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Brain Tumor Segmentation Techniques: A Review

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Abstract: Image segmentation is a process of partitioning an image into subparts or segments. It helps the users to extract the region of interest from the whole image. Segmentation of the brain image plays a crucial rule in the diagnosis of brain tumor. But the major problem is that MR images of a brain also contain noise, discontinuities and inhomogeneities. So it becomes hardwon to segment a brain image into tumor region and healthy tissues. We have presented the review on origin of MRI, normalization of MRI and various brain tumor segmentation techniques.

Keywords: Image Segmentation, MRI, Normalization, Segmentation Techniques

Introduction

The introduction of Fourier transform, magnetic field and unit of magnetic field, Tesla laid the bedrock for modern MRI. Earlier MRI was known to be the NMR (Nuclear Magnetic Resonance). Many scientists have made momentous supplement to put forward the NMR to its present state, MRI. Jean Baptiste Joseph Fourier (1768-1830) explored Fourier Transform. Without his Fourier Transform, it would not be breeze to create MRI. Richard Ernst first used his mathematical method in 1975 to analyze the magnetic resonance signal and restore the image.

Nikola Tesla (1856-1943) explored the rotating magnetic field and unit for strength of magnetic field, Tesla. In the field of NMR, Sir Joseph Larmor (1857-1942) coded an equation called Larmor. The equation states that the precision frequency of precession of the nuclear magnetic moment (ω) is directly proportional to the magnetic field strength product (B_0) and the gyromagnetic ratio (γ): $\omega = \gamma B_0$. This equation is used to determine the rate of absorption of energy by the nucleus. Gerlach and Stern explored the quantum description of the magnetic moment of silver atoms in a non-uniform magnetic field by using deflection of molecular beam.

Isidor Rabi (1898-1988) developed a device based on the origination of ordinary electromagnetic oscillations of the same frequency as that of the Larmor precession in a magnetic field of atomic systems. In 1942, the word "Nuclear Magnetic

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Resonance” was coined by CJ Gorter. Bloch and Purcell in 1946, detected that nuclei absorbed energy when they are placed in the magnetic field and re-emitted this energy when they are placed at their original state. Raymond Damadian measured T1 and T2 relaxation times of excised healthy and cancerous rat tissue and said that tumor tissue had longer period of relaxation than normal tissue. Abe and his colleagues applied and published their technique in 1974 for a patent on a targeted NMR. After two years, Damadian released the same technique after two years with some changes made to the earlier one, ‘field-focusing NMR’, which included an illustration of volume elements scanned through a mouse.

All the work done before was one dimensional and spatial knowledge was also missing. No one could yet determine the exact location within the sample of the origin of the NMR signal. In 1974, Paul C Lauterbur and Peter Mansfield using magnetic field gradients, described the spatial localization of NMR signals. This discovery laid the foundation for the imaging of magnetic resonance. Paul C Lauterbur gave the idea of using gradients of magnetic field in three spatial dimensions and used the back-projection approach of computer-assisted tomography (CAT) to create 2D NMR images. He published in Mrach 1973 in the journal Nature the first pictures of two 1 mm capillaries filled with water immersed in heavy water. Peter Mansfield and Grannell have published a one-dimensional MR interferogram at a resolution of more than1 mm in 1973.

Later in 1975, by using the Fourier transform of phase and frequency, Richard Ernst gave the idea to recreate 2D images. He also explained that, instead of Lauterbur’s back projection, one could use switched magnetic field gradients in the time domain. This method was described in 1975 as a practical method to quickly reconstruct an image from NMR signals.

The root of MRI was also contributed by Computed Tomography. Hounsfield invented CT based on X-ray in 1973. And spatial localization of NMR signals was introduced by Lauterbur and Mansfield in the same year to generate two-dimensional images. In 1975, a line scan method was invented by Peter Mansfield and Andrew Maudsley. Later in 1977, the line scan technique led to the first image of in vivo human anatomy, a cross section through a finger. Hinshaw, Bottomley, and Holland created an image of wrist. Damadian and his colleagues created a cross section of a human chest. In 1978, Hugh Clow and Ian R. Young generated the first transverse NMR image through a human head. Two years later, William Moore and colleagues presented the first circlet and acuminated images through a human head. In 1980,

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Edelstein and his colleagues demonstrated imaging of the body using Ernst's technique. It took five minutes to acquire an image using this technique. In 1986, new advancements were made that reduce the time of five minutes to five seconds without distorting the quality of an image. In 1987, Real Time MR imaging of the heart is developed.

Later in 1991, Filler and his colleagues developed a technique that was based on the imaging of axonal transport of super magnetic metal oxide particles. This later contributed to the concept of imaging of neural tracts. In 1993, the concept of brain MRI came into practice. Before 1990's, MRI was only used in the research centers and large hospitals. But in 1990's, this practice was changed. MRI was also begun to be adopted by small remote hospitals and imaging centers for neuroimaging and musculoskeletal imaging. During 2000's, advancements are made into the Cardiac MRI, Body MRI, Fetal Imaging and Functional MR Imaging. Research centers also make significant pace in the imaging on high field scanners [1,2].

Normalizing the MRI

Image normalization is a process of creating a normal image, normal in context of various attributes such as intensity of pixel values, noise, illumination and occlusion. Image normalization refers to the act of eliminating the irrelevant variations from an image. These variations occur while capturing an image due to various internal and external factors. Image normalization can be used as a preprocessing stage to help computers and humans for object perception. The major goal of image normalization is to obtain a standard image that is free from the entire bygone of the environment in which it was captured. For example, there will be specific range of the pixels, there will be no sign of noise, and there will be no illumination and so on. So there are several reasons that support the concept of image normalization. These are:

1. To remove the irrelevant variations from an image caused by the environment in which it was captured.
2. To be used as preprocessing stage.
3. To provide the facility for human object perception.

There are number of existing image normalization algorithms that are used for reduction of noise, illumination and occlusion from the input image to make it a standard image for various processing purposes. The previously used image normalization algorithms used the concept of Eigen Values. But this method does not perform well in the cases where the variance of noise is larger than the variance of significant components because in this case

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these components will be removed from an image alone with the noise resulting in distorted image.

New method for image normalization is developed to cope up with all the drawbacks by the use of existing algorithms. This method is known as the Normalization by Mutual Information. The mutual information is described using the PCA by calculating the principal components of an image. The existing methods use the concept of Eigen values that closely refers to the variance such as noise, illumination and occlusion instead of the relevance and irrelevance in an image. But the method uses the mutual information that is more suitable to identify the relevant and irrelevant components from an image. The image normalization by mutual information provides pleasing normalizing results and is also successful to reach at the heights of accuracy in identifying the variances. It also handles various types of variance in a unified framework [3].

Complex multimodality, cross-sectional and longitudinal imaging is very popular nowadays in medical and clinical studies. These images are used for investigating disabling and fatal diseases. These studies produce terabytes of complex data, costs millions of dollars and requires years to process. These studies use multi sequence Magnetic Resonance Imaging. Computed Tomography and other imaging techniques are measured in the absolute units that are more suitable for carrying studies. But on the other hand, Magnetic Resonance Imaging is measured in arbitrary units that do not serve the purpose of carrying study easily within a single subject nor across different subjects.

Previously there were no specific standards and principles for the image normalization. But later on 7 principles of normalization are developed. These are known to be the Statistical principles of Image Normalization (SPIN). According to these principles, the normalized images produced are in such a way as given in Table 1.

Sr. No.	**Principle**
1	Irrespective of the location of units in the same tissue, they have a common interpretation.
2	They are replaceable.
3	Safeguard the rank of intensities.
4	They are less sensitive to noise and other variations.
5	Biological abnormality and population heterogeneity do not affect the normalized units.
6	During pathology and other phenomenon, there is no loss of information.
7	Same tissues have similar distributions within and across patients.

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Another approach for the normalization process was proposed by Nyul and Udupa in 1999, which is based on matching of histograms. This approach consists of two stages as shown in Figure 1.

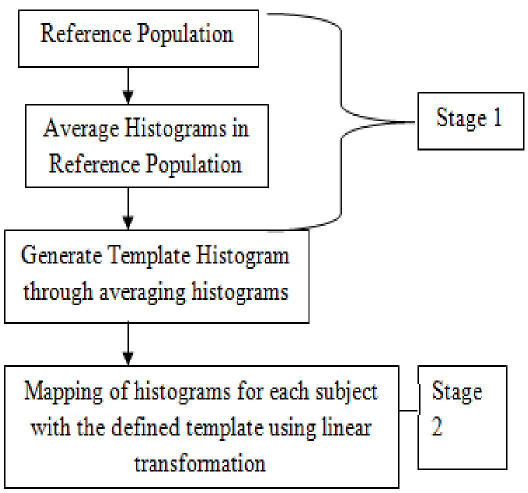

Fig. 1 Histogram Matching

The method of histogram matching is computationally fast and has violated some of the principles of image normalization (SPIN) such as the distribution of type of tissue within and across patient, technical artifacts do not exist and pathology of brains in not abnormal. So all this makes histogram matching technique inappropriate for studying any image form multiple objects.

For quantitative analysis of MRI, normalization of intensity is considered the most important. There are currently no automatic methods for the normalization of brain MRI statistical intensity that satisfy the SPIN. The method of the Hybrid White Stripe is similar to the standardization specific to the modality. This approach works best in the sense of not breaching the ideals of normalization. It also improves comparability across multiple studies, topics and procedures for specific imaging.

There are various MRI intensity normalization methods. Some of them are:

1. Contrast Stretch Normalization (CSN)
2. Intensity Scaling (IS)
3. Histogram Stretching (HS)
4. Histogram Normalization (HN)
5. Gaussian Kernel Normalization (GKN)
6. Histogram Equalization (HE)

Disease characterization and quantification using MRI is based on texture analysis. Texture analysis quantify macroscopic lesion and characterize macroscopic changes that are not provided by the conventional methods. It also provides information to such a great extent that is not easily visible to the human eye. The problem with texture features is that they are very sensitive to the environment in which image is captured such as MR scanners, MR protocols and MR adjustments. This creates intensity changes in an image that may affect the image analysis. So here the need arises for correction of intensity changes.

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The solution to the above problem has been proposed. For direct quantitative evaluation of serial MRI scans, Meier et al. proposed an Intra-scan normalization and Inter-scan normalization method. The contrast stretch normalization method was proposed based on minimum and maximum gray values in an image. For brain MRI, a normalization method was proposed which used histogram even-order derivative analysis. Another one called the histogram matching method was also proposed; used to correct the variations produced by the sensitivity of scanner. The histogram normalization method (HN) performs well while performing quantitative texture analysis of the brain MRI [4].

Segmentation of MRI

[Sai Prasad Raya, 1990] proposed a rule-based low-level segmentation system that identify the space occupied by different structures of the brain via Magnetic Resonance Images (MRI). Different low level features that are derived from the input images are used for handling different aspects of segmentation process. Simple rules for coding different segmentation heuristics are also presented [5].

[Arvid Lundervold, 1995] proposed a method to segment the multispectral MRI into brain parenchyma and CSF. The proposed method performs very well when the structures to be segmented are connected and form closed contour boundaries [6].

[Rachid Sammouda, et al., 1996] proposed a method to improve the segmentation process of MRI of the human brain using unsupervised Hopfield Neural Network(HNN). The results obtained by the proposed method are compared with the results obtained from previous work using HNN, the Boltzmann Machine, and the conventional ISODATA Clustering technique that shows an advantage that the proposed system is better than the previous ones [7].

[Javad Alirezaie, et al., 1998] proposed an unsupervised clustering technique for multispectral segmentation of MRI of the human brain. It utilizes the Self-Organizing Feature Map (SOFM) artificial neural network (ANN) for feature mapping. The c-means algorithm is applied to compare the results with other conventional approaches [8].

[M. Stella Atkins, et al., 1998] proposed a fully automatic method for segmentation of brain from the head MRI acquired from several different MRI scanners, using different resolution images and different echo sequences, which performs better in the presence of radio frequencies inhomogeneities and partial volume effects. The proposed method uses an integrated approach which employs image processing techniques based on anisotropic filters and

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"snakes" contouring techniques, and a priori knowledge [9].

[Georges B. Aboutanos, et al., 1999] proposed an automatic method for segmentation of the brain in MRI. The initial model is first created and then this initial model is deformed to fit the exact contours of the brain in the images. A new method to create the initial model is compared with the traditional methods of creating initial model using brain atlases. The proposed method provides better results when compared with the contours drawn manually [10].

[Nicolaos B. Karayiannis, et al., 1999] proposed a technique for segmenting brain in MRI. The method is based on fuzzy algorithms. These algorithms perform vector quantization through an unsupervised learning algorithm by updating all prototypes of a competitive network. Various algorithms for learning vector quantization (LVQ) are evaluated on the basis of their ability to identify different tissues and to discriminate between normal tissues and abnormalities [11].

[Laszlo G. Nyul, et al., 2000] proposed a method that overcomes the drawbacks of taking MR image of a same person on the same scanner at different times that may be different due to various scanner dependent variations. The proposed method is a two-step method in which the MR images independent of the patient and scanner can be transformed in such a way that the images have similar tissue meaning. The new variants work in the same manner as the original methods [12].

[Dinggang Shen, et al., 2001] presented an adaptive focus statistical shape model (SSM) for automatic segmentation of brain from MR images and to obtain the point correspondences in a hierarchical scheme. The proposed deformable model (DM) is very adaptive because firstly it focuses on region of interest and then it switches the focus to other structures that are closer to the respective targets [13].

[Vincent Barra, et al., 2001] suggested an IFT (information fusion technique) system for automated segmentation of internal cerebral structures. The information is provided by photos as well as expert knowledge and is handled using a fuzzy logic-based fusion scheme. The approach is universal and applies to any structure that can be described through expertise and morphological images [14].

[Alain Pitiot, et al., 2002] proposed a fully automatic hybrid method for segmentation of brain MR images combining a general elastic template matching (TM) approach and an evolutionary heuristic. The TM scheme is capable of exploiting each attraction basin the heuristic finds and the evolutionary heuristic is capable of exploring the solution space. The hybrid

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nature of the approach makes it easy to integrate a Statistical Shape Model [15].

[J. L. Marroquin, et al., 2002] presented a Bayesian method that is fully automatic segmentation method for brain MR images. The proposed method has very salient features. The separate Bayesian parametric smooth models (BPSM) are used for the intensity of each class. The brain atlas is used with a robust registration procedure to find a non-rigid transformation. The novel algorithm is presented that provides a fast and accurate way to find the optimal segmentations [16].

[Alan Wee-Chung Liew, et al., 2003] proposed an adaptive spatial fuzzy c-means clustering algorithm for MR images that may be corrupted by the noise and intensity nonuniformity artifact. The proposed algorithm uses a novel dissimilarity index that considers the local influence of neighboring pixels in an adaptive manner [17].

[Jovan G. Brankov, et al., 2003] proposed a method for segmentation of image sequences by clustering the pixels according to their temporal behavior based on a similarity metric. The advantage of the similarity metric is that it depends on the shape of the time signal rather than its amplitude. The method is useful for automated kinetic-parameter estimation [18].

[Meritxell Bach Cuadra, et al., 2004] proposed a method for brain Atlas deformation in the presence of large space-occupying tumors, based on a priori model (PM) of lesion growth. The proposed method is compared with the other existing methods and shows that the limitations of the existing methods have been overcome by the proposed one [19].

[Ladan Amini, et al., 2004] proposed an automated method to segment the thalamus from brain MR images based on Fuzzy clustering and discrete dynamic contours model (DDCM). The methods are developed for generating the initial contour automatically. The method also solves the problem of discontinuities edges by finding the gray matter edge map [20].

[Shan Shen, et al., 2005] proposed a segmentation method based on an extension of the traditional Fuzzy C-means (FCM) clustering algorithm using Neighborhood Attraction with Neural Network optimization. To demonstrate the superiority of the proposed method, the simulated and real brain MR images with different noise levels are segmented using the proposed method and compared to other FCM-based methods [21].

[Yongxin Zhou, et al., 2007] proposed an automatic brain segmentation method by combining atlas registration (AR), fuzzy connectedness (FC) segmentation, and

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parametric bias field correction (PABIC). The method is proposed to avoid expert human intervention (AHI). The proposed method is validated by applying the process on both simulated and real MRI images [22].

[Jason J. Corso, et al., 2008] proposed an integrated Bayesian Approach (BA) for automatic segmentation of heterogeneous image data. The proposed method bridges gap between bottom-up affinity-based segmentation methods and top-down generative model based methods. The Segmentation by Weighted Aggregation algorithm (SWA) is extended to integrate model based terms into the affinities during the coarsening [23].

[Albert Huang, et al., 2009] proposed a geometric-statistical deformable model for automatic segmentation of brain MRI data of single as well as multiple magnetic resonance sequences. The edge-based geodesic active contour (EGAC) is used for the segmentation purpose by integrating image edge geometry and voxel statistical homogeneity into a hybrid geometric-statistical feature. The geometric-statistical feature acts as a stabilizing regularizing function [24].

[Jao Wang, et al., 2009] proposed a segmentation method known as Fluid Vector Flow active contour model (FVF_{AC}). The method is proposed to overcome the issues of limited capture range and the inability to extract complex contours with acute concavities. The quantitative analysis shows that fluid vector flow has the largest mean (0.61) and median (0.60) with smallest standard deviation (0.05). The algorithm is used to compute FVF and active contour evolution [25].

[Atiq Islam, et al., 2013] proposed a method for detection and segmentation of brain tumors. The brain tumor texture is formulated using a multiresolution model known as multifractional Brownian motion. The novel patient independent tumor segmentation scheme is also proposed by extending the well known AdaBoost algorithm [26].

[Jinyoung Kim, et al., 2014] proposed a method for semiautomatic segmentation of brain subcortical structures such as the basal ganglia and thalamus from high-field MRI. The method combines optimally selected two modalities from susceptibility-weighted, T2-weighted and diffusion-MRI. It also introduces a tailored new edge indicator function [27].

[Antonios Makropoulos, et al., 2014] proposed an accurate intensity-based segmentation method for the developing neonatal brain by introducing a structural hierarchy and anatomical constraints. It also incorporates bias field correction, spatial regularization, and partial volume correction similar to existing methods [28].

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[Ayse Demirhan, et al., 2015] proposed a tissue segmentation method that segments brain MR images into tumor, edema, white matter, gray matter and cerebrospinal fluid. The skull striping algorithm is also developed that is applied to MR image before the segmentation process. The segmentation is performed using Self-Organizing Map (SOM) that is trained with Unsupervised Learning Algorithm and fine tuned with Learning Vector Quantization [29].

[Sergio Pereira, et al., 2016] proposed a segmentation method based on Convolutional Neural Network using very small kernels of size 3*3. Intensity Normalization has been used as a preprocessing step and this provides very effective results for segmentation of tumor in MRI. The proposed method has been tested using various ways such as Brain Tumor Segmentation Challenge 2013 database, online evaluation platform and also using on-site BRATS 2015 challenge [30].

[Chao Ma, et al., 2018] proposed an automated method based on random forests and active contour model for segmentation of gliomas from multimodal volumetric MRI. Modality specific random forests are used to identify local and contextual information from multimodal MRI. Then finally the inferred structures are refined using active contour model. There are some of the disadvantages of the proposed technique also such as it requires a lot of training data and aggregation of imaging modalities needs to be improved [31].

Conclusion

This paper has conferred a far-reaching review of various noise removal and brain tumor segmentation techniques for MRI. The brain tumor segmentation is performed to precisely expose the tumor region so that legitimate medication is provided to the patients by physicians. The present state-of-the-art methods provide accuracy, robustness, and validation. But these are not up-to desired level. The computation time is in minutes that are also not acceptable in some critical cases. The future work will focus on improving these parameters to get desired results.

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