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Brain MR Image Segmentation Methods and Applications

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MR imaging is a powerful tool for representing the soft tissue, organs and also three-dimensional visualization inside of the human body. This tool has different advantages including imaging in different directions and also it is relatively safe as compared to the other imaging modalities such as Computer Tomography (CT) and X-ray. MRI is used to capture images in different modalities such as T1-weighted, T2-weighted, and Proton Density (PD)-weighted. This capability help to better diagnose the different diseases such as cancers and Multiple Sclerosis (MS) [1]. MR has the capability to provide the functional activity of the brain too [2] and many tools have been proposed for the analysis of the fMRI data [3,4].

Brain tissue classification or segmentation is used for detection and diagnosis of normal and pathological tissues such as MS tissue abnormalities and tumors. These abnormalities could be identified by tracking of changes in volume, shape and regional distribution of brain tissue during follow-up of patients. Also, some of the neurological and psychiatric disorders such as Alzheimer's [5], Parkinson's and Huntington's disease, depression, autism, can be diagnosed with detection of changes in the morphology of subcortical nuclei and the cerebellum [6,7].

Furthermore, brain image segmentation plays an important role in clinical diagnostic tools and treatment procedures such as diagnosis and follow-up and also 3D brain visualization for measuring the volume of different tissues in brain such as Gray and White Matter, Thalamus, Amygdala, Hippocampus etc. [8]. However, some authors try to change the problem to a three type tissue classification and they assume multiple gray matter structures as one class. Hence, they label brain volumes into a three main classes like WM, GM, Cerebrospinal fluid (CSF) [9,10]. Internet Brain Segmentation Repository (IBSR) provided by the Center for Morphometric Analysis (CMA) at Massachusetts General Hospital and also, BrainWeb, which has been collected at McConnell Brain Imaging Centre of the Montreal Neurological Institute, McGill University are two well-known dataset for this area of research.

Brain images basically contain a lot of artifacts including Partial Volume Effect (PVE), Intensity Non Uniformity (INU) and some noises and deviations. PVE is happen when multiple tissues are placed into a voxel and a mixing value is laid into each voxel, thus a wrong value is assigned to each pixel. INU happens because of Radio Frequency (RF) coil and some hardware limitation. Hence, an accurate segmentation of brain images is a very difficult task. On the other hand, in most cases an accurate and precise segmentation is crucial for a correct diagnosis by clinical tools. Moreover, manual segmentation of brain MRI images is a time-consuming and labor-intensive procedure; therefore, automatic image segmentation is widely used for this purpose [1,11-13].

We present a compact review of the different methods, which are proposed in recent years for MRI brain segmentation. We try to divide these methods into two main important categories such as supervised (and semi-supervised) and unsupervised methods.

Unsupervised Methods

These methods do not use the prior class labels for segmentation process. Two main categories in this category are the Finite Mixture Model (FMM) [8,14,15] and Fuzzy C-means (FCM) based methods [16,17]. Although, other unsupervised methods like some Neural Network methods such as Self-organizing maps (SOM) [18,19] and Adaptive Resonance Theory (ART) [20] and morphological methods including watershed algorithm have been used for segmentation of brain tissues. Actually, clustering methods are common methods for MRI image segmentation, but these methods just consider the intensity level in the segmentation process; therefore, combination of these methods with other methods like Markov Random Field (MRF) [21-24] and Level Sets (LS) approaches [11,25] is used for incorporating of contextual, textural, spatial, and spectral information.

FMM methods like Gaussian Mixture Model present a proper distribution for different tissues in the brain [9,26-28]. In these methods each tissue is approximated by a distribution, then, the segmentation problem turn into the estimating of the parameters of these distributions. Expectation Maximization (EM) is a common method to estimate these parameters. Combination of EM algorithm with a variant of MRF algorithm also has attracted much attention for MRI brain image segmentation [10,29].

FCM algorithm is another important clustering algorithm, which was proposed in [30]. This method assigns a degree of the membership of belonging each pixel to each cluster; therefore, FCM algorithm has a good robustness against PVE. Different extension of the FCM algorithm have been proposed for increasing the robustness of FCM against INU and noise and improving the result of FCM algorithm for MRI brain image segmentation [16,31-33].

Supervised and semi-supervised methods

These methods use the prior class labels for segmentation process. Two main categories in this category are machine learning based methods and atlas based methods. Machine learning based methods use a database which are divided into two different parts such as training and test set. The learning phase is performed on the training set and the evaluation is done on the test set. Support Vector Machine (SVM) [34-37] and Neural Network (NN) methods like Multi-Layer Perceptron (MLP) [38,39] are the two most important machine learning approaches which are mostly used in this area.

By gathering the data from different subjects, an atlas of a brain is

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constructed; therefore, an atlas is containing of the prior information about different tissues in the brain. The atlas-based methods use these pre-labeled images and prior anatomical information for the segmentation process. These methods mostly are consisted of three main steps such as registration, label propagation and final segmentation. A huge amount of work has been done in this area, because of the ability of these methods for MRI image segmentation [40-45].

Conclusions

Different methods have been proposed for MRI brain image segmentation, but a general method has not been proposed yet. Unsupervised methods do not use prior information; therefore, these methods cannot use this information for increasing their final results, thus they mostly produce a lower accuracy as compared to supervised methods especially in the real datasets. Moreover, supervised methods need label data for training, which are generated by experts; therefore, it consumes many resources and in the most cases this work is expensive. Consequently, medical image segmentation and especially brain segmentation issue is an open problem which needs to be more accurate and precise than the other non-medical image segmentation applications.

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