Review on Automated Brain Tumor Segmentation and classification from Brain MRI

V.VANI
Assistant Professor, Dept of IT
JJ College of Arts and Science

Abstract:

Brain and tumor segmentation has been supported by different methodologies earlier, but struggles with identifying the spatial deformations and identifying the exact boundary regions of the tumor which affects the classification accuracy. Detection of the tumor is very important in earlier stages. Various techniques were developed for detection of tumor in brain. Automating this process is a challenging task because of the high diversity in the appearance of tumor tissues among different patients and in many cases similarity with the normal tissues. MRI is an advanced medical imaging technique providing rich information about the human soft-tissue anatomy. Development and implementation of the related techniques require detailed understanding of the underlying problems, and knowledge about the acquired data, as: nature of data, goal of the study, and scientific or medical interest, etc.

Keywords: *MRI of Brain, Tumor Segmentation, Tumor Detection, Automated System.*

1. Introduction:

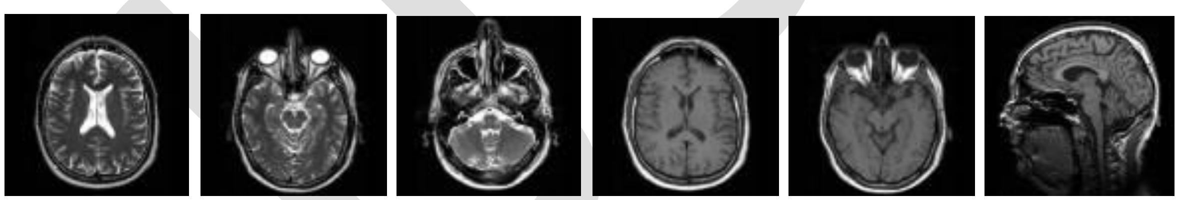
Brain has a very complex structure and is considered as a kernel part from the body. Nature has tightly safeguarded the brain inside a skull that hinders the study of its function as well as makes the diagnosis of its diseases more intricate. But, brain is not prone to diseases and can be affected by the abnormal growth of the cells in that change its normal structure and behavior — a disease generally known as a brain tumor. Brain tumors either include tumors in the central spinal canal or inside the cranium. Automatic defects detection in MRI is quite useful in several diagnostic and therapeutic applications computed tomography and MRI

1.1 Computed tomography

Interest in Computed Tomography comes from the fact that, contrary to nuclear medicine methods, it is widely available and offers high spatial resolution images with fast acquisition modes: a slice can be acquired in less than a second, with common spatial resolution of about 1 mm. Most CT equipment is composed of an X-ray tube and a certain number of detecting elements rotating together around the patient, at the same time as the patient table advances though the detection ring, which provides a "spiral" or "helicoidal" acquisition.

1.2 Magnetic resonance imaging

Magnetic resonance images (MRI) combine a common advantage with CT - high spatial resolution images - but with no ionizing radiation exposure, which makes it a safer technique. These advantages make MRI one of the main imaging tools for neurological studies, even though total examination time is usually longer than with other types. A magnetic resonance imaging instrument or MRI Scanner uses powerful magnets to polarize and excite hydrogen nuclei i.e. proton in water molecules in human tissue, producing a detectable signal which is spatially encoded, resulting in images of the body . MRI mainly uses three electromagnetic fields they are : i) A very strong static magnetic field to polarize the hydrogen nuclei, named as the static field, ii) A weaker time varying field(s) for spatial encoding, named as the gradient field, iii) A weak radio frequency field for manipulation of hydrogen nuclei to produce measurable signals collected through RF antenna. The variable behaviour of protons within different tissues leads to differences in tissue appearance. The different positioning of MRI of brain with T1 and T2 weight is shown below.

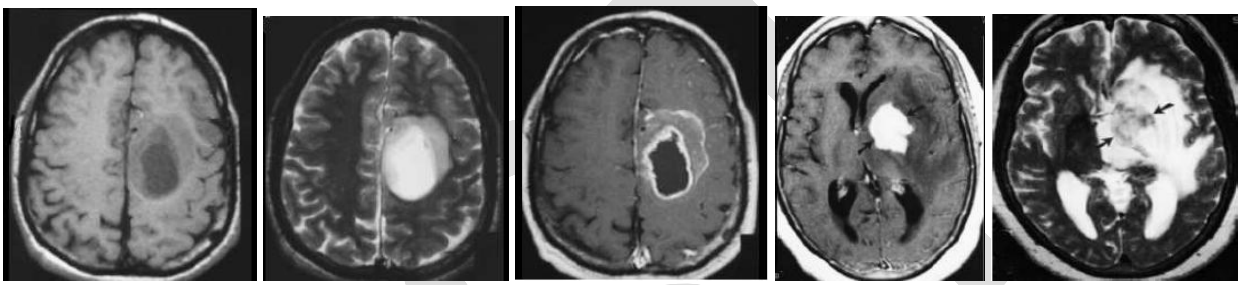


a ***b*** ***c*** ***d*** ***e*** ***f***

Figure 1 : MRI of brain cited by http://www.mr-tip.com/serv1.php?type=isimg. T2 weighted MR image (a) brain shows cortex, lateral ventricle, and falx cerebri, (b) brain shows eyeballs with optic nerve, medulla, vermis, and temporal lobes with hippocampal regions, (c) head shows maxillary sinus, nasal septum, clivus, inner ear, medulla, and cerebellum. T1 weighted MR image (d) brain shows cortex, white and grey matter, third and lateral venticles, putamen, frontal sinus and superior sagittal sinus, (e) brain shows eyeballs with optic nerve, medulla, vermis, and temporal lobes with hippocampal regions,(f) brain shows cortex with white and grey matter, corpus callosum, lateral ventricle, thalamus, pons and cerebellum from the same patients

1.3. Brain Tumor:

A brain tumor is an abnormal growth of cells in the brain, which can be cancerous (malignant) or noncancerous (benign). Is defined as any intracranial tumor created by abnormal and uncontrolled cell division, normally in the brain itself (neurons, glial cells (astrocytes, oligodendrocytes, ependymal cells, myelin producing Schwann cells), lymphatic tissue, blood vessels blood) in the cranial nerves, in the brain envelopes (meninges), skull, pituitary and pineal gland, or spread from cancers primarily located in other organs tumors (metastases). Brain tumors (true) are usually located in the posterior fossa in children and in the anterior two thirds of the cerebral hemispheres in adults, although it can affect any part of the brain. There are different type of brain tumor they are i) Gliomas, ii) Medulloblastoma, iii) Lymphoma, iv) Meningioma, v) Craniopharyngioma, vi) Pituitary adenoma.

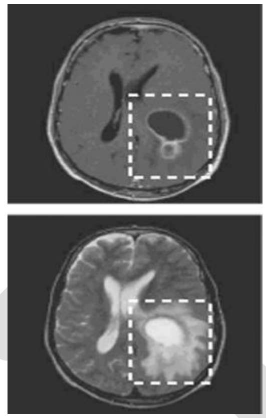


A *b* *c* *d* *e*

Figure 2: A set of brain tumor images from MRI of brain output cited by Herbert H. Engelhard et al.(2003)[7]. a) Axial T1-weighted with tumor, b) T2-weighted with central positioning tumor, c) Contrast enhanced T1-weighted image showing ring formed tumor, d) Contrast enhanced T1-weighted image with high grade oligodendro glioma e) T2-weighted image with high grade oligodendro glioma from the same patient.

1.4. Manual segmentation

Manual segmentation of brain tumors involves manually drawing the boundaries of the tumor and structures of interest, or painting the region of anatomic structures with different labels [4]. In manual segmentation, human experts (radiologists/anatomists/trained technologists) not only make use of the information presented in the image but also make use of additional knowledge such as anatomy. Manual delineation requires software tools with sophisticated graphical user interfaces to facilitate drawing regions of interest and image display. In practice, the selection of the tumor region, which is the region of interest (ROI), is a tedious and time consuming task. MRI scanners generate multiple two-dimensional crosssections (slices), and the human expert has to go through the dataset slice by slice for choosing the most representative ones from which the relevant regions are carefully delineated [1]. Manual segmentation of brain tumors is also typically done based on a single image with intensity enhancement provided by an injected contrast agent [7]. However if the person drawing the ROI is not a radiologist/ anatomist/trained technologist who is well versed with that



Brain anatomy, it will most likely yield poor segmentation results.

1.5. Automated System:

Automated system (detection) of brain tumor through MRI is basically called Computer-Aided Diagnosis (CAD) system. The CAD system can provide highly accurate reconstruction of the original image i.e. the valuable outlook and accuracy of earlier brain tumor detection. It consists of two or more stage. In the initial stage pre-processing has required after that stages post-processing i.e. segmentation are required. Then detection strategies and other information, feature extraction, feature selection, classification, and performance analysis are compared and studied. Pre-processing techniques are used to improvement of image quality and remove small artifacts and noise for the accurate detection of the undesired regions in MRI. Post-processing is used to segment with different strategy the brain tumor from the MRI of brain images. In this review, here focus on the appearance of tumors in MRI images, the grade of tumors and some general information which will be useful in the detection, segmentation and interpretation of brain tumors from MRI images. An automated brain tumor detection procedure follows some steps which is shown diagram below.

2. REVIEW OF LITERATURE

Brain cancer is one of the main reasons for enlarge in humanity amongst kids and mature. Cancers can be compassionate or cruel. Imaging plays an essential function in the analysis and action preparation of brain cancer. Imaging of the cancers can be done by Computed Tomography scrutinize, Ultrasound and Magnetic Resonance Image etc (Mohammad Shajib Khadem, 2010). The Magnetic Resonance imaging technique is the most excellent owing to its superior motion. But (Saif D. Salman and Ahmed A. Bahrani, 2010) there are a lot of difficulties in exposure of brain cancer in Magnetic Resonance imaging as fine. An essential step in the majority of medicinal imaging investigation schemes is to extort the border of a region we are fascinated in. A lot of the techniques are there for the Magnetic Resonance Imaging segmentation (Wenbing Tao, Hai Jin, and Yimin Zhang, 2007). However till at this moment histogram thresholding is used for preprocessing only in several of the segmentation techniques this article demonstrates that it can be used as a dominant device for segmentation (Shen,W. A. Sandham and M. H. Granat,2003). The picture detained from a cancers brain demonstrates the position of the unhygienic part of the brain. The picture does not give the information about the numerical constraints such as region and size of the unhygienic part of the brain. After preprocessing of the picture, first image segmentation is completed by using region growing segmentation. The segmented image illustrates the harmful part visibly. From this picture the unhygienic part (cancer) is picked by yielding the segmented image. From this yielded image, region is evaluated (Orlando J. Tobias and Rui Seara, 2002).

In (Stamatakos et al., 2010*)* an "Oncosimulator" has been proposed, which plans to model tumor sequence on a biological stage, captivating keen on report cell propagation. (Konukoglu et al., 2010*)* used substantial models to enhanced appreciate the series of gliomas by adapting response-dispersal energetic. As gliomas too show an important accumulation-result on the adjacent hankies, biomechanics should be measured as presented by (Hogea et al., 2007*)*.

Brain tumor image investigation is a new traditional meadow than computational oncology; though, energetic investigate is being accomplished to grip the unreliable form of brain cancers, which makes general cancer-manner brain segmentation and registration a difficult task. While the greater parts of techniques are frequently disturbed with cancer segmentation, e.g., (Verma *et al.*, 2008) fewer works has been done on supporting cancer images with a normal pattern using registration. One of the newest hard works to adjust a registration and segmentation technique for cancer descriptions was done by (Zacharaki et al., 2009). In this work, a simply macroscopic biomechanical cancer enlargement representation is used to reproduce cancer enlargement in a healthy atlas, which is consequently recorded to the tolerant figure using deformable registration procedures. In a first step, we simulate tumor growth in a healthy brain atlas. We use the publicly available SRI24 atlas provided by (Rohlfing et al., 2010*)*, which is an average of 24 normal adult subjects. This atlas provides different modalities, including label maps. This cellular level model, while providing a detailed description of the cellular evolution of the imageable component of the tumor, assumes a conformal expansion or shrinkage of the tumor due to a lack of information on preferred growth directions. This motivates the coupling with a biomechanical stress/strain simulation, which can provide pressure gradient information (C. P. May, E. Kolokotroni, G. S. Stamatakos, and P. B¨uchler, 2011). The latter solves a linear elastic model on a brain atlas using values for the Young's modulus E and Poisson ratio v for different constituent brain materials from established publications (O. Clatz, M. Sermesant, P. Bondiau, H. Delingette, S. Warfield, G. Malandain, and N. Ayache, 2005).

3. RELATED WORKS:

The segmentation of the image is very useful in medical applications to diagnose the abnormalities in the image satellite imaging and in computer vision as well as in ANN. The criteria for segmenting the image is very hard to decide as it varies from image to image and also varies significantly on the modality used to capture the image. There is large amount of literature available to understand and analyze the segmentation techniques. The clustering methods have been discussed for medical image segmentation in particularly for MR Images of brain and are successful in combining fuzzy c means and k-means to get novel fuzzy-k means algorithm. Few limitations of the obtained algorithm have been also stated.

3. METHODOLOGY:

3.1. Segmentation

Segmentation plays an important role in medical imaging. Segmentation helps for segmenting the normal and timorous tissues in brain MR images. But accurate segmentation of brain MR images has not been yet done. Because evaluation segmentation requires ground truth images for segmentation. When we perform segmentation on real data, ground truth data for these are not available that is why just qualitative measures are used for measuring the quality of the segmentation. After the classification phase segmentation of the malignant images is performed into two steps. Following are the details of the segmentation. The entire of the effort has been employed using MATLAB R 20013A and extended versions. The flow diagram below describes the phases of the effort accounted in the current statement.

Author	*Year*	*Paper Name*	*Technique*	*Result*
Xie Mli Zhen Zherg wa Bingang Libero	*2009*	*Edge detection of brain tumor*	*Canny edge detection algorithm used*	*Deformable edge that is brain tumor is detected*
Rajeev rattan,sanjay Sharma s.k Sharma	*2009*	*Multiparameter segmentation and Quantizationof brain tumor from MRI images*	*2D Visulizatione*	*The quality of the segmentation was similar*
T.Logeswari and M.karnan	*2010*	*An Enhanced implementation of brain tumor detection using segmentation based on soft computing*	*Artificial Neural Network*	*Adapting More segmentation algorithms*
Luiza Antonie	*2010*	*Automated segmentation and classification of brain MRI*	*Support vector Machine*	*70% clear improved by training the Neural Network*
B.Ramamurthy,S.Aishwarya	*2011*	*Content based image ievalretrieval using invariant moments GLCM and gray scale resolution for medical images*	*Content based image retrieval*	*Good*
S.Selvarajah,S.R Koditu wakku	*2011*	*Analysis and comparison of texture features for content based image retrieval*	*Gabor transform,Wavelet Tansform*	*Better retrieval rate*
Andac Hamamci,Nadir Kucuk ,Katlay Karaman	*2012*	*Tumor Cut:Segmentation of brain tumors on contrast enhanced MR images for Radiosurgery applications*	*CA(Cellular Automata)*	*80-90% Accur ate*
Mr.Rohit S.Kabade Dr.M.S Gaikwad	*2013*	*Segmentation of brain tumor and its area calculation in brain MR images using K-mean clustering and fuzzy c-mean algorithm*	*K-mean Fuzzy c-mean algorithms*	*3d assessment and 3d slicer can be developed.*
Anjum Hayat Gondal, Muhammad Naeem Ahmed Khan	*2013*	A Review of Fully Automated Techniques for Brain Tumor Detection From MR Images	-	-
Mr.Deepak .C.Dhanwani Prof. Mahip M.Bartere	*2014*	Survey on Various Techniques of Brain Tumor Detection from MRI Images	-	-

3.2. Classification

Classification is the procedure for classifying the input patterns into set of categories. Classification classifies the unknown data samples. Selection of a suitable classifier requires consideration of many factors like computational resources it used, accuracy of the classifier for several datasets, and performance of the algorithm. Classifiers can be categorized into two categories, one is super- vised classifier and the second is unsupervised classifier. Supervised classifiers classify unknown data samples using the knowledge of the known dataset. Supervised classification requires detailed knowledge of the related area. Training data must be provided with the labels for supervised classification. Supervised classification is able to identify serious errors by examining training data to determine whether they have been correctly classified. Unsupervised classification is the identification of natural groups, or structures, within multi-spectral data. Unsupervised classification does not require extensive knowledge of the region. Many of the detailed decisions required for supervised classifi- cation are not required for unsupervised classification creating less opportunity for the operator to make errors. Unsupervised classification allows unique classes to be recognized as distinct units. Proposed system used Ensemble base classifier for the classification purpose. This Ensemble base classifier uses support vector machine for classification. Next section describes the details of the classification procedure followed by the proposed system.

4. CRITICAL EVALUATION

In this study, we have studied different techniques for segmentation. The prominent intensity models studied in this paper include neural networks, Gaussian mixture models, wavelet based models, finite mixture models, fuzzy adaptive etc. Majority of the researchers preferred MR images, and CT scanned images are rarely used by the researchers. Some studies focused on trained data while other targeted untrained data; some studies used atlas, and some did not.

5. CONCLUSION:

From Literature survey ,it is conclude that MR images provides much better information about human soft tissues of brain compared to computerized tomography(CT) images. DICOM images (.dcm) produce more efficient result compare to non medical images (.jpg,.png,.bmp). MRI segmentation is one of the essential tasks in medical area. The accurate segmentation is crucial otherwise the wrong identification of disease can lead to several consequences. As diagnosis tumor is a complicated task; therefore accuracy and reliability are always assigned much importance.

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