Automatic MRI Gray Matter Brain Tumor Detection of Segmentation and Deep Brain Structures Based Segmentation Methodology

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Abstract: In this paper a simple strategy for the automatic segmentation of tissues in magnetic resonance images of multispectral classification based mainly on minimum Euclidean distance is presented From a set of 3D images in the T1, T1 modalities with gadolinium contrast, T2 and FLAIR and its segmentation reference descriptors for each tissue type are obtained through the centroid of each class, which are used to classify new input images. Magnetic Resonance Imaging (MRI) offers the possibility of multimodality image acquisition, different imaging studies can be performed on the patient in the same slice position with little movement artifacts so images are acquired virtually registered. Multimodality MRI studies are usually performed to diagnose and characterize brain tumors and typically a set of 4 or more modalities are acquired. In the present work, a method based on multidimensional mathematical morphology is used to classify brain tissues for multimodality MRI comprising Four modalities, allowing for tumor image segmentation and characterization. The method also proposes a general view for image integration or fusion that allows for a targeted application of therapy.

Key words: Segmentation, Gray Matter, MRI, FLAIR, Euclidean Distance Classifier.

1. Introduction

Segmentation of medical images is a fundamental problem in the development assistance related diagnostic applications, monitoring diseases and computer-assisted surgery [1]. Although scientific practice have proposed different solutions, research in the area continues to deepen, mainly influenced by the increase in computing power and the equipment emergence of new forms of capture, both 2 and 3 dimensions [2,3]. In particular, the segmentation of Magnetic Resonance Imaging (MRI) has acquired particularly relevant in the area of cancer medicine, where detection and tumor segmentation allows to study the evolution of the patient before treatment specific medication, and facilitates the planning of surgery and radiotherapy sessions [4,5]. Initially, the radiologist can perform segmentation manually, outlining the contours of tumor through some computational [6] tool. Without However, in the case of three-dimensional images, the segmentation must be done to cut court, which requires an excessive amount of time and effort. Therefore, they have developed numerous strategies, both automatic and semi-automatic, requiring no or minimal user intervention and expert assist in enabling this process. In an earlier [7] work, we addressed a semi-automatic approach based on the combination of growth regions and deformable models, using information intensities or textures to guide the segmentation algorithm, applied to MRI

images with gadolinium contrast T1. The proposal presented in [8], on the other hand, suggests the use of a region growing algorithm fully automatic detection of lesions in any form. A widespread trend in recent years is to use multiple modalities of MRI in one segmentation algorithm, as it allows to increase the amount of information available and more precise results [9-11]. In this work proposes an automatic segmentation algorithm to brain tissues in 3D MRI Multispectral brain tumors with high and low grade. The high-grade tumors (III-IV, according to the World Health Organization) are malignant tumors, highly vascular, prone to infiltration and the presence of necrotic areas.

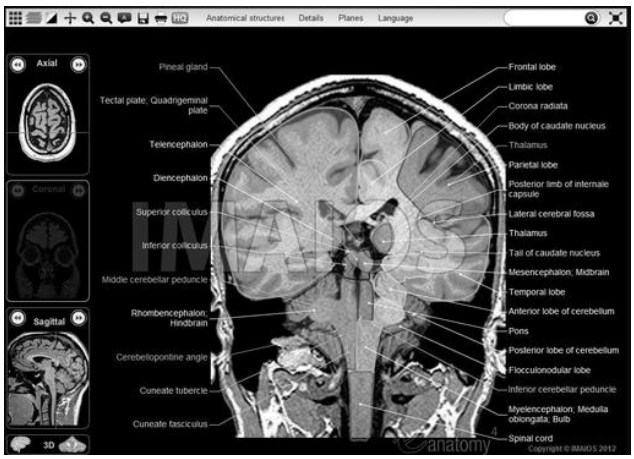

Fig 1. Brain Atlas of human anatomy with MRI

The low-grade tumors (II, according to the World Health Organization) are benign and portend a better prognosis for the patient than high grade [12]. Knowledge discovery in the database data (KDD) is Nerve tissue formation begins with the formation of the neural tube from a Neuro ectoderm induction process that occurs in the human between the third and fourth week of gestation [5]. Subsequently step leading to the formation of the hemispheres, a process that occurs between the fifth and tenth gestational week during which develops active neurogenesis from neural precursor cells occurs. Between the eighth and eighteenth week gestational active neuronal proliferation occurs, the precursor cells begin to differentiate to produce new cells and neuronal precursor cells that differentiate into neurons and glial cells such proper (astrocytes and oligodendrocytes)[6]. What determines this differentiation is still a mystery, although it is known that depends on specific neural factors in the region of the brain where it occurs and shall exercise the functions. Differentiated cells begin to migrate from the ventricular zone (central) to the more peripheral areas of the developing brain (neocortex). The radial migration of neurons to the glial cell periphery used as "guide" as these forms a true scaffold that facilitates the movement of neurons [7]. The objective of this work is classified, without professional intervention, the image in white matter (WM), gray matter (GM), cerebro-spinal fluid (CSF), blood vessels (BV), tumor and edema (Figure 1). The white matter is distributed within the cortex, while that on the outside thereof is located gray matter; cerebro-spinal fluid, by its part, flows into the cerebral ventricles, the subarachnoid space and the ependymal canal [13]. A parametric Fluid Vector Flow (FVF) active contour model is utilized for automatic segmentation of tumor in

brain MR images and the segmented tumor is visualized in three dimensions for depth analysis. Since a tumor doesn't exhibit any prior shape, delineating the tumor accurately is a difficult task. FVF is utilized for segmentation because it can deform in all directions for capturing the tumor. It also addresses the issues of limited capture range and the inability to extract complex contours with acute concavities.Segmentation aids in visualization of area of tumor[14].

Image clustering of various malignant brain tumor tissues of microscopic range in H&E Stain are analyzed through Euclidean distance metric and Fuzzy K-Means clustering and this method can be used for pattern recognition because it provides a good object separation. Developing such tools for characterizing and effectively classifying texture patterns in medical images would greatly assist in the interpretation of clinical images and in investigating the relationship between descriptors of texture and branching patterns and the associations between morphology and function or pathology[15].

Manual segmentation of brain tumors by medical practitioners is a time consuming task and has inability to assist in accurate diagnosis. Several automatic methods have been developed to overcome these issues. But Automatic MRI (Magnetic resonance Imaging) brain tumor segmentation is a complicated task due to the variance and intricacy of tumors to over by this problem we have developed a new method for automatic classification of brain tumor. In the proposed method the MRI Brain image classification of tumors is done based on Fluid vector flow and support vector machine classifier. In this method Fluid Vector Flow is utilized for segmentation of two dimensional brain tumor MR images to extract the tumor and that tumor can be projected into the three dimensional plane to analyze the depth of the tumor. Finally, Support vector machine classifier is utilized to perform two functions. The first is to differentiate between normal and abnormal. The second function is to classify the type of abnormality in benign or malignant tumor[16].

The Proposed system consists of multiple phases. First phase consists of Preprocessing and segmentation, the second phased consists of first order and second order GLCM (Gray level Co-occurrence Matrix) based features extraction from segmented brain MR images. Third phase classify brain images into tumor and non-tumors using Feed Forwarded Artificial neural network based classifier. After classification tumor region is extracted from those images which are classified as malignant using two stage segmentation process. Experiments have revealed that the technique was more robust to initialization, faster, and precise[17].

In this methodology, we have fostered a striking tumor revealing technique by maneuvering kernel

ascertained SVM . The propositioned outlook encompasses of preprocessing, segmentation, feature extraction and classification. In a preprocessing step, the noise is jettisoned and to instigate the image appropriate for the ensuing stages. In segmentation stage , the neoplasm regions are dissected over region growing method. In feature extraction, certain explicit feature will be extorted by manipulating texture as well from intensity. On the classification stage, the kernel based SVM is fabricated and smeared to training of support vector machine (SVM) to maneuver automatic detection of tumor in MRI images. For comparative exploration, our proposed approach is surpassed with existing research[18].

The proposed method consists of four stages namely Preprocessing, feature extraction, feature reduction and classification. In the first stage anisotropic filter is applied for noise reduction and to make the image suitable for extracting the features. In the second stage, Region growing base segmentation is used for partitioning the image into meaningful regions. In the third stage, combined edge and Texture based features are extracted using Histogram and Gray Level Co-occurrence Matrix (GLCM) from the segmented image. In the next stage PCA is used to reduce the dimensionality of the Feature space which results in a more efficient and accurate classification. Finally, in the classification stage, a supervised Radial Basics Function (RBF) classifier is used to classify the experimental images into normal and abnormal. The obtained experimental are evaluated using the metrics sensitivity, specificity and accuracy. For comparison, the performance of the proposed technique has significantly improved the tumor detection accuracy with other neural network based classifier SVM, FFNN and FSVM [19].

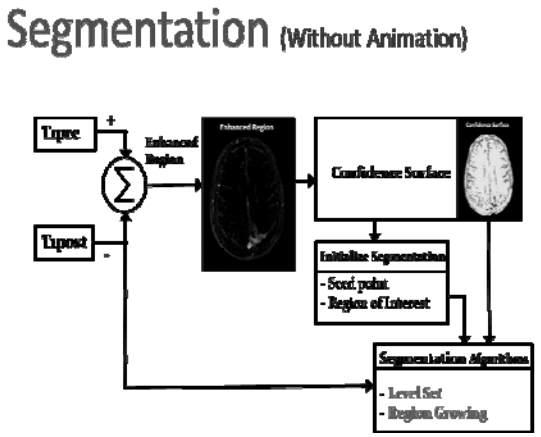

Fig 2. Brain Tumor Detection and Segmentation

The process of neuronal migration occurs between the second quarter and the twenty-fourth week of gestation. During neurogenesis and neuronal migration approximately 50% of the neurons undergo apoptosis, ie die in a programmed manner, probably because they do not follow the right course of migration and / or do not receive adequate stimuli. A certain proportion of neurons (20%) migrate horizontally once the radial migration, allowing the formation of lamination (segmentation) cortex. Neurons find their way, motivated by chemical stimuli (Neuro trophic factors), prolonging its structure at one of its ends, resulting in the so-called "cone" of axonal growth. Simultaneously to

form neuronal migration synaptogenesis occurs, although this is much more intense between the gestational week, but remains very active until the eighth or ninth month postnatal. Synaptogenesis continues even at puberty and begins to decrease markedly with the age of the individual.

2. Methodology

A scientific world for the sole reason that the fatty acid is highly concentrated in this tissue [11]. 60-65% of total brain lipids are polyunsaturated fatty acids and of the percentage more than 85% consists of DHA (35-40%) and arachidonic acid (C20: 4, AA) (40-50 %) [12]. The AA is another highly polyunsaturated fatty acid belonging to the omega-6 series and although its involvement in brain structure and function is no less important than that of DHA, its contribution by the diet (as such or through your precursor, linoleic acid) or during the gestational period (by the mother), is much higher and more consistent [13]. The AA is abundant in all tissues, whereas the DHA is primarily concentrated in nervous tissue (neurons and glia), visual (rods and cones of the retina) and reproductive (sperm flagellum and cells) [8]. For this reason research has focused mostly on the DHA, which is much less available from the diet and the lack of which seems to be crucial during the gestational period and lactation.

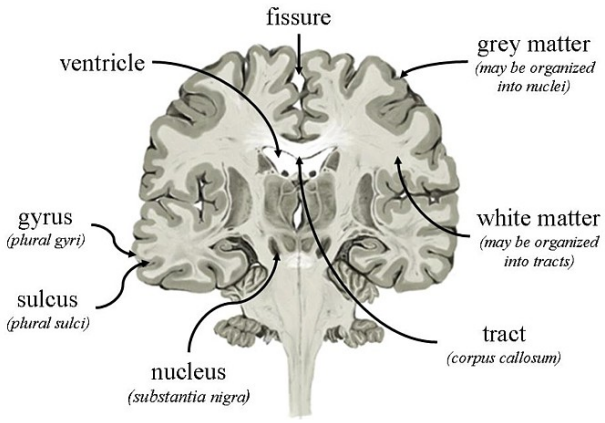

Fig 3. Organization of the Nervous System

Namely, the well-known approach of estimating the noise variance (for linear models) is by fitting the data using low bias (high-complexity) model (say high-order polynomial) and applying the following formula to estimate noise [3,4]

$$\hat{\sigma}^2 = \frac{n}{n-d} \cdot \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \quad (1)$$

Combining expressions, we obtain the following prescription for noise variance estimation via k-nearest neighbor's method:

$$\hat{\sigma}^2 = \frac{n}{n-d} \cdot \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \quad (2)$$

$$= \frac{n}{n - \frac{n}{k}} \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \quad (3)$$

$$= \frac{k}{k-1} \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \quad (4)$$

$$\hat{\sigma}^2 = 1.5 \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \quad (5)$$

A standard method to solve this problem is to apply the theory of Lagrange to convert it to a dual problem. The dual problem is the following:

$$\min_{\alpha}\Psi(\vec{\alpha}) = \min_{\alpha}\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} y_i y_j (\vec{x}_i \cdot \vec{x}_j)\alpha_i\alpha_j - \sum_{i=1}^{N}\alpha_i \quad (6)$$

we aim to build a linear predictive model of the type:

$$\hat{\vec{y}}_n = X_{nm}\vec{w}_m$$

Examples of Support Vector Machine algorithms include the perceptron-like support vector machines (SVMs), and Least-Squares Support Vector Machines (LS-SVM), also known as kernel ridge regression. A straightforward way to estimate the weights is outlined in Equation (2).

3. Results

The parameter estimation dynamics can be based on the value of maximum intensity voxel present at resonance. If a smaller value is chosen dynamically that appropriate intracranial region is divided into more a watershed. If the number of which is reduced is may join manually finish. Conversely, if previous morphological reconstruction operator watershed has been made with a number of dynamics too high, no brain tissue areas are added in the central basin, because the peak separation is exceeded in the reconstruction process. An example is shown segmentation intracranial using the proposed method. Parameter dynamics were used just 14% of dynamic range. We have selected several planes results in full 3D. At the resonance of Figure 3, over 98% of the voxels belonging to brain have been properly assigned (in comparison with manual segmentation performed by an expert)

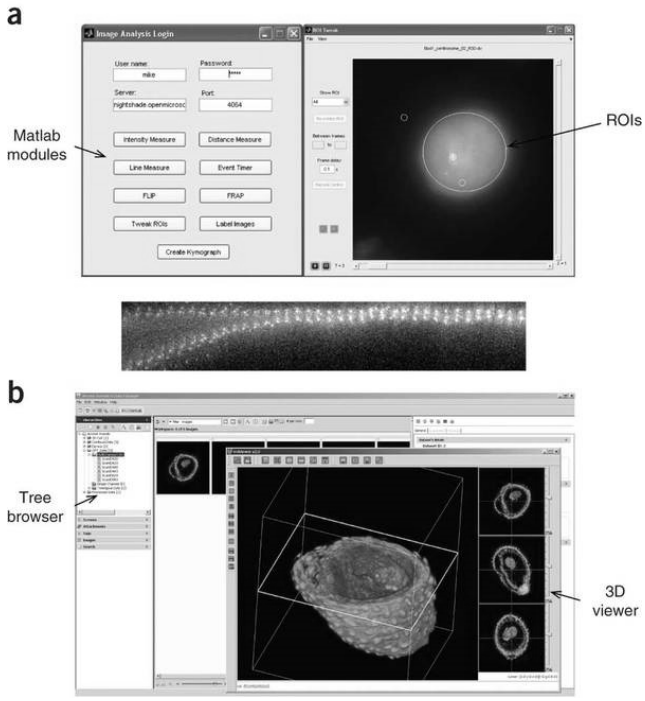

Fig 4. Data Management For Experimental Brain Tumor

A method based MRI segmentation is presented in this paper in a hybrid approach using volumes obtained by a method segmentation based on Growth Regions as input to an algorithm Parametric Deformable Models. The developed method was applied considering different sets of rules for multislice MRI with tumor and edema artificial obtained by simulation, which allows you to compare the results of the segmentation with reference volumes that the simulator provides. Preliminary tests show that the method allows to

obtain segmentations very good quality, useful for monitoring and control of cancer treatments.

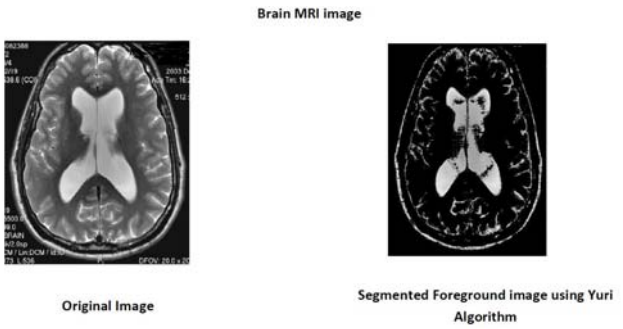

Fig 5. Interactive Segmentation using MATLAB

It includes the results obtained by applying the algorithm Deformable models on the three images of as described in the previous paragraph setup, and using as a model initial mesh of the extracted result of the algorithm for growth regions. The quality indicator used is then described in the beginning of this section. These values show that the application of the full scheme greatly improves the results obtained with the single application of the algorithm of region growing. The results of the segmentation performed on one of the images (red) in the axial, sagittal and coronal views. May observed how the red contour surrounds the region of interest, greatly approaching the tumor boundaries.

4. Discussion and Conclusion

In this paper a complete scheme for the segmentation of tumors in MRI based on combining algorithms are presented region growing with deformable models and information textures. Preliminary studies on the extraction of volumes using Region Growing suggest a better performance of the criterion based on intensities relative to indicators texture, while use of the algorithm improves the output push markedly. Volumetric projection is proposed to analyze the third dimension i.e. the volume or depth o f the tumor. This automatic method for brain tumor segmentation and three dimensional visualization will help physicians in accurate diagnosis[14].Broadly, two approaches act so efficiently in initializing the deformable model scheme extracting from the surface mesh that envelops the ROI. That area, near the edges of the object to segment, is deformed at each step of the algorithm to converge to the limits of the tumor. The results of the evaluation of the quality of the segmentations in synthetic images are highly satisfactory, reaching values near the best studied. The experiment results showed that the brain tumor invading cells has different shape orientation in this proposed scheme with K-Means clustering using MATLAB, the real time operation can be performed on the H&E Stain tumor tissue image and the future enhancements focus on the various types of anaplastic tumor tissue in MRI image are viewed through the Hologram projection of the tissue region in the nano scale ranges[15].

The method presents a robust approach, capable of adapting to complex anatomical structures and variations in shades of gray, which has also been

tested on other imaging modalities with satisfactory results. The accuracy level (94%) for kernel based SVM corroborated that the proposed algorithm graph is virtuous at perceiving the tumors in the brain MRI images[18].Furthermore, the results possible to observe how the combined region growing approach, deformable models greatly enhances the quality of the segmentations obtained with respect to isolated use of the method all getting soft dimensional meshes with a precision sub-voxel. The aim of thus mitigate the high consumption of computational resources and increase scalability, taking advantage of the scheme Operation is highly parallelizable.

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