Paper Reading No.5

Improving 3D U-Net for Brain Tumor Segmentation by Utilizing Lesion Prior

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1 Brief Paper Intro

- ***Paper ref:*** arxiv preprint , https://arxiv.org/abs/1907.00281
- ***Authors:*** See Fig 1.

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Figure 1: authors' brief intro.

- ***Paper summary:*** Authors proposed a method to integrate lesion prior and a 3D U-Net for improving brain tumor segmentation. Different types of lesions' heatmaps are generated and then volume-of-interest (**VOI**) map are generated using prior information about brain tumor lesion. The segmentation results on public benchmark show that it's a simple but effective method.

- ***Reading motivation:*** Prior knowledge plays a significant role in the task of medical image segmentation. This paper shows an interesting way by modeling prior knowledge as volume-of-interest (VOI) map, which can be simply regarded as heatmap, to integrate prior knowledge with segmentation model.

2 Backgrounds

Primary central nervous system (CNS) tumors refer to a heterogeneous group of tumors arising from cells within the CNS and can be benign or malignant. An automatic and accurate brain tumor segmentation tool is under requirement.

Multimodal Brain Tumor Image Segmentation Benchmark (BraTS) 2017 [1] is a widely used public brain MRI benchmark, which provides 285 subjects in the training set and 46 subjects in the validation set. The ground-truth lesion mask comprises three types: the enhancing tumor (ET), edema (ED), and necrotic & non-enhancing tumor (NCR/NET).

3 Generation of Volume-of-interest Map

Heatmap generation: As is mentioned above, the BraTS dataset labelled three types of brain lesions. So, first, the heatmaps of the three types lesion are generated as is indicated in Fig 2. The heatmaps of different brain tumor lesions are shown in Fig 3

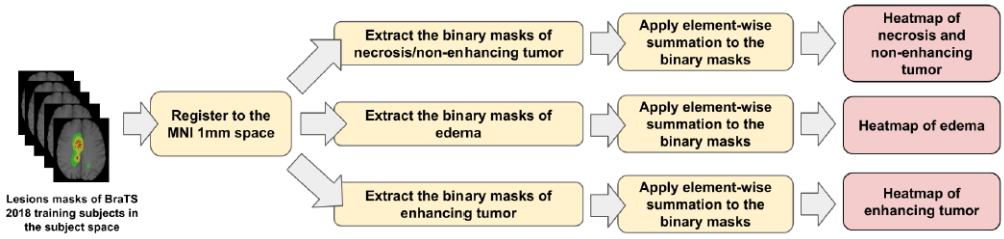

Figure 2: The workflow of building the heatmaps of different types of brain lesions..

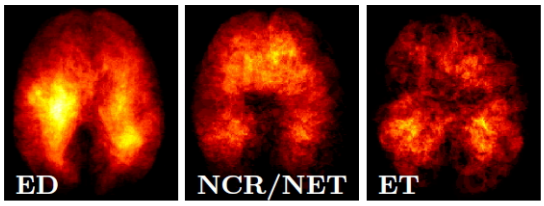

Figure 3: The heatmaps of different brain tumor lesions. The brighter voxels (yellow) represent higher intensity values. Best viewed in color..

VOI map generation: The heatmaps of different brain lesions are then used to create the VOI map. For VOI map generation, given the prior knowledge, the authors make a hypothesis that VOI labels are based on the thresholds which are chosen from the percentiles of non-zero voxels of heatmaps of different types. Authors examined different thresholds, and $(\alpha; \beta; \gamma) = (50; 65; 80)$ percentiles yield the best overall segmentation performance. The overall algorithm is shown in Fig 4.

After VOI map generation, the VOI maps are divided into 10 different colors for better displaying 5. This distribution in the right part shows that (i) the prior probabilities of different lesions depend on their corresponding labels in the VOI label map, and (ii) lesions have higher probabilities to happen in the larger VOI labels.

4 Model Training and Information Integration

Authors choose regular 3D U-Net and data pre-processing procedure, and these are not necessary for much introduction. The proposed network is trained with randomly cropped patches of size 128 * 128 * 128 voxels and batch size 2. Fig 6 shows the pipeline of integrating the VOI map and a 3D U-Net for brain tumor segmentation.

"First, we register the VOI map from the MNI 1mm space to the subject space using FLIRT [9] from FSL, and this registered VOI map is then split into 9 binary masks." (Actually I don't quite understand this part.)

These binary masks are concatenated with the multi-modal MR images (4 image channels + 9 VOI channels).

Algorithm 1: Build the VOI map from the heatmaps of lesions.

input : A heatmap H_{ed} of ED of size $w \times l \times d$
A heatmap H_{ncr} of NCR/NET of size $w \times l \times d$
A heatmap H_{et} of ET of size $w \times l \times d$
output: The VOI map V of size $w \times l \times d$

$h_{ed,1}, h_{ed,2}, h_{ed,3} \leftarrow \alpha, \beta, \gamma$ percentile of non-zero voxels of H_{ed};
$h_{ncr,1}, h_{ncr,2}, h_{ncr,3} \leftarrow \alpha, \beta, \gamma$ percentile of non-zero voxels of H_{ncr};
$h_{et,1}, h_{et,2}, h_{et,3} \leftarrow \alpha, \beta, \gamma$ percentile of non-zero voxels of H_{et};
for $i \leftarrow 1$ **to** w **do**
  for $j \leftarrow 1$ **to** l **do**
    for $k \leftarrow 1$ **to** d **do**
      if $H_{et}[i,j,k] \geq h_{et,3}$ **then**
        $V[i,j,k] \leftarrow 9$;
      else if $H_{ncr}[i,j,k] \geq h_{ncr,3}$ **then**
        $V[i,j,k] \leftarrow 8$;
      else if $H_{ed}[i,j,k] \geq h_{ed,3}$ **then**
        $V[i,j,k] \leftarrow 7$;
      else if $H_{et}[i,j,k] \geq h_{et,2}$ **then**
        $V[i,j,k] \leftarrow 6$;
      else if $H_{ncr}[i,j,k] \geq h_{ncr,2}$ **then**
        $V[i,j,k] \leftarrow 5$;
      else if $H_{ed}[i,j,k] \geq h_{ed,2}$ **then**
        $V[i,j,k] \leftarrow 4$;
      else if $H_{et}[i,j,k] \geq h_{et,1}$ **then**
        $V[i,j,k] \leftarrow 3$;
      else if $H_{ncr}[i,j,k] \geq h_{ncr,1}$ **then**
        $V[i,j,k] \leftarrow 2$;
      else if $H_{ed}[i,j,k] \geq h_{ed,1}$ **then**
        $V[i,j,k] \leftarrow 1$;
      else
        $V[i,j,k] \leftarrow 0$;
      end
    end
  end
end

Figure 4: The algorithm of building the VOI map from the heatmaps of lesions.

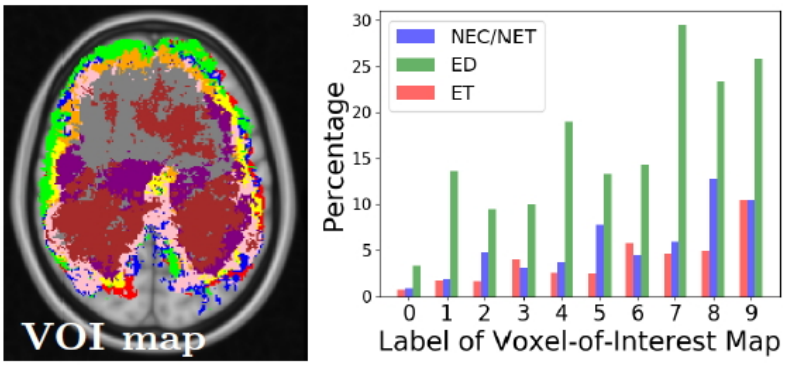

Figure 5: VOI map (background-0, red-1, green-2, blue-3, yellow-4, orange-5, pink-6, purple-7, grey-8, and brown-9) and the distribution of brain tumor lesions (green-ED, blue-NEC/NET, and red-ET) observed in the different labels of VOI map from BraTS 2017 training subjects. Best viewed in color.

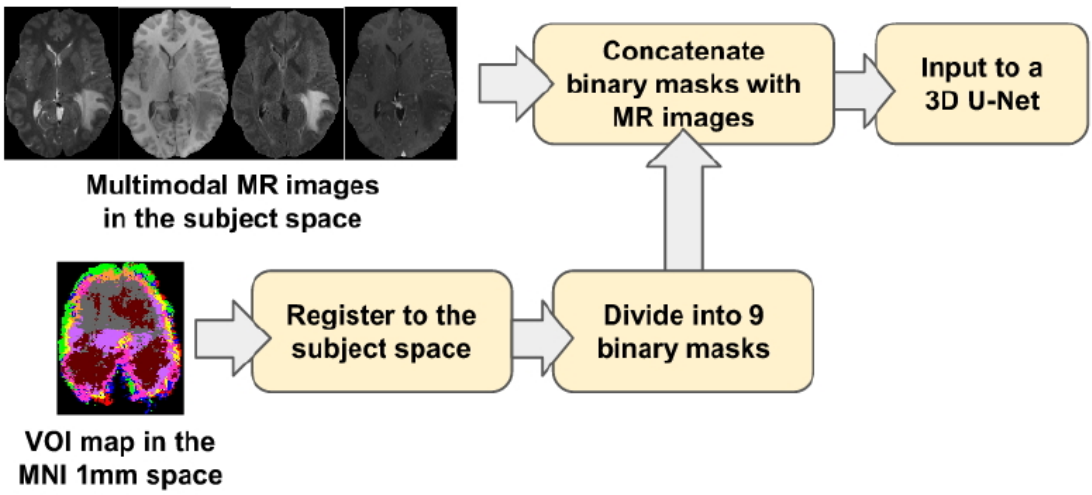

Figure 6: The pipeline of integrating the VOI map and a 3D U-Net.

5 Results

In this part, authors choose (1) Dice similarity coefficient (DSC) and (2)95 percentile of the Hausdorff distance (H95) for metrics. The results in Fig 7 show that the proposed prior knowledge guided method can surpass the base-

Model Descriptions	DSC			H95		
	ET	WT	TC	ET	WT	TC
Single 3D U-Net (baseline)	0.695	0.896	0.762	6.79	6.92	11.38
Single 3D U-Net + VOI (proposed)	0.730	0.899	0.764	4.23	4.53	10.93
Ensemble of five 3D U-Nets (baseline)	0.723	0.902	0.763	5.99	4.75	10.58
Ensemble of five 3D U-Nets + VOI (proposed)	**0.744**	**0.903**	0.780	5.01	**3.86**	9.71
Isensee et al. [7]	0.732	0.896	**0.797**	4.55	6.97	9.48
Kamnitsas et al. [10]	0.738	0.901	**0.797**	**4.50**	4.23	**6.56**

Figure 7: Quantitative results of the different models on BraTS 2017 validation set.

line 3D U-Net. Also, the proposed lesion prior fusion method improves the performance of the ensemble of 3D U-Nets, and gained results comparable to the state-of-the-art method.

6 My thoughts

1) Through an attention map (so called VOI map), this paper integrate prior knowledge to brain tumor mri image segmentation, and the results show the effectiveness of this method.

2) Do the statistical distribution results in Figure 3 make sense? It remains a question. The distribution of 1 10 different types in the three types of lesion does not seem to have a strong correlation, which only indicates that the ED category is relatively high.

3) However, indeed, this paper gives me an inspiration on how to integrate medical prior knowledge to segmentation tasks.

References

[1] Spyridon Bakas, Hamed Akbari, Aristeidis Sotiras, Michel Bilello, Martin Rozycki, Justin S Kirby, John B Freymann, Keyvan Farahani, and Christos Davatzikos. Advancing the cancer genome atlas glioma mri collections with expert segmentation labels and radiomic features. *Scientific data*, 4:170117, 2017.