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

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September 18, 2022

Motivation

Problems:

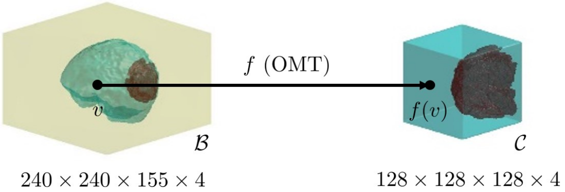
- Due to the large input size for training, we only use small batch sizes.
- Enhancing tumor (ET) is so small and dispersed that models are difficult to detect.

Proposed method:

- Use OMT to deform irregular objects into regular objects, which reduces the shape of model input and speeds up model training.
- Detect the WT roughly in phase 1 and segment the WT, TC, and ET in phase 2. The tumor's proportion can enlarge by the density function in phase 2.
- Generate the data augmentation by using OMT with different density function.

Optimal Mass Transportation (OMT) Problem

OMT Problem [2, 4]:



$$f^* = \underset{f \in \text{MP}}{\arg\min} \sum_{v \in \mathcal{V}(\mathcal{B})} \|v - f(v)\|_2^2 \, m(v), \tag{1}$$

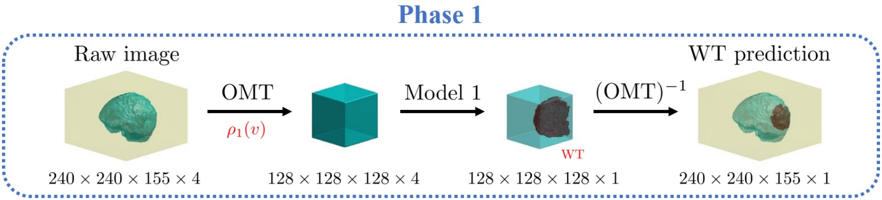
- the function space of mass-preserving map is

$$\text{MP} = \{f : \mathcal{B} \to \mathcal{C} \mid \rho(\tau)|\tau| = |f(\tau)|, \forall \tau \in \mathcal{T}(\mathcal{B})\},$$

- the local mass with the density function is

$$m(v) = \frac{1}{4} \sum_{\tau \in N(v)} \rho(\tau)|\tau|.$$

Two-Phase OMT (2P-OMT) Framework: Phase 1

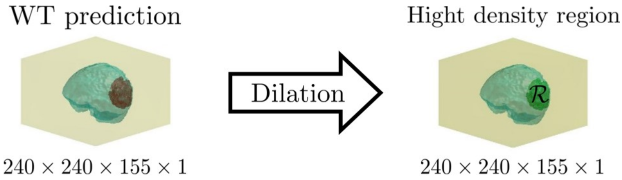


In phase 1, the density function is defined as

$$\rho_1(v) = \exp(\gamma \cdot \text{HE}(g(v))), \tag{2}$$

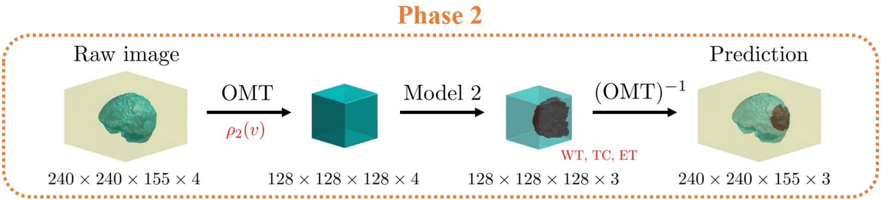
where g is the grayscale of flair mode, HE is the histogram equalization, and $\gamma > 0$ is a hyper-parameter.

Two-Phase OMT (2P-OMT) Framework: Phase 2



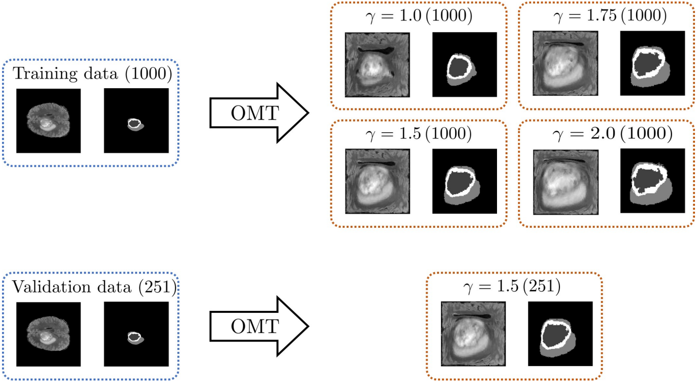
In phase 2, the density function is defined as

$$\rho_2(v) = \begin{cases} \exp(\gamma \cdot \mathrm{HE}(g(v))), & \text{if } v \in \mathcal{R} \\ 1.0, & \text{if } v \in \mathcal{B} \setminus \mathcal{R} \end{cases}. \tag{3}$$



Data Pre-processing and Augmentation (I)

- Split the dataset into 1000 for training and 251 for validation.
- Generate the OMT data with different densities (γ: $1.0, 1.5, 1.75$, 2.0) and randomly choose one of the densities of OMT data for training.
- Choose the OMT data with $\gamma = 1.5$ for validation step.



Data Pre-processing and Augmentation (II)

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

Table 1: Average proportion of tumor.

- Use min-max normalization to rescale the grayscale to $[0, 1]$.
- Use the data augmentation with following probability:

Transformation	Flip	Rotate	Add noise	Adjust brightness
Probability	0.25	0.25	0.1	0.1

Table 2: Probability of data augmentation.

Training Processing

- Epoch: 1000
- Batch size: 12
- Model: SegResNet [3] (MONAI package)
- Loss function: Dice Loss + Focal Loss
- Optimization: Adam + Weight decay + Cosine decay

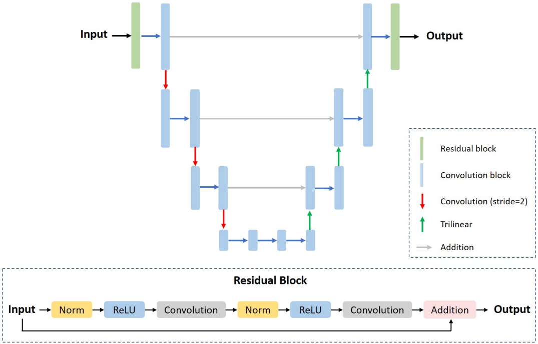
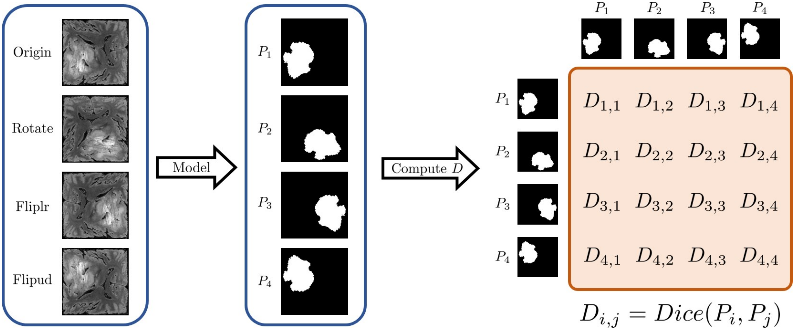


Figure 1: Architecture of SegResNet.

Post-processing: Adaptive Ensemble



Let w be the normalized eigenvector corresponding to the spectral radius of D. Then the final prediction is

$$\widehat{P} = \sum_{i=1}^{4} w_i P_i.$$

Experiment Results

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 3: Compared to the Dice score of different preprocessing with SegResNet.

Paper [1]	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 4: Comparison results with other participants in the BraTS2021 Challenge.

Conclusion

1. We developed the 2POMT framework, which significantly improved performance compared with random crop pre-processing.
2. We can use density function to enlarge tumor proportion to help the model detection the tumor.
3. We can generate OMT data with different densities achieving data augmentation, which can avoid over-fitting and enhance the robustness of a model.
4. We proposed a novel ensemble method for post-processing, which can adaptively compute the weighted sum of predictions.

Reference

[1] Alessandro Crimi and Spyridon Bakas. *Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries: 7th International Workshop, BrainLes 2021 Held in Conjunction with MICCAI 2021 Virtual Event, September 27, 2021 Revised Selected Papers, Part I*. 2022.

[2] Wen-Wei Lin et al. "A novel 2-phase residual U-net algorithm combined with optimal mass transportation for 3D brain tumor detection and segmentation". In: *Sci. Rep.* 12 (2022), pp. 1–16.

[3] Andriy Myronenko. "3D MRI brain tumor segmentation using autoencoder regularization". In: *BrainLes@MICCAI*. 2018.

[4] Mei-Heng Yueh et al. "Projected Gradient Method Combined with Homotopy Techniques for Volume-Measure-Preserving Optimal Mass Transportation Problems". In: *J. Sci. Comput.* 88.3 (Sept. 2021). ISSN: 0885-7474.

Thanks for listening!