect the brain tumor surface area in MRI. By using mean shift algorithm pre-processing step is performed in order to form segmented regions. In the next step region nodes clustering are processed by normalized cut method. In the last step, the brain tumor is detected through component analysis.

Kumar and Mehta [11] highlight that segmentation results will not be accurate if the tumor edges are not sharp, and this case occurs during the initial stage of tumor. Texture-based method is proposed in this paper. Along with brain tumor detection, segmentation is also done automatically using this method. Meenakshi and Anandhakumar [12] emphasize that MRI are useful for analyzing brain images because of its high accuracy rate. The proposed technique combines the clustering and classification algorithm to minimize the error rate. Segmentation task is performed using orthonormal operators and classification using BPN. Images having the tumor are processed using K-means clustering and significant accuracy rate of 75% is obtained. T. Paul et al. [13] state that brain segmentation is automated using Dual Localization method. In the first step of their process scull mask is generated for the MRI images. White matter and tumor region is used to improvise K-means algorithm. In the last step of their method, they assessed the breath and length.

Corso et al. [14] state that bottom up affinity-based segmentation and top down generative model techniques were not enough to get good results, and propose a novel methodology of automatic segmentation of heterogeneous images. Main difference in this paper is the use of Bayesian formulation to make complex calculations on soft models. It uses multichannel MR volumes to detect and segment brain tumor. Calculation in this model is more efficient than the conventional presented models and results are presenting improved output in the form of quantitative analysis. A 2D portion of MR image can be used to detect multiform brain tumor and an outline can be drawn to label the edema or active part of tumor.

Paul and Bandyopadhyay [15] They present an automated two-step segmentation procedure which will stripped the skull by generating a skull mask and then after that by using an advanced K-means algorithm to provide two-level granularity for assessing the length and breadth of brain tumor. In a given algorithm, MRI image is read and image is enhanced using a 3 by 3 unsharpened filters. A clearer picture can be obtained by removing all the blurred area of the previous image. The two-dimensional array can be using to hold the output and values are rounded off in case if they are in the form of fraction. Mask can be generated for skull stripping and using a method automatically a histogram shape based image threshold is performed.

It has a bi-model histogram. If threshold is successful, then we get a binary image with skull. Finally K-Means algorithm based segmentation is performed. K-points of the objects are clustered and assign each point a group and recalculate the position of K points until they no longer move. After performing the above task in the form of segmentation, one can calculate the histogram of the segmented imaged and different peaks of this histogram will show the different image grey values against the grey and matter for tumor detection. Finally, after the segmentation, a line is applied to the image to know the maximum breadth and the length of the tumor. This methodology gives better results as compared to the qualitative and quantitative techniques. MRI of three different angles also improves the results and gives satisfactory results using segmentation.

3. Rough Sets: Fundamentals

Suppose we are given a set of objects U called the universe and an in discernibility relation $R \subseteq U \times U$ representing our lack of knowledge about elements of U. For the sake of simplicity we assume that R is an equivalence relation. Suppose that X is a subset of U. We want to characterize the set X with respect to R. To this end we will need the basic concepts of rough set theory:

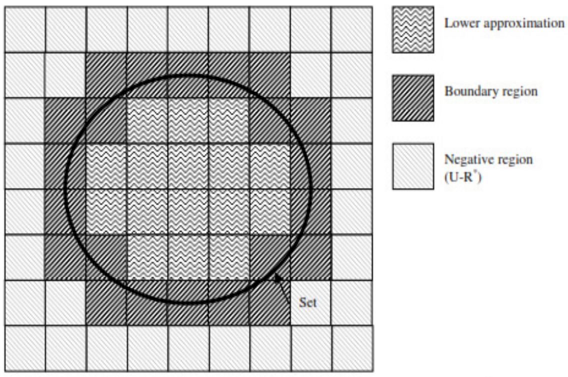

Fig. Fundamental of Rough Set Theory

Lower approximation – the set of items, which can be certainly classified as items of X.
Upper approximation – the set of items, which can be possibly classified as items of X.
Boundary region – the set of items, which can be classified either as items of X or not.

Set X is crisp with respect to R, if the boundary region of X is empty. Set X is rough with respect to R, if the boundary region of X is nonempty. More exact definition acquires specification of the concepts of approximation and boundary region. Approximation is defined as a union of equivalence classes with determined characteristics. We can define rough image processing as understanding, representation and processing the images and their segments and features as rough sets. In this section, we first describe the ability of rough sets to handle and represent images followed by the various rough-set-based approaches developed for handling the different functional aspects to solve medical imaging problems.

3.1 Rough Images

In grey scale images boundaries between object regions are often ill-defined because of grayness or spatial ambiguities [16], [17]. This uncertainty can be effectively handled by describing the different objects as rough sets with upper (outer) and lower (inner) approximation can be viewed, respectively, as outer and inner approximations of an image region in terms of granules.
Definition 1 (Rough image): Let the universe U is an image consisting of a collection of pixels. Then, if we partition U into a collection of non overlapping windows of size $m \times n$, each window can be considered as a granule G. Given this granulation, object regions in the image can be approximated by rough sets. A rough image is a collection of pixels along with the equivalence relation induced partition of an image into sets of pixels lying within each non overlapping window over the image. With this definition, the roughness of various transforms (or partitions) of an image can be computed using image granules for windows of different sizes.

3.2 Rough Representation of an ROI

An ROI is a selected subset of samples within an image identified for a particular purpose. The concept of ROI is commonly used in medical imaging. For example, the boundaries of a tumor may be defined on an image or in a volume for the purpose of measuring its size. Hirano and Tsumoto [18] introduced the rough direct representation of ROIs in medical images. The main advantage of this method is its ability to represent inconsistency between the knowledge-driven shape and image-driven shape of an ROI using rough approximations. The method consists of three steps. First, they derive feature values that describe the characteristics of an ROI. Second, using all features, they build up the basic regions (categories) in the image so that each region contains voxels that are indiscernible on all features. Finally, according to the given knowledge about the ROI, they construct an ideal shape of the ROI and approximate it by the basic categories.

Then, the image is split into three sets of voxels.

1) Certainly included in the ROI (positive region).
2) Certainly excluded from the ROI (negative region).
3) Possibly included in the ROI (boundary region).

The ROI is consequently represented by the positive region associated with some boundary regions.
Hirano and Tsumoto [18] described procedures for rough representation of ROIs under single and multiple types of classification knowledge. Usually, the constant variables defined in the prior knowledge, e.g., some threshold values, do not meet the exact boundary of images due to inter image variances of the intensity.

The approach tries to roughly represent the shape of the ROI by approximating the given shapes of the ROI by the primitive regions derived from feature of the image itself. It is reported that the simplest case occurs when we have information only about the intensity range of the ROI.

In this case, intensity thresholding is a conventional approach to obtain the voxels that fall into the given range. Let us denote the lower and upper thresholds by Th_L and Th_H, respectively. Then, the ROI can be represented by

$$\mathrm{ROI} = \{\ x(p) \mid \mathrm{Th}_L \le I(x)P \le \mathrm{Th}_H\ \} \qquad (1)$$

Where $x(p)$ denotes a voxel at location p and $I\ (x(p))$ denotes intensity of voxel $x(p)$.

3.3 Rough Sets in Medical Image Segmentation

The basic idea behind segmentation-based rough sets is that while some cases may be clearly labeled as being in a set X (called the positive region in rough sets theory), and some cases may be clearly labeled as not being in set X (called the negative region), limited information prevents us from labeling all possible cases clearly. The remaining cases cannot be distinguished and lie in what is known as the boundary region. Among many difficulties in segmenting MRI data, the partial volume effect arises in volumetric images when more than one tissue type occurs in a voxel. In such cases, the voxel intensity depends not only on the imaging sequence and tissue properties, but also on the proportions of each tissue type present in the voxel.

3.4 Rough Sets in Feature Reduction and Image Classification

Many researchers have endeavored to develop efficient and effective algorithms to compute useful feature extraction and reduction of information systems, and mutual information and discernibility matrix-based feature-reduction methods. Swiniarski and Hargis [19] presented applications of rough set methods for feature selection in pattern recognition. They emphasize the role of the basic constructs of rough set approach in feature selection, namely reduces and their approximations, including dynamic reducts. Their algorithm for feature selection is based on an application of a rough set method to the result of principal components analysis (PCA) used for feature projection and reduction. They present various experiments including mammogram recognition.

4. Conclusions

We are studied various types of method for the detection and classification of brain tumor from MRI image. The above mention method is having various limitations such as, it does not generate perfect results in case of high invariability of brain MRI, particularly in terms of contrast between brain tissues and intensity ranges, removing intensity in homogeneity from MR images is also a difficult task as it invariably changes if different MRI acquisition parameters are used, and it varies from slice to slice and from a patient to a patient as well etc. We are trying to resolve these limitations by using Rough Set Theory. Feature extraction and reduction will be carried out by using RST and classification will be performing by using neuro fuzzy classifier to generate better results.

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