Brain Tumor Synthetic Segmentation in 3D Multimodal MRI Scans

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Abstract. The magnetic resonance (MR) analysis of brain tumors is widely used for diagnosis and examination of tumor subregions. The overlapping area among the intensity distribution of healthy, enhancing, non-enhancing, and edema region makes the automatic segmentation a challenging task. Here, we show that a convolutional neural network trained on high-contrast images can transform intensity distribution of brain lesion in its internal subregions. Specifically, generative adversarial network (GAN) is extended to synthesize high-contrast images. A comparison of these synthetic images and real images of brain tumor tissue in MR scans showed significant segmentation improvement and decreased the number of real channels for segmentation. The synthetic images are used as a substitute for real channels and can bypass real modalities in the multimodal brain tumor segmentation framework. Segmentation results on BraTS 2019 dataset demonstrate that our proposed approach can efficiently segment the tumor areas.

Keywords: Segmentation · Synthetic image · GAN · Brain tumor · MRI.

1 Introduction

Glioma is the most aggressive and widespread tumor is grouped into low-grade gliomas (LGGs) and high-grade gliomas (HGGs). Multimodal MR channels in BraTS 2019 datasets, included of FLAIR, T1, T1c, and T2, are routinely used to segment internal parts of the tumor, i.e., whole tumor (WT), tumor core (TC), and enhancing tumor (ET). Several segmentation approaches have been proposed to segment regions of interest through classic and modern machine learning methods, especially brain tumor segmentation techniques.
Fig. 1. The pipeline outlines the steps in the current (top) and proposed synthetic (bottom) segmentation techniques. We displace the real T1 channels with the synthetic image.

The focus of current research is to form a generator that increases the contrast within subregions of the brain tissue. The generator, which is a deep neural network model, employs real channel as input to produce the synthetic one. Our framework comprises two stages: (1) we generate high tissue contrast images based on FLAIR sequence in our convolutional neural network (CNN) model, (2) we train a 3D fully convolutional network (FCN) \[5, 9, 16, 12\] based on the synthetic images to segment region of interests.

2 Method

Our goal is to segment tumor subregions based on multimodal 3D magnetic resonance (MR) volumes. Fig. 1 demonstrates an overview of the proposed method based on synthetic high-contrast images. In contrast to the current methods, we use both real and synthetic volumes for the segmentation task. Following, we first introduce the synthetic image generator module, based on the generative adversarial networks (GANs) model \[6\], and then 3D FCN architecture for segmentation will be discussed.

2.1 Synthetic Image Generator

We extend the image-to-image translation method \[11\] to deal with the synthesis of high-contrast 2D images. Our model train on high-contrast images, building based on manual labels, in an adversarial framework. The synthesis model contains a Generator, based on 2D-U-Net \[15\], and a Discriminator, build on 2D FCN network. Fig. illustrates the image translation framework, where both the generator and the discriminator blocks are trained on FLAIR with a patch size of 128 × 128 pixels. In implementation details, we follow \[11\], including the
number of epochs, the number of layers, and the kernel sizes. For each subject in BraTS’19 dataset, we provide a 3D synthetic volume for the next stage, segmentation.

### 2.2 Synthetic Segmentation

The output volumes from synthetic image generator block are concatenated with real modalities (FLAIR, T1c, and T2) and fed into segmentation block to predict region of interests. The segmentation network allows jointly capturing features from FLAIR, synthetic, T1c, and T2 modality. For 3D segmentation block, we rely on 3D FCN of, ensemble three 3D FCN on axial, sagittal, and coronal plane.

## 3 Experimental Results

### 3.1 Implementation Details

We implement the proposed design employing the KERAS with 12GB NVIDIA TITAN X GPU. We have scaled image patches to sizes 128 × 128 pixels for translation. The model is trained through the ADADELTA [19] optimizer (learning rate = 0.9, ρ = 0.90, epsilon=1e-5). Dropout is employed to avoid over-fitting over the training (p_{drop} = 0.4).

### 3.2 Datasets

The performance of the proposed method is evaluated on BraTS’19 dataset, that has two datasets of pre-operative MRI sequences: Training (335 cases) and
Table 1. DSCs and HD95 of the synthetic segmentation method on BraTS’19 Validation set (training on 335 cases of BraTS’19 training set).

|       | Dice | Sensitivity | Specificity | HD95 (mm) |
|-------|------|-------------|-------------|-----------|
| Mean  | ET   | WT          | TC          | ET        | WT          | TC          | ET        | WT          | TC          |
|       | 76.65 | 89.65       | 79.01       | 76.88     | 91.32       | 77.71       | 99.85     | 99.39       | 99.76       |
|       | 25.86 | 9.44        | 23.31       | 25.35     | 8.84        | 26.13       | 0.23      | 0.69        | 0.33        |
| Std.  | 94.73 | 92.15       | 89.47       | 95.47     | 94.53       | 90.08       | 99.93     | 99.58       | 99.88       |
|       | 25    | 13.8        | 12.4        | 4.1       | 5.1         | 10.3        |
| Median| 84.73 | 92.15       | 89.47       | 95.47     | 94.53       | 90.08       | 99.93     | 99.58       | 99.88       |
|       | 2.2   | 3.3         | 4.1         | 1.4       | 2.0         | 2.0         |
| 25 quantile | 77.88 | 87.94       | 74.29       | 72.82     | 88.65       | 73.26       | 99.82     | 99.15       | 99.70       |
| 75 quantile | 90.21 | 94.81       | 93.98       | 91.97     | 97.28       | 95.16       | 99.98     | 99.83       | 99.97       |

Validation (125 cases). Each patient is giving $155 \times 240 \times 240$ with four channels: T1, T2, T1c, and FLAIR. In the manual label of BraTS’19, there are three tumor regions: non-enhancing tumor, enhancing tumor, and edema. The evaluation is figured out by CBICA IPP online platforms. Metrics computed by the online evaluation platforms in BraTS’19 are Dice Similarity Coefficient (DSC) and the 95th percentile of the Hausdorff Distance (HD95). DSC is considered to measure the union of prediction and manual segmentation. It is measured as $DSC = \frac{2TP}{2TP + FP + FN}$ where TP, FP, and FN are the numbers of true positive, false positive, and false negative detections, respectively.

3.3 Segmentation Results on BRATS’19

Fig. 3 shows examples of brain tumor prediction in LGG and HGG slides on BraTS19 along with corresponding labels, where the subject IDs are "BraTS19-TCIA10-175-1" and "BraTS19-CBICA-APK-1" for LGG and HGG, respectively. The results in Table 1 show that our method performed competitive performance on validation set (125 cases) of BraTS dataset. Results are reported in the online processing platform by BraTS’19 organizer. Moreover, Table 2 reports the average results on 335 training case of the BraTS’19.

4 Conclusion

This paper provided a framework for the synthetic segmentation that translated FLAIR MR images into high-contrast synthetic MR ones for segmentation. Synthesizing based on GAN network empower our model to decrease the number of real channels in multimodal brain tumor segmentation challenge 2019.

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Fig. 3. Segmentation results are overlaid on FLAIR axial slices on BraTS’19 Training Data. The yellow label is edema, blue color means enhancing tumor, and the green one shows the necrotic and non-enhancing tumor core. The first and second rows illustrate LGG brain tumor, prediction (Pred.) and ground truth (GT), respectively. The third and fourth rows are related to HGG tumors. Computed DSCs by the Challenge organizer are reported for the LGG subject as: WT = 96.55% and ET% = 88.85, as well as HGG subject as: TC = 93.80%, WT = 93.97%, and ET = 95.00%.

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Table 2. DSCs and HD95 of the synthetic method on BraTS’19 Training set.

|          | Dice | Sensitivity | Specificity | HD95 (mm) |
|----------|------|-------------|-------------|-----------|
| ET WT TC | ET WT TC | ET WT TC | ET WT TC |
| Mean     | 79.26 91.65 90.76 | 84.49 91.89 90.76 | 99.86 99.51 99.77 | 3.5 5.7 3.4 |
| Std.     | 23.96 05.59 7.13 | 14.46 08.04 08.17 | 0.178 0.47 0.34 | 7.3 11.0 4.6 |
| Median   | 87.04 93.29 92.88 | 88.12 94.35 93.22 | 99.92 99.64 99.88 | 1.4 2.8 2.0 |
| 25 quantile | 79.49 89.89 88.34 | 80.69 88.99 87.96 | 99.831 99.37 99.74 | 1.0 1.8 1.4 |
| 75 quantile | 91.54 95.39 95.28 | 93.78 97.23 96.43 | 99.975 99.80 99.95 | 2.2 4.9 3.6 |

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