3D brain tumor segmentation through integrating multiple 2D FCNNs

Xiaomei Zhao[1,2] ✉, Yihong Wu[1] ✉, Guidong Song[3] Zhenye Li[4] Yazhuo Zhang[3,4,5,6] and Yong Fan[7]

[1] National Laboratory of Pattern Recognition,Institute of Automation, Chinese Academy of Sciences, Beijing, China
[2] University of Chinese Academy of Sciences, Beijing, China
[3] Beijing Neurosurgical Institute, Capital Medical University, Beijing, China
[4] Department of Neurosurgery, Beijing Tiantan Hospital, Capital Medical University, Beijing, China
[5] Beijing Institute for Brain Disorders Brain Tumor Center
[6] China National Clinical Research Center for Neurological Diseases, Beijing, China
[7] Department of Radiology, Perelman School of Medicine, University of Pennsylvania, Philadelphia, PA, USA
zhaoxiaomei14@mails.ucas.ac.cn; yhwu@nlpr.ia.ac.cn

Abstract. The Magnetic Resonance Images (MRI) which can be used to segment brain tumors are of 3D. To make use of 3D information, 3 2D Fully Convolutional Neural Networks (FCNNs), each of which is trained to segment brain tumor images from axial, coronal, and sagittal views respectively, are integrated. The 3 FCNN models are integrated by fusing their segmentation results rather than by being fused into one deep network, which makes sure that each FCNN model is still allowed to be tested by 2D slices, guaranteeing the testing efficiency. A majority voting strategy is applied to do the fusing job. The proposed method can be easily extended to integrate more FCNN models which are trained to segment brain tumor images from more views, without retraining the FCNN models that we already have. In addition, Conditional Random Fields (CRFs) are applied to make sure the appearance and spatial consistency of our segmentation results. Experimental results show that, integrating the segmentation results of multiple 2D FCNNs obviously improve the segmentation accuracy.

Keywords: Brain Tumor Segmentation, Fully Convolutional Neural Networks, Conditional Random Fields, Multi-views

1 Introduction

Brain tumor segmentation results provide the volume, shape, and localization of brain tumors, which are crucial for brain tumor diagnosis and monitoring. Brain tumor segmentation technologies develop fast in recent years, especially those methods based on deep learning.

Besides in brain tumor segmentation area, deep learning has been successfully used in many other medical image segmentation areas. According to statistics, segmentation is the most common subject among the literatures that apply deep learning to medical images, and Convolutional Neural Networks (CNNs) are the most successful type of deep learning models for image analysis [1]. CNNs based methods have won many medical image segmentation challenges, such as Multimodal Brain Tumor Segmentation Challenge (BRATS) [2] and International Symposium on Biomedical Imaging (ISBI) cell tracking challenge [3].

Many kinds of medical images, such as the Magnetic Resonance Images (MRI) which can be used to segment brain tumors, are of 3D. To take full use of 3D information for medical image analysis, it is better to use 3D CNNs. However, 3D CNNs have large memory and training time requirements [4]. Therefore, many researchers have tried to integrate multiple 2D CNNs for segmenting 3D medical images, such as [4] and [5]. These methods integrated their multiple 2D CNNs into one deep network, and the 2D patches in multi-views centered at the same voxel should be sent into their deep networks at the same time. Under this situation, 3D images could only be segmented patch by patch, which is a very slow testing strategy, even if we change their CNNs into FCNNs. To improve the testing efficiency, we integrate multiple 2D FCNNs by integrating their segmentation results. Each FCNN model is trained by patches but tested by 2D slices, which improves the testing speed greatly. In this paper, we train 3 2D FCNN models using 2D patches of axial, coronal and sagittal views respectively. During testing, we use these 3 networks to segment brain tumors slice by slice in 3 different views, yielding 3 segmentation results. Then we fuse these 3 segmentation results by voting. Experimental results show that this strategy is useful to improve segmentation accuracy. We also use CRF to make sure the appearance and spatial consistency of our segmentation results.

2 Method

The proposed segmentation method consists of 5 main steps: pre-processing, segmenting brain images slice by slice using 3 2D FCNN models, processing segmentation results using CRF, fusing segmentation results obtained in 3 different views, and post-processing. The fusing operation is performed before or after CRF, as shown in Fig. 1-(a) and Fig.1-(b) respectively.

2.1 Pre-processing

To make similar intensities in MRI scans have similar tissue meanings, pre-processing steps are utilized. Our pre-processing steps include N4ITK [6] and intensity normalization [7].

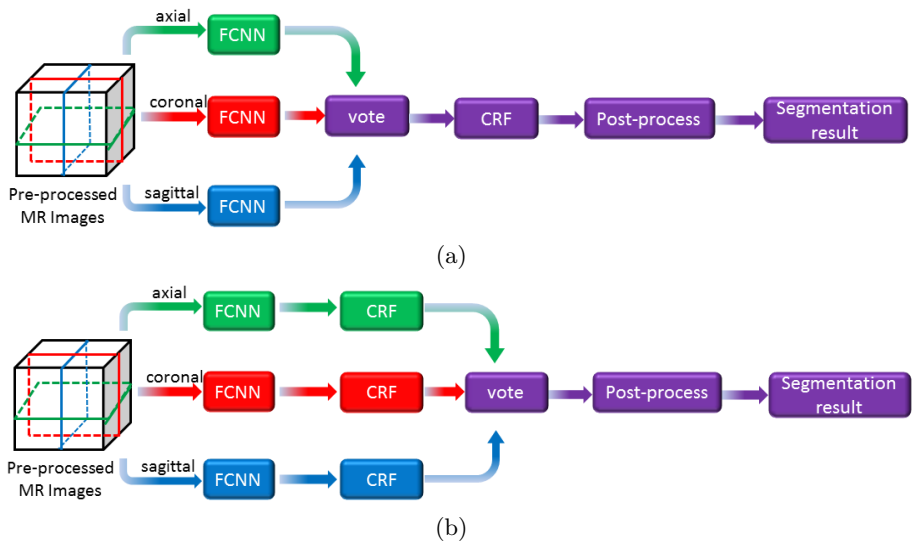

Fig. 1. Flowchart of our brain tumor segmentation method: (a) fusing the segmentation results obtained from different views before CRF; (b) fusing the segmentation results obtained from different views after CRF

2.2 Segmenting brain images by FCNNs

We use the same FCNN structure proposed in [7] as shown in Fig. 2, which has two different sizes of inputs. The large inputs pass through a series of convolutional and pooling layers and turn into feature maps with the same size of small inputs. These feature maps together with small inputs are used to predict their center pixels label. Different from [7], we train 3 FCNN models in this paper using 2D patches extracted from axial, coronal, and sagittal slices respectively. During testing, we use these 3 segmentation models to segment brain images slice by slice from 3 different views and obtain 3 segmentation results.

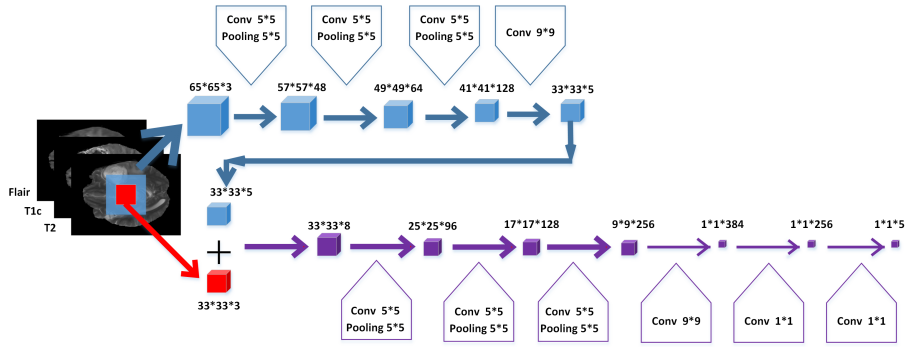

Fig. 2. The structure of our FCNN model

2.3 Processing segmentation results by 3D CRF

To make sure the appearance and spatial consistency of segmentation results, we use CRF to optimize our segmentation results. We have tried Conditional Random Fields as Recurrent Neural Networks (CRF-RNN) [8] and 3D CRF [9]. Experimental results showed that 3D CRF performed slightly better than CRF-RNN.

2.4 Fusing segmentation results obtained in 3 different views

As described in Section 2.2, 3 FCNN models are trained to segment brain images from 3 different views. During testing, their segmentation results are fused to make better use of the 3D information provided by the 3D MRI scans. In our experiments, the 3 segmentation results obtained in 3 different views are fused by majority voting.

We fuse the segmentation results as a post-processing step rather than fuse the 3 FCNN networks in one deep network, aiming to make sure that each FCNN model still has the ability to segment brain images slice by slice for efficiency. In this way, our method improves the efficiency of integrating multiple 2D CNNs while achieves better accuracy than using a single 2D CNN network.

2.5 Post-processing

We remove small isolated areas and correct some voxels label to post-process our segmentation results automatically by a simple thresholding method.

3 Experiment

3.1 Dataset

BRATS 2017 training dataset contains 210 HGG (High Grade Glioma) and 75 LGG (Low Grade Glioma). Currently, we just use the 210 HGG in our experiments. We separate the 210 HGG into 2 subsets as 168 HGG and 42 HGG respectively. The subset of 168 HGG is used as the training dataset and the subset of 42 HGG is used as the testing subset.

3.2 Evaluation results

The evaluation scores of our method are shown in Tab. 1. Tab. 1 indicates that fusing the segmentation results obtained from different views obviously improve the segmentation accuracy.

We also train a U-net [3] to segment brain tumors and compare its performance with our method. U-net won ISBI cell tracking challenge in 2015 and it is one of the most popular deep network used to segment medical images in

recently years. The evaluation scores in Tab. 1 show that the segmentation performance of U-net is much better than the performance of FCNNs. However, FCNNs+3D CRF works much better than U-net+3D CRF.

In Tab. 1, the method called Fusing(FCNNs)+3D CRF fuses the segmentation results before 3D CRF, as shown in Fig. 1-(a), and the method called Fusing(FCNNs+3D CRF) fuses the segmentation results after 3D CRF, as shown in Fig. 1-(b). The evaluation scores shown in Tab.1 indicate that Fusing(FCNNs)+3D CRF+post-process has a better performance on PPV, while Fusing(FCNNs+3D CRF)+post-process has a better performance on Sensitivity. From the view of Dice, Fusing(FCNNs)+3D CRF+post-process performs slightly better on enhancing core, while Fusing(FCNNs+3D CRF)+post-process performs better on complete tumors.

Table 1. Evaluation scores

Methods	Dice			PPV			Sensitivity		
	Comp.	Core	Enh.	Comp.	Core	Enh.	Comp.	Core	Enh.
U-net(axial)	0.807	0.749	0.752	0.787	0.829	0.799	0.856	0.743	0.763
U-net(axial)+3D CRF	0.811	0.750	0.754	0.798	0.834	0.804	0.850	0.740	0.763
FCNNs(axial)	0.623	0.701	0.633	0.480	0.602	0.530	0.971	**0.916**	0.877
FCNNs(coronal)	0.666	0.738	0.675	0.578	0.664	0.594	0.963	0.896	0.865
FCNNs(sagittal)	0.662	0.703	0.653	0.526	0.607	0.574	0.957	0.912	0.846
Fusing(FCNNs)	0.696	0.800	0.730	0.562	0.753	0.663	**0.974**	0.901	0.877
Fusing(FCNNs)+3D CRF	0.859	0.867	0.824	0.931	**0.915**	0.804	0.816	0.850	0.880
Fusing(FCNNs)+3D CRF +post-process	0.864	**0.868**	**0.831**	**0.941**	0.909	**0.825**	0.818	0.854	0.873
FCNNs(axial)+3D CRF	0.857	0.843	0.787	0.873	0.840	0.731	0.857	0.875	**0.895**
FCNNs(coronal)+3D CRF	0.862	0.843	0.800	0.898	0.869	0.765	0.845	0.850	0.880
FCNNs(sagittal)+3D CRF	0.845	0.848	0.797	0.887	0.853	0.762	0.827	0.869	0.874
Fusing(FCNNs+3D CRF)	0.865	0.864	0.816	0.906	0.894	0.784	0.845	0.861	0.887
Fusing(FCNNs+3D CRF) +post-process	**0.873**	**0.868**	0.828	0.920	0.895	0.813	0.846	0.865	0.879

4 conclusion

In this paper, we segment 3D brain images by integrating the segmentation results of multiple 2D FCNNs, which are trained to segment brain images from axial, coronal, and sagittal views respectively. Each of the 2D FCNN networks is tested slice by slice, guaranteeing the segmentation efficiency of our method. We also use CRF to optimize our segmentation results. Experimental results show that our fusing strategy improves segmentation accuracy. Moreover, the proposed

method is not limited to fuse the 3 segmentation results from 3 different views. It could be extended to fuse the more from more views.

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