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A Comparative Study of Segmentation Techniques for Brain Magnetic Resonance Images

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Abstract

Segmentation is a core process for automatic detection and identification of brain tumors as it plays a vital role in extracting the information of the image as measuring and visualizing the brain's anatomical structures and analyzing the brain changes. From this point the need for accurate and automatic segmentation techniques has risen as manual segmentation is not a realistic solution and yet time consuming. This paper examines the various automated segmentation techniques used by researchers on brain magnetic resonance images (MRI), giving the most important features for the most common techniques used in the area of brain tumors. Moreover, a comparative study to address the differences, limitations, advantages and challenges of each technique mentioned when being used on brain MRI to find out their efficiency in this area and to put guidelines that should be considered when using these techniques.

Keywords: Brain Tumors, Magnetic Resonance Images, Machine learning, Segmentation.

Introduction

In the last decades, medical imaging was used for basic visualization and anatomical structures' inspection to become the most important tool not only for diagnosing, treatment planning but also for follow up evaluations of the tumor's development like brain tumors which are the leading cause of cancer death in young people with more than 120 different types of brain tumors [1, 2, 3].

Magnetic resonance imaging (MRI) is the most effective and common imaging tool for brain tumors. MRI is an advanced technique which can detect the abnormal changes in different parts of the brain even in early stages since it provides a good contrast and comprehensive insight with detailed information about what happens in the brain including the common brain structures e.g. white matter (WM), grey matter (GM), and cerebrospinal fluid (CSF), and lesion regions located in single common structures or overlapped areas of them. Thus, it's the method of choice over other imaging techniques eg. Computerized Tomography (CT) for diagnosing and evaluating brain tumors [3, 4, 5, 6, 7].

However, it is not feasible to directly diagnose using the original MRI images due to the complexity of brain MRI images due to the high variability in shape, structure and location of tumor tissue, also the anatomical variability between subjects. In addition, in some cases the variations in the contrast of the same tissue due to noise, shading effects caused by magnetic field variations result in intensity overlapping regions. [7]. Therefore, Segmentation can provide a way to a precise detection and identification of many brain tumors such as glioma, sarcoma or Alzheimer's disease (AD) through accurate segmentation of the brain images into WM, GM and CSF that become the basis of the analysis and diagnosis process.

In fact, brain tumor segmentation is one of many clinical applications that are quite complicated and challenging as it separates the different tumor tissues from normal brain tissues in spite that the images could be corrupted by noise or other MRI challenges which result in time consumption and subjected to errors difficult to characterize if to be performed manually by medical experts. Moreover, automating this process is challenging due to the large volume of data involved, similarity between tumor and normal tissue in many cases and the tumor mass effect may change the arrangement of the surrounding normal tissues [8, 9, 10].

In this paper we examine various automated segmentation techniques used by researchers on brain MRI, giving detailed description for the most important features of the most common techniques used in the area of brain tumors during the last 5 years and discuss the differences, limitations and advantages of each technique mentioned and the purpose it has been used for, to put guidelines that should be considered when using these techniques.

The paper is organized as follows: the brief introduction to the brain MRI segmentation, the section MRI segmentation methods is a selection of segmentation algorithms and their classification and most important features, the section a comparative study between the segmentation techniques is a comparison between a selected segmentation methods that have been recently used in brain MRI segmentation during the last 5 years which is the main contribution of this paper and then the section conclusion.

MRI Segmentation Methods

The importance of an effective segmentation technique is to accurately recognize and group the different anatomical tissues, structures and fluids where the unrecognized tissues or fluids to be suspected as a brain tumor [10, 11]. The segmentation process can be carried out in two ways: manually and automatically where in the first way the process is performed manually by medical experts. However, the second way is more time saving and to achieve an accurate results many techniques have been developed [11, 12].

The difficulties and the complexity of brain MRI images required the development of automatic segmentation techniques to improve the accuracy of diagnosing and treatment and to precisely identify the tumor tissues for surgical planning. Thus, automatic brain tumor segmentation become an interesting research field in Machine Learning and various techniques were developed to find the regions directly and segment brain tumors automatically from MR images with different degrees of accuracy and complexity during the last few years which can be classified, with application to brain MRI, into the three groups [12]: (i)supervised learning methods, (ii)semi-supervised learning and (iii)unsupervised learning techniques based on the utilization of labels of training samples.

Supervised learning techniques use of training data that have been manually labeled to be used in the learning process and the number of the classes are previously known. However, unsupervised techniques specify the number of classes automatically by clustering algorithms that may be based on the similarity of pixels or other image-based features. Supervised classification involves both a training phase that uses labeled data to learn a model that maps from features to labels, and a testing phase that is used to assign labels to unlabeled data based on the measured features. In supervised segmentation the choice of accurate training data is crucial because different training sets can lead to great disparities in training time, as well as potential differences in segmentation results [10]. We briefly mentioned some of the machine learning-based segmentation techniques in Figure 1 and their important features in Table 1.

Figure 1. *Machine Learning-based Segmentation Techniques*

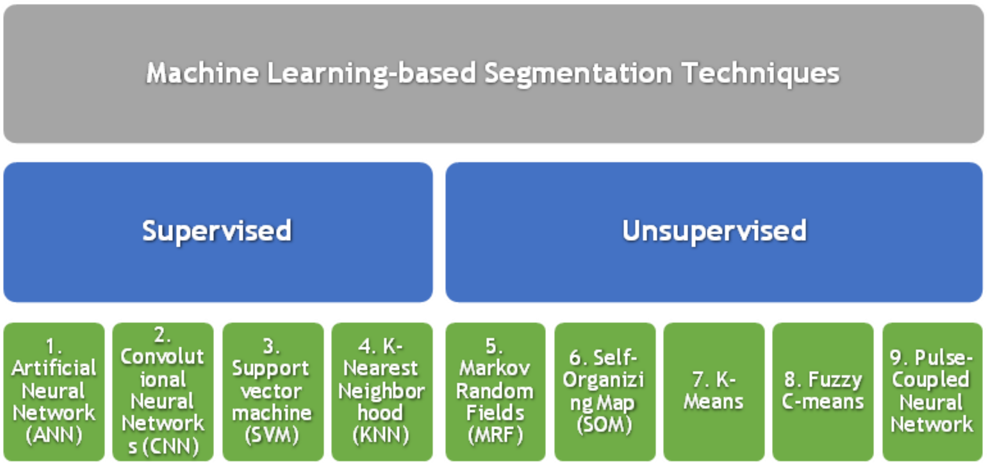

Table 1. *Segmentation Techniques Important Features*

Segmentation Technique	**Important Features**
Marcov Random Field (MRF)	It provides a way to integrate spatial information into the clustering or classification process. In the particular case of brain tumor segmentation, if a region is strongly labeled as brain tumor or non-brain tumor, MRF will determine if the neighbor of the labeled region is the same [17].
Self-Organized Map (SOM)	Its' important feature is topology preservation where data in the input space is mapped onto a neighboring location in the output space. It gives high performance in identification of Alzheimer's, brain tumors, dementia and schizophrenia [13].
Support Vector Machine (SVM)	This method had the ability of learning the nonlinear distribution of the image data without prior knowledge [17].
Convolutional Neural Networks (CNN)	It has overcome image segmentation challenges by automatically learning a hierarchy of increasingly complex features directly from the data. That type of learning called Deep Learning [8].
Fuzzy C-Means (FCM)	It gives the best result for overlapped data set and assigns the membership of data points to more than one cluster center [15]. Using this technique, it is possible to generate segmentation images that display clinically important neuroanatomic and neuropathologic tissue contrast information from raw MR image data [17].
K-means	The simplest unsupervised algorithm assigns the membership of data points to one cluster center. All it needs is an initial certain number of clusters to classify and assign a given set of data to the clusters [15].
K-Nearest Neighbour (k-NN)	It is the simplest technique that provides good classification accuracy. It depends on calculating the distance between the query instance and the training samples and the instance to be assigned to the nearest class. The k-NN has higher accuracy and stability for MRI data than other common statistical classifiers, but requires manual selection for large training data and has a slow running time [15].

Artificial Neural Network (ANN)	Neural network based segmentation has High parallel ability and fast computing, the segmentation results can be improved when the data deviates from the normal situation [15]. However prior knowledge is required and sometimes it takes a lot of time and large data to train the network that's not available in all cases [10].

A Comparative Study between the Segmentation Techniques

Table 2 shows a comparison between 12 of the most common used segmentation techniques that were published during the last 5 years. Some of these techniques used hybrid techniques and others are the modified version of its basic.

From the table we can recognize that the recent techniques are hybrid techniques of segmentation and classification in addition to preprocessing techniques to reach better performance in identifying the tumor regions and overcome the brain MRI issues like noise or intensity overlapping.

In fact, one of the limitations of the unsupervised techniques that it often needs the number of regions to be pre-specified, tumors can be divided into multiple regions as tumors may not have clearly defined intensity or textural boundaries, thus to overcome these problems segmentation is preceded by a preprocessing phase where the image noise is removed and the image background is homogenized to overcome the intensity overlapping or other problems that make the segmentation process difficult or incorrect, also at this stage the removal of undesired structures (i.e., skull and scalp) can be done.

After the preprocessing phase comes the segmentation and we can notice from the table that Self-Organizing Maps (SOM) and its modified versions are the techniques of choice to be used as a segmentation and clustering techniques accompanied by other techniques to form a hybrid method having the advantage that SOM doesn't require prior knowledge to be learned from the distribution of the training sample in which can overcome the limitation of variability of tumors shapes, locations and size along with the variability between the subjects.

Table 2. *Segmentation Techniques for Medical Images*

Author	Segmentation Technique	Purpose	Additional Features	Identify Tumor type
Selvy et al. (2011) [23]	K-Means clustering technique	Brain MRI segmentation for different regions and segment the tumor after clustering selection and region eliminating	Apply pseudo color transition then perform k-means clustering	Segment the tumor area but undefined the tumor type
Selvy et al. (2011) [23]	Self-Organized Map (SOM)	Brain tumor segmentation in MRI after cluster selection and histogram clustering	Apply pseudo color transition then perform SOM clustering	Segment the tumor area but undefined the tumor type
Ortiz et al. (2012) [11]	Volume image histogram + SOM (HFS-SOM)	Segment and cluster the different brain structures and tissues in brain MRI	A preprocessing is performed for better results, Used the k-means to cluster the SOMs	Segmented the image only into WM, GM and CSF
Ortiz et al. (2012) [11]	SOM + Entropy-gradient method (EGS-SOM)	Segment the different brain structures and tissues in brain MRI	A feature extraction process was performed to find the most discriminant features then the hybrid technique been used	Segmented the image only into WM, GM and CSF
Ortiz et al. (2013) [14]	SOM-FCM Based	segmentation of different brain tissues brain MRI: white matter(WM), grey matter(GM) and cerebrospinal fluid(CSF)	A feature extraction with 3D statistical descriptors is performed then apply the SOM for segmentation	Segmented the image only into WM, GM and CSF
Goncalves et al. (2014) [22]	Discriminative Clustering using labels obtained from Consistent SOM	segmentation of different brain tissues brain MRI: white matter(WM), grey matter(GM) and cerebrospinal fluid(CSF) as well as brain lesions	A preprocessing is required in advance	Segment multiple sclerosis (MS) from the image

Author	**Segmentation Technique**	**Purpose**	**Additional Features**	**Identify Tumor type**
Mohsen et al. (2014) [16]	Feedback Pulse-coupled neural network (FPCNN)	Segmentation of tumor in brain MRI	Use the feedback feature where the input experience feedback shunting that is not uniform for the entire input	Differentiate between normal and abnormal images
Kong et al. (2015) [18]	Information Theoretic Discriminative Segmentation (ITDS)	Segmentation of different brain tissues brain MRI: white matter (WM), grey matter(GM) and cerebrospinal fluid(CSF)	Feature extraction was performed first using simple linear iterative clustering (SLIC)	Segmented the image only into WM, GM and CSF
Payan et al. (2015) [19]	Convolutional Neural Networks (CNN)	Segment the tumors and classify the images	Sparse Auto-encoder NN for feature extraction was performed first	Alzheimer's disease
Pereira et al. (2016) [8]	Convolutional Neural Networks (CNN)	Segment and cluster the image to identify the tumors	A preprocessing using bias field correction, intensity normalization was performed first and post-processing removing clusters in the segmentation smaller than a predefined threshold	Low Grade Gliomas (LGG) and High Grade Gliomas (HGG)
Nichat et al. (2016) [20]	Modified Fuzzy C-Means (FCM)	Segment the image to find out the suspicious region from brain MRI image	A preprocessing was performed first and based on the segmented area feature extraction using Gray Level Co-occurrence Matrix (GLCM) and classification using SVM was performed	Differentiate between normal and abnormal images
Si et al. (2016) [21]	Multi-Layer Perceptron Neural Network	segment the test MR images into lesion and healthy tissues in brain	Segmentation is based on four statistical features extracted from the MR images (Mean, Standard Deviation, Skewness, Kurtosis)	Differentiate between normal and abnormal images

Some learning techniques like the Support vector machine (SVM) are learning the distributions directly from the data and it is not required that the distribution follow a specific statistical model but with embedding some prior probabilistic prediction to achieve smoother segmentations and avoid some voxels misclassification [8].

Other methods like Convolutional Neural Networks (CNN) have overcome image segmentation challenges by automatically learning a hierarchy of increasingly complex features directly from the data. That type of learning is called Deep Learning.

However, from our observations we have found that the same segmentation technique cannot be fitted to automatically segment different types of tumors at the same time. In some cases, more than one phase of preprocessing is needed (eg. Feature extraction, feature reduction,…etc) so that the technique can accurately identify the tumor type such as in [8] where CNN was used to identify Low Grade Gliomas (LGG) and High Grade Gliomas (HGG), but it was required to go deeper in the preprocessing phase to identify HGG, while going deeper with LGG resulted in over fitting.

All these techniques were aimed to find the regions automatically with achieving better performance when it comes to brain MRI issues like uncertainties, variations in the contrast of the same tissue due to noise, shading effects caused by magnetic field variations or intensity overlapping regions with all its different models and hybrid methods. However, not all techniques are used only for segmentation purposes but also for clustering and classification as segmentation and classification are interlinked processes.

Conclusions

MRI is an important non-invasive imaging technique that provides excellent spatial resolution and very detailed high contrast diagnostic images of the brain and it’s been used for last decades to detect abnormal changes in different parts of the brain in early stages. But MRI has some challenges due to noise, image artifacts because of image acquisition techniques or overlapping intensity distributions of different tissue classes in MRIs that may result in voxel misclassification. To resolve such ambiguities, a preprocessing can be used for better and more accurate results of segmentation which is inter-related with the classification process to identify the tumor regions and different brain structures and tissues.

Accurate automatic segmentation is the field of interest and machine learning based segmentation techniques would be the best techniques in this area and a lot of techniques are used and modified to achieve a better performance and they have been classified to supervised and unsupervised techniques. However, sufficient data, for training for that reason the unsupervised techniques superior the supervised ones, is not always available.

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