WMH Segmentation Using an Adjusted DeepMedic Architecture and an Improved Learning Approach

Boris Shirokikh[1,2] and Mikhail Belyaev[1,2]

[1] Skolkovo Institute of Science and Technology, Moscow, Russia
[2] Kharkevich Institute for Information Transmission Problems, Moscow, Russia
m.belyaev@skoltech.ru

1 Data and Preprocessing

For our purposes we used the following preprocessed images: *3DT1*, *T1* and *FLAIR*. Firstly, we generated Brain Mask (BM) using *3DT1* with fsl-BET [5] (to produce high quality BM on T1 with high resolution), then saved parameters of ANTs [1] transformation from *3DT1* to *T1* and applied them to BM. Finally we applied Brain Mask to both *T1* and *FLAIR*.

After the brain extraction procedure, we zeroed both the first and the last 5 slices along vertical axis to remove possible artifacts of brain extraction. Then we scaled images intensities: lower bound of intensity became 0 and the upper 95th-quantile of intensity distribution became 1. This scaling approach is robust to the presence of outliers in intensity values. In our experiments, it performed better than normalization and simple scaling.

2 Augmentation

We used two simple approaches to online data augmentation. The first approach is random rotation or flipping of each image. The second approach is the addition of random noise with low amplitude to the image. Both approaches improved the validation results slightly.

3 Network

We started with the experimental comparison of two the most popular 3D MRI-images segmentation approaches: 3D U-Net [4] and DeepMedic [2] architectures. After comparing different experimental setups and tuning of model parameters, DeepMedic outperforms U-Net by a wide margin. So we decided to use DeepMedic architecture as the core one and then implemented the following modifications of the standard DeepMedic architecture and learning process:

1. We expand the size of patches of incoming image to be $63 \times 63 \times 63$ and $31 \times 31 \times 31$, comparing to standard $57 \times 57 \times 57$ and $25 \times 25 \times 25$.

2. According to the article [3] we use adjusted patch sampling technique called Tumor Sampling, and adjusted ratio of patches with lesions. Parameter *nonzero fraction* was set to 0.25.

Both modifications significantly improved the validation results.

4 Postprocessing

Smoothing prediction maps with a Gaussian kernel, deleting small connected components as possible false positives (FP) and other methods to correct network prediction didn't noticeably contribute to the final quality.

We used is averaging the predictions of 5 neural networks with the same architecture and training procedure, but different initialization. After averaging the prediction we removed predictions (if they appear) from the first and the last 5 slices along the vertical axis.

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