DASN: Data-Aware Skilled Network for Accurate MR Brain Tissue Segmentation

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Abstract

Accurate segmentation of MR brain tissue is a crucial step for diagnosis, surgical planning, and treatment of brain abnormalities. Automatic and reliable segmentation methods are required to assist doctors. Over the last few years, deep learning especially deep convolutional neural networks (CNNs) have emerged as one of the most prominent approaches for image recognition problems in various domains. But the improvement of deep networks always needs inspiration, which is rare for the ordinary. Until now, there have been reasonable MR brain tissue segmentation methods, all of which can achieve promising performance. These different methods have their own characteristic and are distinctive for data sets. In other words, different models performance vary widely on the same data sets and each model has what it is skilled in. It is on the basis of this, we propose a judgement to distinguish data sets that different models are good at. With our method, the segmentation accuracy can be improved easily based on the existing models, neither without increasing training data nor improving the network. We validate our method on the widely used IBSR 18 dataset and obtain average dice ratio of 88.06%, while it is 85.82% and 86.92% when only using separate one model respectively.

Keywords: image segmentation, brain tissue, MRI, convolutional neural network, data-aware skilled network

1 Introduction

Both the central nervous system degenerative disease and epilepsy are related to the morphological changes in the brain tissue. The accurate segmentation of the brain tissue is the first step in the volume and quantitative analysis of the brain. It is important for the diagnosis and treatment of brain diseases, especially the neurodegenerative diseases.

MRI can be more clearly and safer to display the structure of the brain because of its non-invasive, non-radioactive, free selection profile, higher signal to noise ratio, and higher resolution of the soft tissue with smaller density difference, so as to provide more information for the pathological diagnosis of brain diseases. It has become a common method for the examination of brain diseases. In medical institutions, when doctors get the MRI images of the patients, they often need to judge whether the patient’s brain atrophies by their experience. When dividing the MRI brain tissue, it is necessary to sketch each slice, which is not only time-consuming, but also very tiring. At the same time, it is easy to produce fatigue error. On the other hand, in remote areas and hospitals, with
insufficient medical resources and lack of experienced doctors, segmentation of MRI images has become a difficult problem.

Computer aided diagnostic technology (CAD) is used to help doctors diagnose patients through a computer, thus reducing the burden for doctors and improving the efficiency and accuracy of diagnosis. This technique has been applied to a variety of medical diagnosis problems, and an automatic segmentation method which can provide high precision near the expert segmentation standard, is urgently needed to assist the doctor.

The traditional MR brain tissue segmentation algorithms\cite{4}\cite{3}\cite{8}\cite{5} use artificial designed features and classifies the extracted features. However, the gray level changes of the MR brain images are large and the gray values of different types are not very different. This image feature leads to the complexity of features extraction and the difficulties to artificially design satisfactory features, which makes the segmentation results still have long way to go.

With the popularity of deep learning algorithms in the field of computer vision, more and more people begin to use convolution neural networks to classify, detect and segment images, which have achieved shocking effects in the field of natural images. The same work is being done in medical field and has become a hot topic.

Many scholars have proposed many MR image segmentation methods based on convolution neural network \cite{13}\cite{7}\cite{6}\cite{1} and these methods have also achieved good results. But without exception, these methods performances are very different in different data sets. In other words, different models performance vary widely on the same data sets and each model has what it is skilled in. It is of great significance in medical field of data scarcity that how to exploit the aspects that different methods are good at, to strengthen the combination of precision and not to improve the network or to increase the data sets. It is on the basis of this, we propose a judgement to distinguish data sets that different models are good at and an accurate segmentation method of MR brain tissue based on two existing deep learning models is proposed.

The remainder of this paper is organized as follows. In section 2, we present our method. Experiments and results are detailed in section 3. Finally, the discussion and the main conclusions are presented in section 4 and section 5 separately.

2 Method

In this paper, we propose our method based on the modified U-Net\cite{11} and VoxRes-Net\cite{2}. The process of the proposed method is below.
2.1 Pre-processing

Firstly, the N4ITK is used to correct the bias field in each MRI sequence and the intensities are linearly transformed to $[0, 1]$. To limit the number of voxels considered in the classification, brains masks were generated with BET [10]. In each of the experiments, the samples from the training images were only selected from within the brain masks volumes. For each test image, only voxels within the brain mask volume were considered in the classification.

2.2 Judgement

We calculate the histogram of each volume and judge whether this volume will be segmented better with the VoxResNet model[2]. The judgement is below.

\[
\begin{align*}
  x_n - x_{n-1} &> \frac{1}{x_N} \quad (1) \\
  y_n &\geq 0.8 \times y_{n-1} \quad (2) \\
  x_n &\leq 0.8 \times x_N \quad (3)
\end{align*}
\]

while $(x_n, y_n)$ is the coordinate of peak point $P_n$, $n$ is the amount of peak(always $n \geq 2$), $(0, x_N)$ is the range of the abscissa.

The schematic diagram is as follows.

Figure 1: The overview of Data-Aware Skilled Network
If the input volume meets the judgements above, we sent it to the VoxResNet model and if not, we sent it to the modified U-Net model. It is important to note that the two models have been trained on the same training sets.

2.3 Network architecture

2.3.1 Modified U-net

![U-Net diagram](image)

Different from the purely U-net, our network can segment CSF, GM and WM three tissues at once because we use our own loss function below.

$$L(y, y') = 4 - \sum_{i=0}^{3} DSC(y_i, y'_i)$$

(4)

where $y_i$ and $y'_i$ are predicted and ground-truth for class i, respectively.

In the stage of segmentation reconstruction, we found the maximum probability among four classes and returned the corresponding label for each voxel rather than finding the optimized threshold. At the same time, the shape of output is the same as input owing to the use of padding.
2.3.2 VoxResNet [2]

It consists of stacked residual modules (i.e., VoxRes module) with a total of 25 volumetric convolutional layers and 4 deconvolutional layers, which is the deepest 3D convolutional architecture so far. The details can be found in [2].

3 Results

We validate our method on the widely used IBSR 18 dataset. To avoid accidental error, we train the two model on several different training sets. The evaluation criterion is the three brain tissue (including CSFGMWM) average DCS (dice coefficient), which is defined by:

\[
DSC = \frac{2TP}{2TP + FP + FN}
\]

Table 1: Testing sets result of different methods with different training sets

| Method     | Training set 1 | Training set 2 | Training set 3 | Training set 4 |
|------------|----------------|----------------|----------------|----------------|
| VoxResNet  | 0.8552         | 0.8393         | 0.8439         | 0.8692         |
| Modified U-net | 0.8645      | 0.8514         | 0.8771         | 0.8582         |
| Ours       | **0.8713**     | **0.8638**     | **0.8796**     | **0.8806**     |

4 Discussion

According to an ancient Chinese saying, sometimes a foot may prove short while an inch may prove long. Every model should has its own advantages and disadvantages. Finding the advantages of every model and making best use of the advantages to achieve megamerger are good ways of...
thinking, which have broad prospects.

In this paper, we achieved promising segmentation results based on exiting two models only by designing a simple judgement of histogram. In our future research, we will use more deep learning models and make a more accurate judgment by calculate the features of every sequence like [12][14] rather than the whole patient volume. Moreover, we can propose more stable judgement such as texture features, shape features and spatial relationships to distinguish different data sets, which are special for skilled model.

We believe that our thinking is also applicable in other various domains not limited to MR brain tissue segmentation and expect more researches to make a contribution in this area.

5 Conclusions

In this paper, we design a data-aware skilled network that can select the data sets that different deep learning models are good at and achieve more accuracy segmentation without changing the net or enhancing the data.

References

[1] S. Bao and A. C. S. Chung, “Multi-scale structured cnn with label consistency for brain MR image segmentation,” pp. 1–5, 2015.

[2] H. Chen, Q. Dou, L. Yu, J. Qin, and P. A. Heng, “Voxresnet: Deep voxelwise residual networks for brain segmentation from 3d MR images,” Neuroimage, vol. 170, 2017.

[3] I. Despotovi?, B. Goossens, and W. Philips, “MRI segmentation of the human brain: challenges, methods, and applications.” Computational and Mathematical Methods in Medicine, 2015(2015-3-1), vol. 2015, no. 6, pp. 1–23, 2015.

[4] H. Greenspan, A. Ruf, and J. Goldberger, “Constrained gaussian mixture model framework for automatic segmentation of MR brain images,” IEEE Transactions on Medical Imaging, vol. 25, no. 9, pp. 1233–45, 2006.

[5] J. L. Marroquin, B. C. Vemuri, S. Botello, F. Calderon, and A. Fernandez-bouzas, “An accurate and efficient bayesian method for automatic segmentation of brain MRI,” IEEE Transactions on Medical Imaging, vol. 21, no. 8, p. 934, 2002.

[6] P. Moeskops, M. A. Viergever, A. M. Mendrik, L. S. de Vries, M. J. Benders, and I. Isgum, “Automatic segmentation of MR brain images with a convolutional neural network.” IEEE Transactions on Medical Imaging, vol. 35, no. 5, pp. 1252–1261, 2016.

[7] D. Nie, L. Wang, Y. Gao, and D. Shen, “Fully convolutional networks for multi-modality isointense infant brain image segmentation,” Proc IEEE Int Symp Biomed Imaging, vol. 108, pp. 1342–1345, 2015.

[8] Z. Qin, F. Wang, Z. Xiao, T. Lan, and Y. Ding, “Brain tissue segmentation with the gka method in MRI,” in IEEE International Conference on Signal and Image Processing, 2017, pp. 273–276.

[9] O. Ronneberger, P. Fischer, and T. Brox, U-Net: Convolutional Networks for Biomedical Image Segmentation. Springer International Publishing, 2015.

[10] S. M. Smith, “Fast robust automated brain extraction,” Human Brain Mapping, vol. 17, no. 3, pp. 143–155, 2002.

[11] D. Yang, S. Yao, Y. Zhu., M. Zhu., and Y. Kehong, “A strategy of MR brain tissue images suggestive annotation based on modified U-Net,” arXiv:1807.07510[cs.CV], 2018.

[12] K. Yuan, Z. Tian, J. Zou, Y. Bai, and Q. You, “Brain CT image database building for computer-aided diagnosis using content-based image retrieval,” Information Processing & Management, vol. 47, no. 2, pp. 176–185, 2011.
[13] W. Zhang, R. Li, H. Deng, L. Wang, W. Lin, S. Ji, and D. Shen, “Deep convolutional neural networks for multi-modality isointense infant brain image segmentation,” *Proc IEEE Int Symp Biomed Imaging*, vol. 108, pp. 1342–1345, 2015.

[14] J. Zou, “Research on content-based brain CT image retrieval for computer aided diagnosis,” *Master’s degree thesis of Tsinghua University*, 2009.