An UNet-based Brain Tumor Segmentation Framework via Optimal Mass Transportation Pre-processing

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Abstract

This thesis aims to build a brain tumor segmentation framework in MRI images using the deep learning method. For this purpose, we develop a novel 2-Phase framework to enlarge the proportion of brain tumors by using Optimal Mass Transportation (OMT). Moreover, due to the scarcity of training data, we change the density function by different parameters to increase the data diversity. Then we train deep learning models and provide cross-validation results. For the post-processing, we propose an adaptive ensemble that can adaptively compute the weighted sum of predictions. Finally, the online validation dice score of WT, TC, and ET are 0.9214, 0.8823, and 0.8411, respectively. Compared with random crop pre-processing, OMT is far superior.

Problem description

Brain tumor segmentation is vital in automatic diagnosis. There are many four different modalities in a brain scan, fluid-attenuated inversion recovery (FLAIR), T1-weighted (T1), T1-weighted contrast-enhanced (T1CE), and T2-weighted (T2). Annotations include the necrotic and non-enhancing tumor core (NCR/NET), the peritumoral edema (ED), and the GD-enhancing tumor. Among the sub-regions to be evaluated are the whole tumor (WT), the tumor core (TC), and the enhancing tumor (ET).

There are two difficulties with brain tumor segmentation. First, due to the large input size for training, we only use small batch sizes. Second, tumor ET is so small and dispersed that models are difficult to detect.

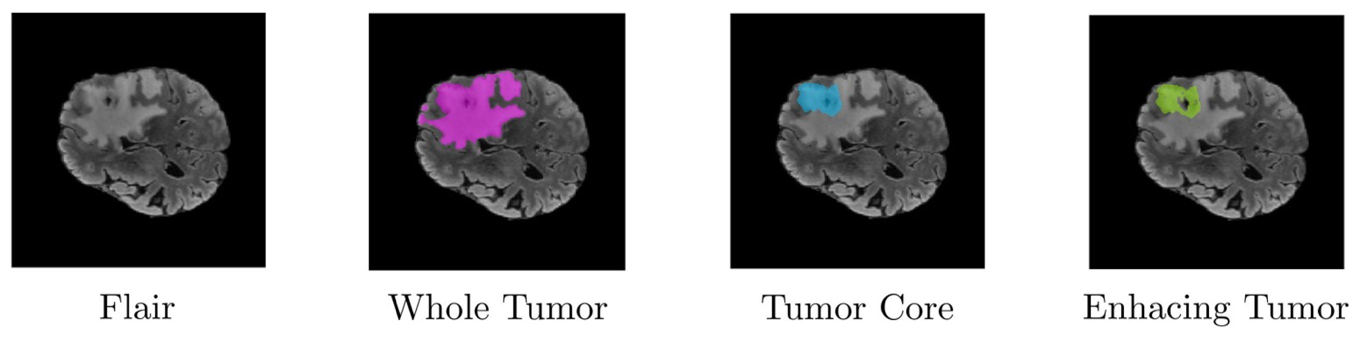

Figure 1: Three types of brain tumors with flair grayscale.

To deal with the problems above, we propose a novel framework combining OMT and deep learning. OMT has two advantages. First of all, it can deform irregular objects into regular objects, which reduces the shape of model input and speeds up model training. Second, it can enlarge specific regions by controlling density. Based on the advantages above, we designed a 2-Phase framework to detect and segment brain tumors.

OMT Problem [1, 2]. Let MP $= \{f : \mathcal{B} \to \mathcal{C} \mid \rho(\tau)|\tau| = |f(\tau)|, \forall \tau \in \mathcal{T}(\mathcal{B})\}$ be the set of mass-preserving maps and the local mass with the density function is $m(v) = \frac{1}{4}\sum_{\tau\in N(v)} \rho(\tau)|\tau|$. The OMT problem is to find a map $f^* \in$ MP that minimizes the transportation cost as the following:

$$f^* = \underset{f\in \mathrm{MP}}{\arg\min} \sum_{v\in\mathcal{V}(\mathcal{B})} \|v - f(v)\|_2^2\, m(v),$$

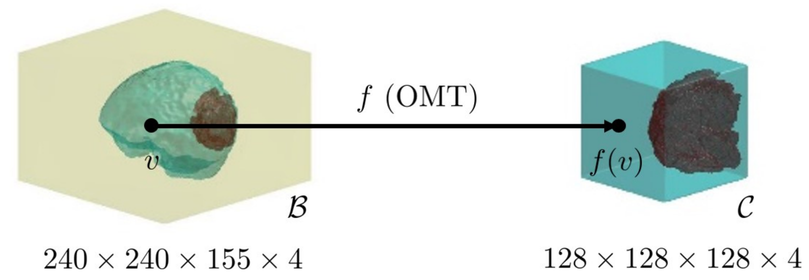

Figure 2: An illustration for the OMT.

Results and discussion

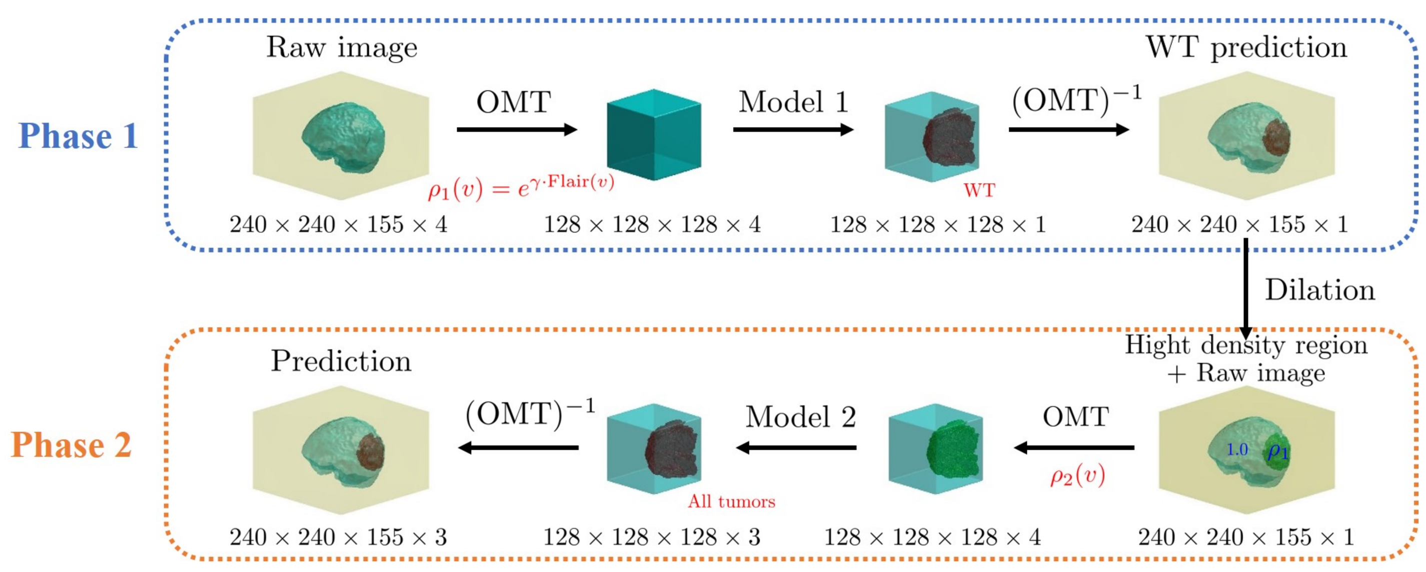

Figure 3: 2-Phase OMT framework.

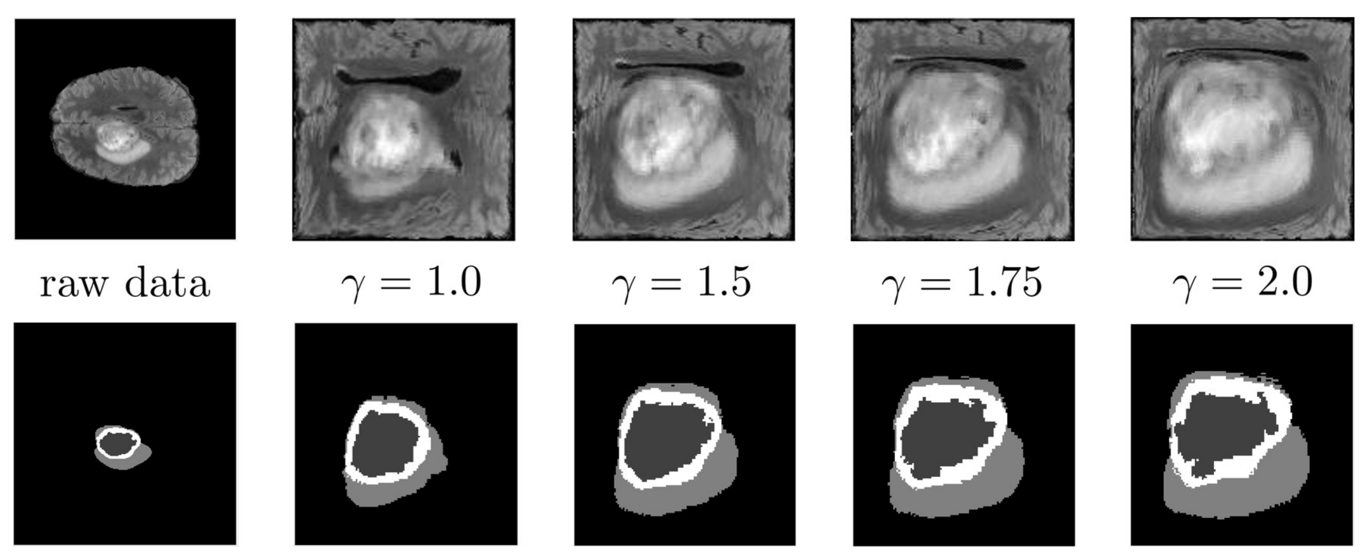

Figure 4: Phase 2 OMT image with different γ.

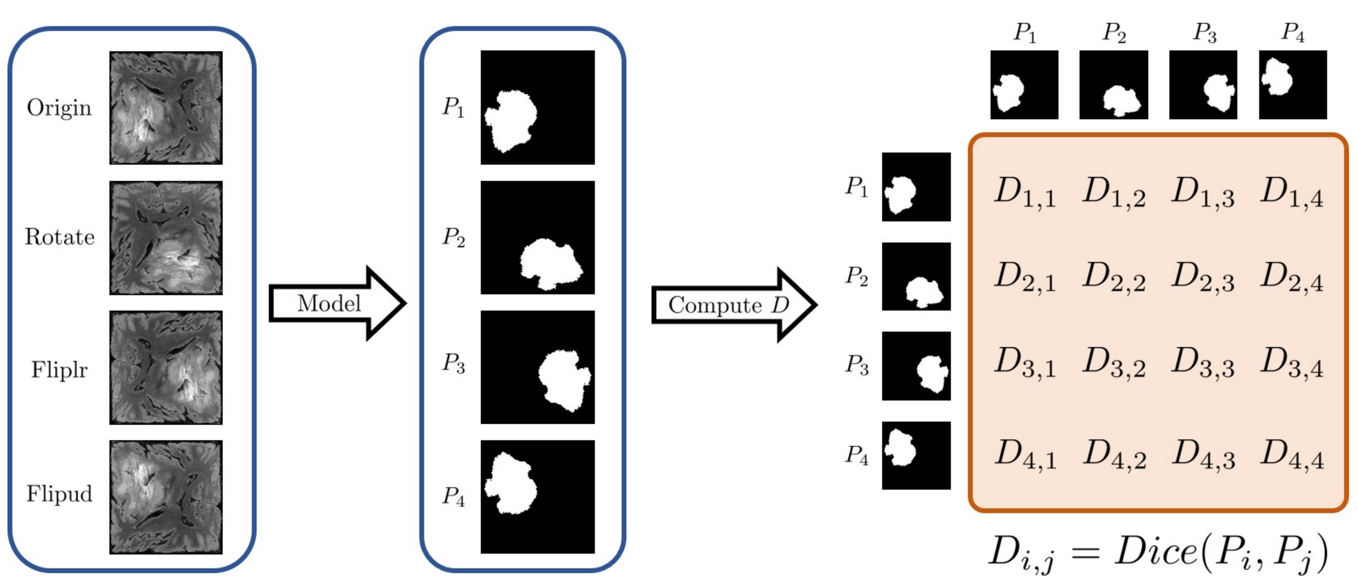

Figure 5: Adaptive ensemble.

The dataset is provided by MICCAI Brain Tumor Segmentation Challenge 2021. It has 1,251 training data and 219 validation data without labels. We used those data to develop the 2-Phase OMT framework, shown in Figure 3.

In phase 1, we use OMT to map the brain to the cube and predict the WT by SegResNet [3]. Then we expand the four voxels by using morphology dilation. It can cover above 99.9% TC and ET. In phase 2, we redefine the density function to enlarge the region's proportion generated from phase 1. Then we predict the WT, TC, and ET by using SegResNet.

We show the average proportion of tumors in raw images, phase 2 OMT images in Table 1, and visualize one case in Figure 4. The proportion of tumors is enlarged as increasing with γ.

For the post-processing, we compute the weight of predictions by solving the normalized eigenvector corresponding to the spectral radius of D in Figure 5. The final prediction represent as $\widehat{P} = \sum_{i=1}^{4} w_i P_i$.

Finally, we show the dice score of the different pre-processing in Table 2 and compare our result with other BraTS2021 challenge participants in Table 3.

Tumor	Raw image	γ =1.0	γ =1.5	γ =1.75	γ =2.0
WT	6.49%	13.47%	18.27%	20.93%	23.72%
TC	2.42%	5.03%	6.84%	7.84%	8.90%
ET	1.45%	3.04%	4.14%	4.75%	5.40%

Table 1: Tumor average proportion of raw images and OMT images.

Preprocessing	Cross-validation			Online validation		
	WT	TC	ET	WT	TC	ET
Random Crop	0.9340	0.9082	0.8650	0.9194	0.8542	0.8242
2P-OMT	**0.9371**	**0.9157**	**0.8819**	**0.9214**	**0.8823**	**0.8411**

Table 2. Comparison results with different preprocessing.

Paper [4]	Preprocessing	Model	WT	TC	ET
P. Druzhinina et al.	Random Crop	scan lite-20	0.9220	0.8680	0.8300
H.-Y. Wu et al.	Random Crop	HarDNet-BTS	0.9260	0.8793	0.8442
J. Ma et al.	Random Crop	NnUNet	0.9259	0.8786	0.8217
H. S. Singh et al.	Random Crop	Attention UNet	0.9080	0.8600	0.8170
Proposed	2P-OMT	SegResNet	0.9214	0.8823	0.8411

Table 3. Comparison results with other participants in BraTS2021 Challenge.

Conclusions

In this thesis, we propose a novel 2-Phase OMT framework and adaptive ensemble for MRI brain tumor segmentation. In pre-processing, we use OMT to transform a brain of $240 \times 240 \times 155 \times 4$ into a cube of $128 \times 128 \times 128 \times 4$, which reduces the computation of the deep learning model and training time with keeping the global information of the raw image. Moreover, we design the density function zoom on specific regions to help model detection and make data augmentation by different densities to enhance the model robustness. Compared with random crop pre-processing, the dice score improved significantly.

References

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