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A Review on Volume Calculation of Brain Abnormalities from MRI of Brain using CAD system

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ABSTRACT

Brain abnormalities and the tumor segmentation using computer aided design (CAD) is a challenging task because of the high diversity in the appearance of abnormal and tumor tissues among different patients and in many cases similarity with the normal tissues. Magnetic resonance imaging (MRI) is advanced medical imaging technique from which a lot of information about human soft tissue is gathered. Using this MRI of brain volume measurement by the CAD system is more realistic for diagnosis of tumor or abnormalities. Here these volume measurement approaches are reviewed with an importance placed on enlightening the advantages and drawbacks of these methods for brain abnormality and tumor quantification.

Index Terms— *Abnormal region detection, Volume Calculation, MRI of brain, CAD System, Automated Segmentation, Manual Segmentation.*

I. INTRODUCTION

Now a day's brain abnormality mainly brain tumors are one of the most common brain diseases, so detection and quantification of tumor in MRI are important in medical diagnosis. Through past many researchers have prepared important research in the field of brain abnormality segmentation but still now it is very important research fields due to the large number of variation of MRI of brain. The accurate segmentation of internal structures of the brain is of great interest for the study and very helpful for the treatment of tumors. It aims at reducing the mortality and improving the surgical or radiotherapeutic management of tumors. The most important aim of medical image analysis in general and brain MRI analysis in particular, is to extract clinical information that would improve diagnosis and treatment of disease. The aim is to provide information associated to anatomical structures as well as potential abnormal tissues necessary to treatment planning and patient follow-up.

There are different brain tumor detection and segmentation methods to detect and segment a brain tumor from MRI images. These detection and segmentation approaches are reviewed [1] with an importance placed on enlightening the advantages and drawbacks of these methods for brain tumor detection and segmentation. One major advantage when segmenting medical images as opposed to natural scenes is that structural and intensity characteristics are well known up to a natural biological variability or the presence of pathology. The measurement of brain tumor volume can assist tumor staging for brain tumor volume measurements is developed which overcome the problem of inter-operator variance, besides partial volume effects and shows satisfactory performance for segmentation, thus segmentation is very important for volume calculation. Different segmentation techniques such as thresholding based segmentation methodology, Region Growing based segmentation, K-nearest neighbours (KNN), Bayesian approach, Markov Random Field Models , Expectation maximization (EM), Support vector machine (SVM), Fuzzy c-means algorithms, K-means algorithms, Morphology-based segmentation, Atlas-guided based segmentation, Knowledge based segmentation, Texture-based segmentation, Artificial neural networks (ANNs), Fusion-based, Fuzzy connectedness, Watershed Methods, Level set based segmentation, Hybrid Self Organizing Map (SOM), SOM, Graph Cut based segmentation, Fractal-based segmentation, Parametric deformable models (snakes), Boundary based methods, Geometric deformable model, The Combination of Watershed and Level Set segmentation , Spatio Temporal Model, Hidden Markov Model, Genetic algorithms based segmentation, Kohonen Self Organizing Map(SOM) are described by Roy et al. [1] with a common phase pre-processing and segmentation and its steps are shown below.

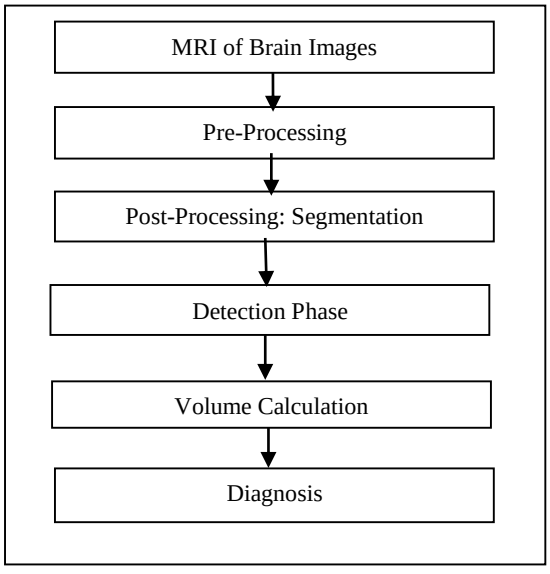

Figure 1: Brain abnormal regions volume calculation steps

Thus accurate segmentation over full field of view is another very much problem but during the segmentation procedure verification of results is another source of difficulty. Statistical

classification may not allow differentiation between non-enhancing tumor and normal tissue due to overlapping intensity distributions of healthy tissue with tumor and surrounding edema.

Over the last 10 years increasingly complex mathematical models of cancerous growths have been developed, especially on solid tumors, in which growth primarily comes from cellular proliferation. The invasiveness of gliomas, however, requires a change in the concept to include cellular motility in addition to proliferative growth.

Traditionally, the boundary of a tumor in magnetic resonance imaging is usually traced by hand. Then the practitioner is confronted with a succession of boundary which he mentally stacked up to be made a 3D representation of the tumor. This reconstruction is inevitably subjective and becomes infeasible when dealing with large data sets, there is also an information loss in all the in three-dimensional images directions and then the process is time-consuming and very difficult.

Thus automatic quantitative measurements of tumor response rate in three dimensions (3D) and volume measurement of abnormal region become more reasonable with the use of advanced technology imaging during therapy, especially when the tumor morphological changes remain restrained, asymmetrical and difficult to assess by clinical examination. MRI is being increasingly used in oncology for staging, assessing tumor response and also for treatment planning in radiotherapy. Both conformal and intensity-modulated radiotherapy requires improved means of defining target volumes for treatment planning in order to achieve its intended benefits. MRI can add to the radiotherapy treatment planning (RTP) process by providing excellent and improved characterization of soft tissues compared with CT.

Rest of the paper is organized as follows: Section 2 describes the different approach of volume calculation and advantage with drawback. In section 3 different performance evaluation criteria has been described, which can produce volumetric delineations of brain tumor boundaries comparable to those done by experts and finally in section 4 we summarized and conclude our paper.

II. REVIEW

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. 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. In the remaining of this section, we review the existing methods for segmentation of brain tumors in MR images.

A. Stochastic Approximation Based Approach

Registration by extremizing properties of the joint signal has been investigated by Hill et al. 1994 [2] for the alignment of MRI, CT and other medical image modalities. They showed interesting scatter-plots of the joint data as the registration is disturbed, and used third-order moments of the joint histogram, as well as other measures to characterize the clustering of the joint data.

A new information-theoretic approach is obtainable for finding the registration of volumetric medical images of conflicting modalities which is based on stochastic approximation [3]. Registration is accomplished by adjustment of the comparative position and orientation until the mutual information between the images is maximized. There no pre-processing steps are required. This technique is, however, more flexible and stronger than other intensity-based techniques like correlation. It requires registration by maximization of mutual information then estimating entropies and their derivatives with mutual information after that stochastic maximization of mutual information with estimating the covariance has been calculated. This method is very much useful for radiological examinations of several MRI acquisitions indicated that the patient had a tumor of the frontal lobes bilaterally and a skull base meningioma which consisted of both intra- and extra-cranial parts. The 3-D models were made from CT images and two sequences of MR images.

These stochastic approximation based approach [3] techniques are dependent on the a priori quality of the available segmentations. Alternatively, intensity-based techniques can work directly with the volumetric data. It can be used to register 3-D volumetric information directly to video images of patients and a unified registration system that can accommodate various planar and volumetric images.

B. Spiral-scanning technique and optimal outline methods

Jiahui Wang, et al., 2008 proposed a spherical volume of interest (VOI) was produced at the central location [4] of a tumor and was converted to a polar coordinate system by use of a spiral-scanning technique, in which a number of radial lines originated from the center of the VOI formed a spiral scanning line that covered the VOI. The voxels examined by the radial lines were arranged successively to generate a transformed 2D image. The surface of a brain tumor in 3D image thus became a curve in the transformed 2D image. To determine the volume of a tumor in 3D MRI, each edge candidate on the 2D outline of a tumor was transformed back to 3D image space. After the 2D to 3D transformation, we obtained a sparse point cloud, from which the volume of a tumor was resolute by use of a new interpolation procedure. Because this segmentation was performed in 2D image space, the segmentation scheme was simplified significantly. Segmentation result for partially solid tumor with an agreement value of 91.4%. But agreement values for partially solid tumors are generally lower than those for solid tumors because of the inhomogeneous intensity inside the tumors. This

method would be useful for the management of various brain tumors, including estimating the interval changes in tumor volumes during and after treatment and planning of radiation therapy.

C. Level-Sets Based Approach

The level-set method was devised by Osher and Sethian, [5] as a straightforward and adaptable method for computing and analyzing the movement rely on partial differential equations to model deforming iso-surfaces. Aaron Lefohn et al. [6] update the level-set surface model at interactive rates on product graphics cards, such as those that are frequently found on consumer-level personal computers. K. Aloui et al.2009 [7] proposed a new level-set deformation solver to achieve inter-active rates which are approximately fifteen times faster than previous solutions and a new numerical scheme for maintaining a thin band structure in the solution, and quantitative and qualitative confirmation that interactive level-set models are effective for brain tumor segmentation. A compression plan of 3D brain structures based for the meshes simplification, adapted for time to the detailed needs of the telemedicine and to the ability limited by network communication. Advantages of the contour embedded formulation of the deformable model over parametric formulation include: no parameterization of the contour, topological flexibility, good numerical firmness and straightforward expansion of the 2D formulation to n-D. In level set methods, 3D segmentation of a brain tumor by the stacking of 2D boundary. It consists in applying to each slice the level-sets method in 2D and to propagate the result by taking as initial data the result of the preceding slice. It's the 3D reconstruction from 2D tumor contours using a sequence of 2D contours, detected by 2D level-sets method in the parallel cross-sectional MRI images. Algorithm based on level set technique, rely on two central embeddings; first the embedding of the interface as the zero level-set of a higher dimensional function, and second, the embedding of the interface's velocity to this higher dimensional level-set function. It guarantee a weakest coding cost to accelerate some tasks as the 3D graphic reconstruction, the transmission on a communication channel by preserving the geometrical characteristics of the tumor so that it remains adapted to later treatments. Usefulness of level set has been limited by two problems. First, 3D level sets are relatively slow to compute. Second, their formulation usually entails several free parameters which can be very difficult to correctly tune for specific applications. Olivier Clatz et al. [8] proposed a new method which based upon two coupled models; they are multiplication and diffusion and expansion model. The coupling between these two models leads to a four step algorithm: in the first phase image segmentation and registration, in second phase meshing and initialization, in the third phase simulation and finally comparison. It describes a proof-of-concept aspiring to express the feasibility of modeling complex tumors, here consider the comparison of the simulated tumor growth with the follow-up MR image of the patient as a preliminary step toward a clinical validation.

D. Mathematical models

Cancer research has been abundant ground for mathematical modeling and it is a powerful tool for analyzing biological problems that allows one to develop and test hypotheses which can lead to a better appreciative of the biological process. Due to the sound understanding, appreciation of the biological problem, realistic mathematical representation of the important biological phenomena, finding useful solutions, preferably quantitative, biological understanding of the mathematical results in terms of insights and predictions.

Kristin R et al. [9] briefly described the evolution of mathematical models for glioma growth and invasion beginning in simple homogeneous tissue, with or without gross anatomical boundaries, extending to complex heterogeneous tissue, with varying proportions of grey and white matter in cerebral cortex , deep cerebral nuclei, brainstem and cerebellum. Such realistic mathematical modeling has been helpful in highlighting and demonstrating the fact that any local treatment of a diffusely invading glioma will fail. Mathematical modeling can be critical in deducing the extent of sub-microscopic spread of the tumor and thus in determining the locations of active invasion of the tumor.

E. Radiotherapy Treatment Planning (RTP) based approach

MRI developments using new dissimilarity media, such as ultrasmall super paramagnetic iron oxide particles for abnormal lymph node recognition, techniques such as dynamic contrast enhanced MRI and dissemination MRI to better characterize tissue and tumour regions as well as ultrafast volumetric MR progression to define temporal patterns of target and organ at risk irregularity and variations in spatial location have all increased the scope and utility of MRI for radiotherapy treatment planning (RTP) proposed by V S Khoo et al. [10] in 2006 . Information from these MR developments may permit treatment individualization, strategies of dose appreciation and image-guided radiotherapy. There are lot of advantage using RTP; firstly increased number of imaging parameters for more imaging flexibility, secondly understanding the surgical bed or altered anatomy secondary to surgery and finally distinguishing between post-treatment fibrosis or tumour recurrence but MR image and object induced distortion systems are the problem for RTP. Thus superior characterization of soft tissues and visualization of tumor extent from MRI can benefit RTP by improving target volume measurement and estimation of planning margins in many cancer subtypes in sites such as the brain, spinal cord, soft tissues of the head and neck, trunk and limbs.

F. Partial Volume Modeling based

Su Ruan et al.[11] consider that in a brain dataset there are not only the three main types of brain tissue: gray matter, white matter, and cerebro spinal fluid, called pure classes, but also mixtures, called mix-classes. classify a brain into three types of brain tissue and deal with the problem of partial volume effects, the proposed algorithm uses two steps: 1) segmentation of the brain into pure and mix-classes using the mixture model; 2)

reclassification of the mix-classes into the pure classes using knowledge about the obtained pure classes. Both steps use Markov random field (MRF) models. The multifractal dimension, describing the topology of the brain, is added to the MRFs to improve discrimination of the mix-classes. The algorithm is evaluated using both simulated images and real MR images with different T1-weighted acquisition sequences. The algorithm is unsupervised, fully automatic, and uses only T1-weighted images. Mixtures of multiple tissue types within a voxel are taken into account in the process of classification. The Gaussian distribution of the mixel intensities is demonstrated, which allows us to simplify the image model, as well as the segmentation method. But due to poor contrast, some inaccuracy is present in the gray nuclei region; therefore, improvement in the method based on a priori anatomical knowledge is needed and is actually in progress.

G. Modified Region Growing Method

Region-based methods segment difficult cases of tumors with a high level of automation but they have a main drawback at the boundary of tumors. Volume can be calculated by symmetric analysis of tumor. Due to the partial volume effect the region-based techniques suffer from misclassification of voxels and hence, it is difficult to have a crisp region of tumor. On the other hand boundary-based methods were proposed to solve this problem but they also suffer from initialization problems. To obtain a good result they must be well initialized. The tumor region has been segmented using both traditional region growing methods and modified region growing methods [12] segmentation techniques, the tumor volume calculations are performed in this segmented region. Yasser et al. [13] proposed new automatic calculation of the volumetric size of brain tumor has been applied based on modified region growing method. First a pre-processing technique applied because noise presented in the image can reduce the capacity of the region growing filter to grow large regions, or may result in a fault edges. To calculate the volume of segmented tumor region, the automatic labeling of the entire volumetric tumor region has been done slice by slice and by calculating the total number of pixels into the labeled regions. Areas of the labeled region were calculated and multiplied by the MR slice thickness plus the inter-slice gap to obtain a per-slice tumor volume. The total tumor volume was then obtained by summing the tumor-bearing slices. By quantitative analysis of brain tumors based on modified region growing methods has a higher accuracy and precision against traditional region growing method compared to expert manual computation.

H. Atlas-Based Segmentation

Pierre-Yves Bondiau et al. [14] study the atlas-based segmentation inclinical context shows that fully automated software is useful in radiotherapy and demonstrates that the method is repeatable and leads to reproducible segmentation, volume and labeling. The automatic delineation used for the automatic segmentation and labeling suggest that this method provides a good trade-off between accuracy and robustness. It can be improved by elevating the atlas with additional information about the tumor or by using different laws of deformation for the different structures.

I. K-means base segmentation and volume calculation

K-Means clustering [17] generates a specific number of disjoint, flat (non-hierarchical) clusters. It is well suited to generating globular clusters. The K-Means method is numerical, unsupervised, non-deterministic and iterative. K-Means Algorithm are i) always K clusters, ii) always at least one item in each cluster, iii)The clusters are non-hierarchical and they do not overlap, iv) Every member of a cluster is closer to its cluster than any other cluster because closeness does not always involve the center of clusters. Thus the K-Means Algorithm Process in very shortly a)The dataset is partitioned into K clusters and the data points are randomly assigned to the clusters resulting in clusters that have roughly the same number of data points, b) For each data point: Calculate the distance (Mahalanobis or Euclidean) from the data point to each cluster, c) If the data point is closest to its own cluster, leave it where it is and if the data point is not closest to its own cluster, move it i to the closest cluster, d) Repeat the above step until a complete pass through all the data points results in no data point moving from one cluster to another. At this point the clusters are stable and the clustering process ends, e)The choice of initial partition can greatly affect the final clusters that result, in terms of inter-cluster and intra-cluster distances and cohesion. Then maintain a stack and pushed all image which detect the brain abnormal and sum up all the quantified value of abnormality and we find the volume. As can be seen by the results, the number of partitions used in the segmentation has a very large effect on the output [18]. By using more partitions, in the RGB setup, more possible colors are available [18] in the output. The same is true for the setup checking greyscale intensity. By adding more partitions, a greater number of intensities are available to use in the output image. The algorithm also runs quickly enough that real-time image segmentation could be done with the K-Means algorithm. The clustering algorithms essentially work such as classification methods without use of training data set.

J. Fusion-based Segmentation

Fusion techniques are based on various theories such as probabilistic and Bayesian fusion, fuzzy set theory, possibility and belief functions theory. Since a tumor consists of different biological tissues, one type of MRI cannot give complete information about abnormal tissues. Therefore, different MRI modalities information of a patient is combined to take a decision on the location, extension, prognosis and diagnosis of the tumors discussed by Ruan et al. (2007) [19]. Data fusion is a growing research field, and the goal of data fusion is to obtain an information synthesis by combining different data [20]. Data coming from different sources and techniques are usually redundant but also complementary.

Problem using fusion and registration is accuracy of volume of abnormal image.

III. PERFORMANCE EVALUATION CRITERIA

The purpose is to determine if the methods can produce volumetric delineations of brain tumor boundaries comparable to those done by experts (e.g. radiologists or neurosurgeons) using traditional hand-contouring. Manly three ways we can define the criteria; Validity of the results (accuracy), Reproducibility of the results (precision), and efficiency of the method (time) [6]. It is impossible to obtain MR images of the human brain with known proportions of mixel components within each voxel. Therefore, a quantitative assessment of the performance of the classification method requires the use of simulated data.

First let AV and MV denote [15] the volume of the automatically and manually segmented objects and |x| represents the cardinality of the set of voxels x. In the following equations Tp = MV ∩ AV, Fp = AV − MV and Fn = MV − AV denote to the "true positive", "false positive" and "false negative" respectively. The Kappa index between two volumes is calculated by the following equation:

$$K_i(AV, MV) = \frac{(2|AV \cap MV|)}{(|AV| + |MV|)} * 100\%$$

The similarity index is sensitive to both differences in size and location. The Jaccard index between two volumes is represented as follow:

$$J_i(AV, MV) = \frac{|AV \cap AM|}{|AV \cup AM|} * 100\%$$

This metric is more sensitive to differences since both denominator and numerator change with increasing or decreasing overlap. Correct detection ratio or sensitivity is defined by the following equation:

$$T_P = \frac{|AV \cap MV|}{MV} * 100\%$$

This metric indicates the correct detection volume normalized by the reference volume and is not sensitive to size.
Kappa index is sensitive to both differences in size and location. For the similarity index, differences in location are more strongly reflected than differences in size and greater 70% indicates a good agreement. Jacard index is more sensitive to differences since both denominator and numerator change with increasing or decreasing overlap. Correct detection ratio indicates the correct detection volume normalized by the reference area and is not sensitive to size. Therefore Correct detection ratio solely cannot indicate the similarity and should be used with false detection ratio or other volume metrics. False detection ratio shows the error of the segmentation and indicates the volume that is not located in the true segmentation. Using this metric with the correct detection ratio can give a good evaluation of the segmentation.

Histogram of Error [11] is the ratio of the number of classified voxels to the number of gold standard voxels within each range was calculated. The higher the value of the histogram for proportions 50% and the lower for proportions 50%, the better the results. In this way, histograms corresponding to the three classes can be drawn for the final results. The Relative Error [13] (RE) for tumor volume can be calculated as "AV" tumor volume using 3D quantitative methods, "MV" is tumor volume calculated using expert

$$RE = \frac{(AV - MV)}{MV} * 100\%$$

IV. SUMMARY AND CONCLUSION

Here several existing brain tumor and abnormalities volume calculation methodology has been discussed for MRI of brain image. Stochastic approximation is very much useful for radiological examinations of several MRI acquirements indicated that the patient had a tumor which consisted of both cranial parts with volumetric information of a variety of planar and volumetric images. Spiral-scanning techniques accorded values for moderately solid tumors, lesser than those for solid tumors because of the inhomogeneous intensity inside the tumors. This method would be useful for the management of various brain tumors, including estimating the interval changes in tumor volumes during and after treatment and planning of radiation therapy. 3D level sets are relatively slow to compute and difficult to correctly tune for specific applications are the limitation of Level-sets but it is very much efficient for volume calculation. Mathematical modeling has been useful in highlighting and demonstrating the fact that any local treatment of a diffusely invading glioma will fail. RTP superior for soft tissue target volume measurement and estimating of planning margins in many cancers. In partial volume modeling, inaccuracy is present in the gray nuclei region for poor contrast; therefore, development in the method based on a priori anatomical knowledge is desirable and is actually in progress. Performance and accuracy (volume calculation) of brain tumors based on modified region growing methods has a higher correctness and meticulousness against traditional region growing method compared to expert manual computation but seed selection problem still exists. The automatic delineation used for the automatic segmentation and labeling suggest that this method provides a good trade-off between accuracy and robustness. Although advanced image analysis techniques has lots advantage and still are being developed to optimally use MRI data and to solve the problems associated with previous techniques.

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