Multi-scale Patch-wise 3D CNN for Ischemic Stroke Lesion Segmentation

Yilin Niu[1,2], Enhao Gong †[1], Junshen Xu[1,3] John Pauly[1], and Greg Zaharchuk*[4]

[1] Department of Electrical Engineering, Stanford, CA, 94085, US,
[2] Department of Computer Science, Tsinghua University, Beijing, China, 100084
[3] Department of Engineering Physics, Tsinghua University, Beijing, China, 100084
[4] Department of Radiology, Stanford, CA, 94085, US

1 Introduction

For the ISLES challenge, we developed a deep network model with patch-wise multi-scale 3D CNN architecture[1]. The selection of this model is based on improved efficiency in utilizing information from the limited MRI dataset available for training.

2 Method

The detailed network structure we are using is shown in the figure 1 below. Compared with traditional CNN networks, our model has three main contributions and features:

3D CNN is used here to more efficiently utilize available spatial information and exploit the relationship between signals in different slices.

Patch-wise approach is used to take in small 3D patches instead of the entire images as input. By using the patch based approach we can avoid using redundant information from entire image to predict a single voxel, assuming the correlation between distant voxels is weak. Another advantage to the patch based approach is to augment the dataset, which avoids overfitting. Training on patches, however, can avoid overfitting by augment each dataset to thousands of patches.

Multi-scale structure is used by taking inputs with different resolutions. Segmentation based on a single scale image is unlikely to generalize since the local information may vary and the contextual information is lost. Here we use two scales of patches to learn both local and global contextual information.

3 Preliminary Results

We separated data prepared for ISLES2017 into two parts: 70% for training and 30% for testing. With proper data augmentation using flipping and rotations, we are able to achieve a mean DICE coefficient of 0.43 ± 0.18 on the testing set.

4 Future Work

To further improve the segmentation, we will explore more architecture options and additional methods to refine the results, such as using CRF and GAN.

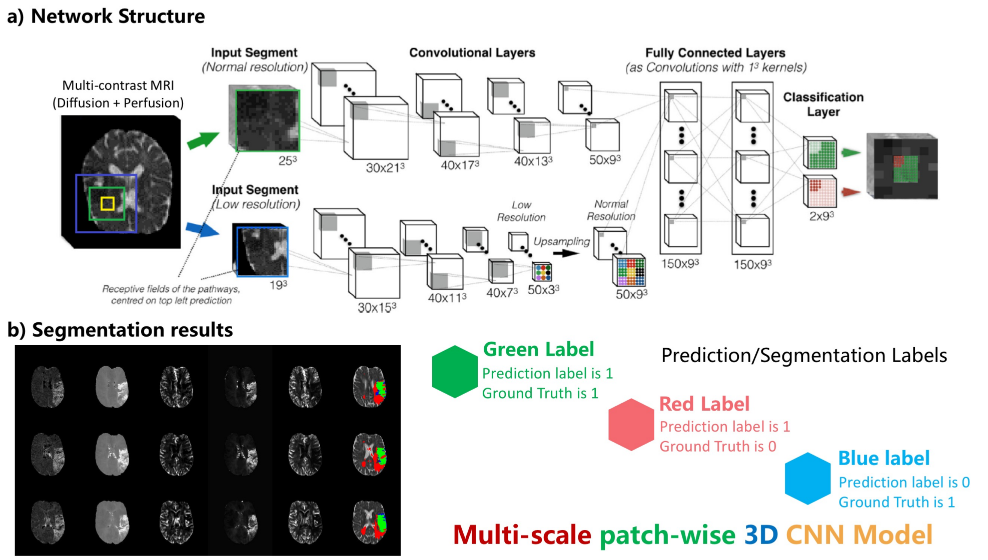

Fig. 1. Network Structure of the Patch-wise Multi-scale 3D CNN model and example segmentation results.

References

1. Kamnitsas, Konstantinos and Ledig, Christian and Newcombe, Virginia FJ and Simpson, Joanna P and Kane, Andrew D and Menon, David K and Rueckert, Daniel and Glocker, Ben : Efficient multi-scale 3D CNN with fully connected CRF for accurate brain lesion segmentation. Medical image analysis. 36, 61–78, (2017)