WMH segmentation challenge MICCAI 2017

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1. Preprocessing

A further preprocessing on the basis of the image initial processing is of great helpful for invariance and robustness in the automated lesion segmentation system. The following steps are used to construct the input feature:

(i) We empirically set a threshold t_f for FLAIR images to create the brain masks. The brain image is obtained by multiplying the T1 and FLAIR images under the pre folder with the brain masks.

(ii) Each training image is first subtracted by its mean and divided from its variance, in order to reduce the variations of input data and speed-up training.

(iii) For each provided image, all the axial slices were cropped or padding to the uniform size $p=192$ automatically. We compute 3D axial volumes by stacking images as $V=[n\times p\times p\times a\times c]$, where n represents the number of volumes, a represents the number of slices in the axial direction and c denotes the number of the available input modality.

2. Network architecture

A large body of literature[1-2] proves that 3D volumes have richer context knowledge. To realize the automated WMH segmentation efficiently, we propose Hybrid Attention - Densely Connected Networks(HA-DCNs), see in Figure 1. Firstly, we adopt 3D U-net architecture[3] as the backbone, extracting high-level characteristics of multi-modal images. Then, the densely-connected operation[4] is introduced at the central layer of the network to improve the utilization of features. Finally, a hybrid attention block is designed during the decoding phase to filter out redundant information[6]. In addition, a focal Tversky loss function[5] is used for the issue of data unbalanced.

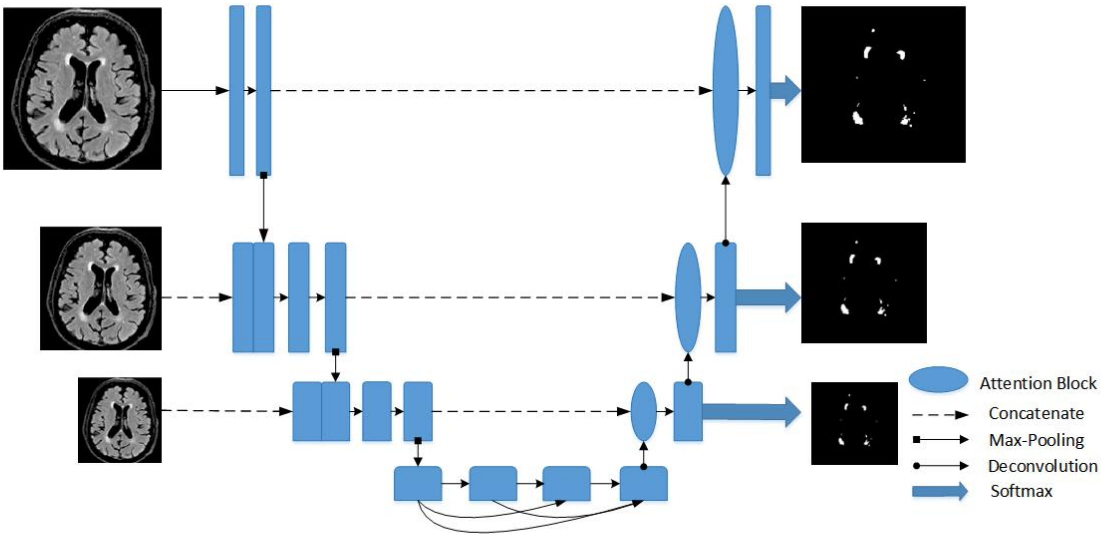

Figure 1: Overview of the hybrid attention - densely connected networks(HA-DCNs).

3. Training

Network parameters of HA-DCNs are learned using the Stochastic Gradient Descent(SGD) with the learning rate of 0.01, the decay of 1E-6, and momentum of 0.9. The number of iteration is 150. The proposed method has been implemented in the Python language, using Keras based on Tensorflflow backend. We performed all experiments on a single GTX 1080TI GPU.

Five stack HA-DCN models with the same architecture were trained with different random initialization value, which is used to improve the performance of segmentation. Then each subject will be segmented based on the averaged probability maps generated by the five HA-DCNs when given a new testing subject.

4. Post-processing

Corresponding to the pre-processing, the post-processing operation restores the output of models to the original image size. The details as follows:

(i) The first 1/8 portion and the last 1/8 portion of the image are all set to non-lesion areas by observing the patient's WMH distribution[7];

(ii) The prediction results is then resized to the original size;

(iii) The prediction results of the overlapping parts of the model are averaged corresponding to the data pre-processing.

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