Segmentation of White Matter Hyperintensities with an Ensemble of Multi-Dimensional Convolutional Gated Recurrent Units

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1 Method overview

Method. Our method is an ensemble of Multi-Dimensional Convolutional Gated Recurrent Units (MD-GRU) [1]. MD-GRUs have significantly less parameters than commonly used U-net methods, which can avoid overfitting on the training dataset. Furthermore, using MD-GRU mimics the slice by slice manual annotation process by considering a spatial dimension as a sequential dimension, and is very adapted for anisotropy.

Dataset. To train our algorithms we used the bias filed corrected (BCR) FLAIR-w MRI and BCR T1-w registered with FLAIR of 60 subjects. We only used images available in the challenge's training set.

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2 Preprocessing

For each modality, the skull is first removed with Brain Extraction Tool [5] with the factional intensity set to 0.4 and the vertical gradient set to -0.4. The images are then split in tiles of 70 * 70 * 22 or 72 * 72 * 24 voxels (depending on the depth of the network) both at train and at test time, with a 50% overlap, to fit in the GPU memory and give a more robust (averaged) prediction. Finally, to be robust to outliers a 1%-99% percentile normalization is applied. Intensity values between 1% and 99% are consequently rescaled between 0 and 1.

3 Recurrent Neural Network

Model. A MD-GRU network takes a multi-channels array of tiles as an input (FLAIR or FLAIR and T1) ; and outputs a single channel array of tile. The architecture is composed of MD-GRU layers linked with channelwise fully

Table 1: Model architectures of the ensemble

	MD-GRU 1	MD-GRU 2	MD-GRU 3
1	y, z both ways	y, z both ways	y, z both ways
2	x, y, z both ways	x, y, z both ways	x, y, z forward
3	x, y, z both ways	x, y, z both ways	x, y, z forward
4	x, y, z both ways	x, y, z both ways	/
5	x, y, z both ways	x, y, z both ways	/

connected layers, as in [1]. Our MD-GRU applies a non padded Convolutional Gated Recurrent Unit [1], with a 2D convolution followed by batch-normalization in several spatial dimensions before summing the outputs. The parameters are optimized with Adadelta [4] with Keras' default learning rate (1.0) and the activation function of the last layer is a sigmoid.

Training. Five models were trained with a Dice loss on randomly selected train and validation splits with different architectures referenced in table 1. The first three models use FLAIR and T1 as input ; the last two use only FLAIR. During training, on-the-fly random translations, rotations and flipping were used. Training one model lasts 1 day on a single GPU.

4 Post-processing

Reconstruction. A reconstruction algorithm transforms the tiled output of a network into a full size output. Overlapping predictions are averaged.

Ensemble of 5 models. After reconstruction, the probabilistic outputs of the five models are averaged. A 0.5 threshold is applied.

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