Adversarial Correction Networks for Brain MRI Segmentation in 2D Manner

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1 Introduction

The development of deep learning techniques has largely improved the state-of-the-art segmentation methods [2, 3, 8]. Recently, fully convolutional networks (FCN) [3] provides a great choice for semantic image segmentation [2–4, 6–9]. Thus, we propose a FCN-like network to automatically segment the brain MRI. Due to a lot of issues in medical image field (small data set size, 3D format and so on), we propose several mechanisms (such as using a transmission module, residual learning module and intermedia-supervision modules) to solve the training problems of the network. Most importantly, we provide an adversarial correction network [1, 5] to evaluate the quality of segmentation network and thus we can improve the training for difficult cases. Dropout is also involved to relieve overfitting. We use generalized dice loss hybrided by softmax loss as the objective function.

This work is done in a 2D manner due to time limit. Personally, it is worth to run the 3D version if time allowed.

2 Experiments

We use MRBrain2018 dataset (see the description in the below paragraph) for training in a leave-one-out manner. And the patch size we extracted for training is 3x192x192. We are planning to evaluate our proposed approach on the test dataset of brain MRI segmentation.

The results on training validation likes (show case 7):

dice1= 0.893537644759 dice2= 0.965670723041 dice3 = 0.914421178163 dice4 = 0.999999997917 dice5 = 0.881257114503 dice6 = 0.983529680882 dice7 = 0.93848676381 dice8 = 0.99472058969 dice9 = 0.0 dice10 = 0.0

And the results on validation validation (show case 1):

dice1 = 0.846024607653 dice2 = 0.837783064583 dice3 = 0.890493967206 dice4 = 0.68446979516 dice5 = 0.827850313027 dice6 = 0.942282799052 dice7 = 0.904149703592 dice8 = 0.754513481823 dice9 = 0.0 dice10 = 0.0

"Image data used in this challenge were acquired on a 3T scanner at the UMC Utrecht (the Netherlands). For each of the 30 subjects, fully annotated multi-sequence (T1-weighted, T1-weighted inversion recovery and T2-FLAIR) scans are available. The 30 subjects include patients with diabetes, dementia and Alzheimers, and matched controls (with increased cardiovascular risk) with varying degrees of atrophy and white matter lesions (age $>$ 50)."

References

[1] Ian Goodfellow and et al.. Generative adversarial nets. In *NIPS*, 2014.

[2] Konstantinos Kamnitsas, Christian Ledig, Virginia FJ Newcombe, Joanna P Simpson, Andrew D Kane, David K Menon, Daniel Rueckert, and Ben Glocker. Efficient multi-scale 3d cnn with fully connected crf for accurate brain lesion segmentation. *Medical Image Analysis*, 36:61–78, 2017.

[3] Jonathan Long and et al.. Fully convolutional networks for semantic segmentation. In *CVPR*, pages 3431–3440, 2015.

[4] Fausto Milletari and et al.. V-net: Fully convolutional neural networks for volumetric medical image segmentation. In *3DV*, pages 565–571. IEEE, 2016.

[5] Dong Nie, Roger Trullo, Caroline Petitjean, Su Ruan, and Dinggang Shen. Medical image synthesis with context-aware generative adversarial networks. *arXiv preprint arXiv:1612.05362*, 2016.

[6] Dong Nie, Li Wang, Ehsan Adeli, Cuijin Lao, Weili Lin, and Dinggang Shen. 3-d fully convolutional networks for multimodal isointense infant brain image segmentation. *IEEE Transactions on Cybernetics*, 2018.

[7] Dong Nie, Li Wang, Yaozong Gao, and Dinggang Sken. Fully convolutional networks for multi-modality isointense infant brain image segmentation. In *2016 IEEE 13th International Symposium on Biomedical Imaging (ISBI)*, pages 1342–1345. IEEE, 2016.

[8] Olaf Ronneberger and et al.. U-net: Convolutional networks for biomedical image segmentation. In *MICCAI*, pages 234–241. Springer, 2015.

[9] Lequan Yu and et al.. Volumetric convnets with mixed residual connections for automated prostate segmentation from 3d mr images. In *AAAI*, 2017.