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CLASSIFICATION AND SEGMENTATION OF INTERNAL BRAIN STRUCTURES IN THE PRESENCE OF A TUMOR

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ABSTRACT : *Tumor is one of the most common brain diseases, so its diagnosis and treatment have a vital importance for more than 400000 persons per year in the world (based on the World Health Organization (WHO) estimates). On the other hand, in recent years, developments in medical imaging techniques allow us to use them in several domains of medicine, for example, computer aided pathologies diagnosis, follow-up of these pathologies, surgical planning, surgical guidance, statistical and time series (longitudinal) analysis. Among all the medical image modalities, Magnetic Resonance Imaging (MRI) is the most frequently used imaging technique in neuroscience and neurosurgery for these applications. MRI creates a 3D image which perfectly visualizes anatomic structures of the brain such as deep structures and tissues of the brain, as well as the pathologies. Segmentation of objects, mainly anatomical structures and pathologies from MR images is a fundamental task, since the results often become the basis for other applications. Methods for performing segmentation vary widely depending on the specific application and image modality. Moreover, the segmentation of medical images is a challenging task, because they usually involve a large amount of data, they have sometimes some artifacts due to patient's motion or limited acquisition time and soft tissue boundaries are usually not well defined.*

KEYWORDS *: DWP, WDM, Enhanced (Modified) DWP, Rerouting and MTV WR.*

1. INTRODUCTION

A brain tumor is an intracranial mass produced by an uncontrolled growth of cells either normally found in the brain such as neurons, lymphatic tissue, glial cells, blood vessels, pituitary and pineal gland, skull, or spread from cancers primarily located in other organs. Brain tumors are classified based on the type of tissue involved, the location of the tumor, whether it is benign or malignant, and other considerations. Primary (true) brain tumors are the tumors that originated in the brain and are named for the cell types from which they originated. They can be benign (non cancerous), meaning that they do not spread elsewhere or invade surrounding tissues They can also be malignant and invasive (spreading to neighboring area). Secondary or metastasis brain tumors take their origin from tumor cells which spread to the brain from another location in the body. Most often cancers that spread to the brain to cause secondary brain tumors originate in the lumy, breast, kidney or from melanomas in the skin.

Each primary brain tumor, in addition to the solid portion of the tumor, may have other associated parts such as edema and necrosis as in Figures 1 and 2. Edema is one of the most important factors leading to mortality associated with brain tumors. By definition, brain edema is an increase in brain volume resulting from increased sodium and water content and results from local disruption of the blood brain barrier (BBB). Edema appears around the tumor mainly in white matter regions [Prastawaet al., 2005]. Tumor associated edema is visible in MRI, as either hypointense (darker than brain tissue) or rarely isointense (same intensity as brain tissue) in T1-weighted scans, or hyperintense (brighter than brain tissue) in T2-weighted and FLAIR MRI (Figure 2). Necrosis is composed of dead cells in the middle of the brain tumor and are seen hypointense in T1-weighted images (Figure 1). A brain tumor may also infiltrate the surrounding tissues or deform the surrounding structures.

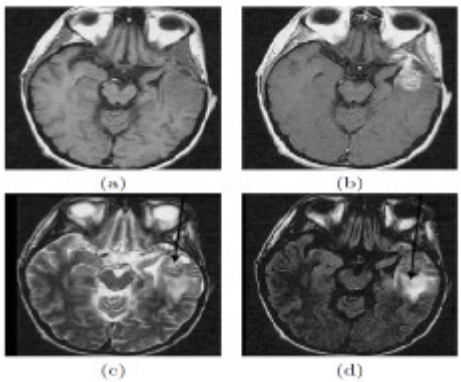

Figure 1: MRI of brain. (a) T1-weighted image without contrast enhancement. (b) T1-weighted image with contrast enhancement. (c) T2-weighted image. (d) FLAIR Image

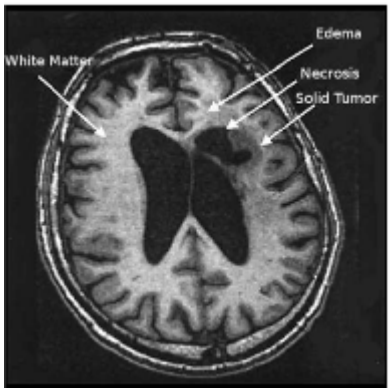

Figure 2: One axial slice of a MR image of the brain showing tumor areas

2. CLASSIFICATION OF BRAIN TUMORS

The classification of primary brain tumors is usually based on the tissue of origin, and occasionally on tumor location. The degree of tumor malignancy is determined by the tumor's histopathologic features. Because of the substantial variety and unusual biology of brain tumors, it has been extremely difficult to develop a widely accepted histological classification system [Doolittle, 2004].

The earliest brain tumor classifications were provided by Bailey and Cushing in 1926 [Doolittle, 2004]. Their classification scheme proposed 14 brain tumor types, directed important attention to the process of cell differentiation, and dominated views of gliomas until 1949 when a new system was introduced by Kernohan and Sayre [Doolittle, 2004]. Kernohan and Sayre made the important realization that different histopathologic appearances may not represent separate tumor types but rather different degrees of differentiation of one tumor type. They classified tumors into five subtypes: astrocytoma, oligodendroglioma, ependymoma, gangliocytoma, and medulloblastoma and very importantly added a four-level grading system for astrocytomas. The grading system was based on increasing malignancy and decreasing differentiation with increasing tumor grade. The addition of a grading system was a very important advance in classifying brain tumors, and provided information not only regarding tumors' biologic behavior but also information that could be used to guide treatment decisions.

Based on radiologic appearance of tumors in contrast enhanced T1-weighted and without considering the histology of tumors we can classify the brain tumors into 4 classes: non-enhanced, full-enhanced without edema, full-enhanced with edema and ring-enhanced tumors.

a) Non-enhanced tumors

The tumors of this type do not take contrast agent and appear hypointense (darker than GM) in contrast enhanced T1-weighted and T1-weighted images (Figure 3). They are usually without edema or little edema. In FLAIR and T2-weighted images, they appear as hyperintense. Low grade astrocytomas, gangliogliomas and oligodendrogliomas are most common tumors of this type.

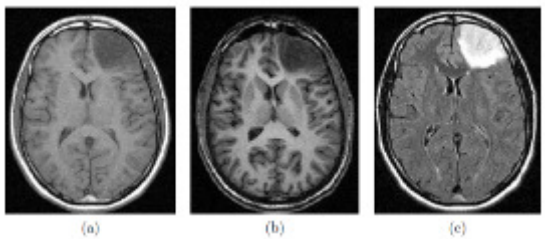

Figure 3: A non-enhanced tumor. a) Axial slice of T1-weighted. b) The same slice of contrast enhanced T1-weighted. c) FLAIR image

b) Full-enhanced tumors without edema

These tumors enhance with contrast administration in T1w images and approximately all voxels of the tumor appear hyperintense in CE-T1w (Figure 4). These tumors are without edema and appear hypointense in T1-weighted images and hyperintense in T2- weighted and FLAIR images. Meningimoas (some types), ependymomas, lymphomas, craniopharyngiomas and pituitary adenomas are in this category.

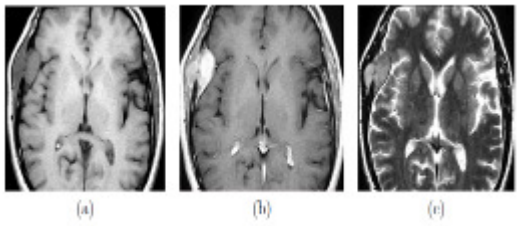

Figure 4: A full-enhanced tumor without edema. a) Axial slice of T1-weighted image. b) The same slice of contrast enhanced T1-weighted image. c) T2-weighted image.

c) Full-enhanced tumors with edema

These tumors have two sections, the solid section and edema. The solid section takes contrast agent and appears hyperintense in contrast enhanced T1-weighted images and hypointense in T1-weighted images, while the edema appears hypointense in T1-weighted images and contrast enhanced T1-weighted images (Figure 5). In FLAIR and T2-weighted images both sections of the tumor appear hyperintense. Anaplastic astrocytomas (high grade), high grade oligodendrogliomas, PNETs and some type of meningiomas can be included in this category.

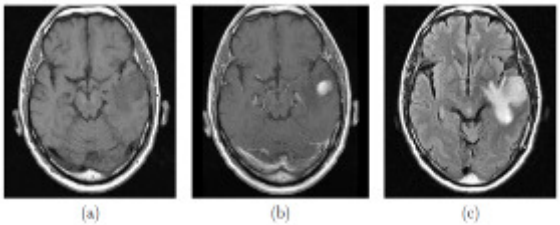

Figure 5: A full-enhanced tumor with edema. a) Axial slice of T1-weighted image. b) The same slice of contrast enhanced T1-weighted image. c) FLAIR image.

d) Ring-enhanced tumors

These tumors have 3 sections. The central section is necrosis and appears hypointense in contrast enhanced T1-weighted and T1-weighted images. The solid section surrounds the necrosis and takes contrast agent, hence appears hyperintense in contrast enhanced T1-weighted images and hypointense in T1-weighted images (Figure 6). The third section is the edema which surrounds the solid section. The edema appears hypointense in both T1-weighted and contrast enhanced T1-weighted images. In T1-weighted images the solid section, edema and necrosis are hypointense, while the necrosis is darker than the other sections. FLAIR images show the edema and solid section as hyperintense signal, while the necrosis section appears hypointense. GBMs and high grade oligodendrogliomas have these characteristics.

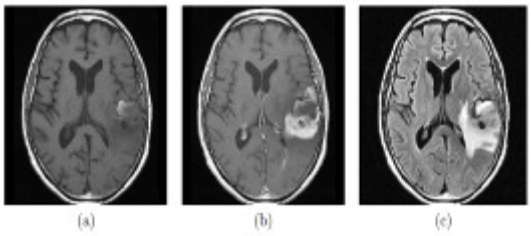

Figure 6: A ring-enhanced tumor. a) Axial slice of T1-weighted image. b) The same slice of contrast enhanced T1-weighted image. c) FLAIR image

3. TUMOR SEGMENTATION METHODS: A SURVEY

The most important aim of medical image analysis in general, and brain magnetic resonance image (MRI) analysis in particular, is to extract clinical information that would improve diagnosis and treatment of disease. Brain tumors are one of the most common brain disease, so detection and segmentation of brain tumors in MRI are important in medical diagnosis. The aim is to provide information associated to anatomical structures as well as potential abnormal tissues necessary to treatment planning and patient follow-up. The segmentation of brain tumors can also be helpful for general modeling of pathological brains and the construction of pathological brain atlases [W.Toga et al., 2001].

Despite numerous efforts and promising results in the medical imaging community, accurate and reproducible segmentation and characterization of abnormalities are still a challenging and difficult task because of the variety of the possible shapes, locations and image intensities of various types of tumors. Some of them may also deform the surrounding structures or may be associated to edema or necrosis hat change the image intensity around the tumor. Existing methods leave significant room for increased automation, applicability and accuracy. In this chapter we classify and study the existing methods for detection and segmentation of brain tumors in MR images.

Conventionally, simple thresholding or morphological techniques have been used on each image to segment the tissue or region of interest for diagnosis, treatment planning, and follow-up of the patients. These methods are unable to exploit all information provided by MRI. Advanced image analysis techniques have been and still are being developed to optimally use MRI data and solve the problems associated with previous techniques. Most of the methods presented for tumor detection and segmentation have used several techniques and we cannot make a clear division between them but in general, as classically done in image segmentation, we can divide the methods into three groups: region-based, contour-based and fusion of region- and boundary-based method.

Region-based methods seek out clusters of voxels that share some measure of similarity. These methods reduce operator interaction by automating some aspects of applying the low level operations, such as threshold selection, histogram analysis, classification, etc. They can be supervised or non-supervised.

Boundary-based methods rely on the evolution of a curve, based on internal forces (e.g. curvature) and external forces, such as image gradient, to delineate the boundary of brain structure or pathology. These methods can also be supervised or nonsupervised. They can be further classified into two classes: (1) parametric deformable model (classical snake) and (2) geometric deformable model (level sets).

The third core class of tumor segmentation methods is the fusion of region- with boundary-based methods. This class has been the most successful, as this technique uses information from two different sources: region and boundary. Due to its large success, it has recently received much attention.

In the image segmentation domain, classification algorithms are either supervised, or unsupervised. A supervised classifier requires input from the user, typically a set of class samples, for determination of the data structures. Unsupervised classification (clustering) on the other hand relies on cluster analysis to drive the natural structures of the data from the data themselves. Here we review tumor segmentation methods based on supervised classification techniques and unsupervised methods will be studied in the clustering-based section. We can distinguish five classes of methods based on

supervised classification:

- K-nearest neighbors (KNN),
- Bayesian approach,
- expectation maximization (EM),
- Markov random field,
- support vector machine (SVM).

Clustering consists of unsupervised classification of patterns (observations, data items, or feature vectors) into groups (clusters).The clustering algorithms

essentially work such as classification methods without use of training data set [Jain et al., 1999]. Two commonly used clustering algorithms are the k-means or ISODATA algorithm and the fuzzy c-means (FCM) algorithm. The k-means clustering algorithm clusters data by iteratively computing a mean intensity for each class and segmenting the image by classifying each pixel/voxel in the class with the closest mean. The fuzzy c-means algorithm generalizes the k-means algorithm, allowing for soft segmentations based on fuzzy set theory. It should be mentioned that the membership functions to classes have a counter intuitive shape, which limits their use. This is improved in the possibilistic c-means (PCM) algorithm [Krishnapuram and Keller, 1993].

[Phillips et al., 1995] have used the FCM algorithm for GBM brain tumors segmentation. Their system used T1-weighed, T2-weighted and PD-weighted MRI with a vectorial FCM to segment the pathological brain to WM, GM, CSF, tumor and edema. Although the FCM algorithm is simple, fast and unsupervised, it cannot segment the tumor and edema accurately because of the intensity overlapping of tissues. In addition FCM is very sensitive to noise and initialization values. This method was not validated and only tested for one case.

Another FCM based brain tumor segmentation has been presented in [Masulli and Schenone, 1999]. This possibilistic neuro fuzzy c-means (PNFCM) algorithm combines a bootstrap based on the capture effect model (CENN) [Firenze and Morasso, 1993] with the second version of the PCM-II [Krishnapuram and Keller, 1996]. The CENN avoids the estimation of the fuzzification parameter m and gives a robust estimation of the class numbers c and of their centers. This method has been applied to segment full-enhanced tumors (such as meningioma) using T1-weighted, T2-weighted and PD MR images. Although this method is fast and fully automatic, it is very sensitive to noise and heterogeneity.

In the previous FCM-based methods the spatial information of pixels were not considered, so that they are very sensitive to noise. To solve this problem, [Shenet al., 2003] have proposed a more recent system, which incorporated intensity standardization (using the pixel histograms) as a preprocessing step, and a modified FCM algorithm which involves dependencies between neighbor pixels. This method is more robust to noise and provides a better segmentation quality in comparison with the other FCM based approaches.

4 CONCLUSION AND FUTURE WORK

When dealing with brain tumors, other problems arise, which make their segmentation more difficult. There is a large class of tumor types which have a variety of shapes and sizes. They may appear at any location and in different image intensities. Some of them may also deform the surrounding structures or may be associated to edema or necrosis that change the image intensities around the tumor. In addition, the existence of several MR acquisition protocols provides different information on the brain. Each image usually highlights a particular region of the tumor. Thus, automated segmentation with prior models or using prior knowledge is difficult to implement. The accurate segmentation of internal structures of the brain is of great interest for the study and the treatment of tumors. It aims at reducing the mortality and improving the surgical or radiotherapeutic management of tumors. In brain oncology it is also desirable to have a descriptive human brain model that can integrate tumor information extracted from MRI data such as its localization, its type, its shape, its anatomo-functional positioning, as well as its influence on other brain structures.

Despite numerous efforts and promising results in the medical imaging community, accurate and reproducible segmentation and characterization of abnormalities are still a challenging and difficult task. Existing methods leave significant room for increased automation, applicability and accuracy.

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