SEGMENTATION-BASED METHOD COMBINED WITH DYNAMIC PROGRAMMING FOR BRAIN MIDLINE DELINEATION

Shen Wang, Kongming Liang, Chengwei Pan, Chuyang Ye, Xiuli Li, Feng Liu, Yizhou Yu, Yizhou Wang

1Center for Data Science, Peking University, Beijing, China; 2Deepwise AI Lab, Beijing, China
3Computer Science Department, School of EECS, Peking University, Beijing, China
4Center on Frontiers of Computing Studies, Peking University, Beijing, China
5Advanced Institute of Information Technology, Peking University, Beijing, China
6School of Information and Electronics, Beijing Institute of Technology, Beijing, China

ABSTRACT

The midline related pathological image features are crucial for evaluating the severity of brain compression caused by stroke or traumatic brain injury (TBI). The automated midline delineation not only improves the assessment and clinical decision making for patients with stroke symptoms or head trauma but also reduces the time of diagnosis. Nevertheless, most of the previous methods model the midline by localizing the anatomical points, which are hard to detect or even missing in severe cases. In this paper, we formulate the brain midline delineation as a segmentation task and propose a three-stage framework. The proposed framework firstly aligns an input CT image into the standard space. Then, the aligned image is processed by a midline detection network (MD-Net) integrated with the CoordConv Layer and Cascade AtrousConv Module to obtain the probability map. Finally, we formulate the optimal midline selection as a pathfinding problem to solve the problem of the discontinuity of midline delineation. Experimental results show that our proposed framework can achieve superior performance on one in-house dataset and one public dataset.

Index Terms—Brain midline delineation, Computer-aided diagnosis, Segmentation, Dynamic programming

1. INTRODUCTION

The anatomical structure of the human brain consists of two symmetrical hemispheres, which are separated by the ideal midline (as shown in Fig. 1). In general, midline structures in the non-contrast CT images are often associated with high intracranial pressure. Therefore, they provide abundant information for physicians to make an accurate diagnosis on the severity of stroke or TBI e.g. Immediate surgery may be indicated when there is a midline shift of over 5 mm.

Automated midline delineation can quantify midline shift and speed up brain interpretation and decision making of emergency physicians. Since the brain CT reading reliability of the emergency physicians is often questioned, the quantification results of the midline can improve the assessment of stroke or TBI. Combined with other information (e.g. gender, age), the pathological image features related to midline can benefit the clinical diagnosis and prognosis treatment.

Previous methods mainly focus on localizing the predefined points or parts based on anatomical information of the human brain. Liao et al. [3] proposed a deformed midline model according to the biomechanical properties of intracranial tissue. Chen et al. [4] estimated the position of the midline using shape matching among multiple regions. Similarly, Qi et al. [5] presented a variational level set to extract the ventricle contours. Then the position of midline was detected based on the identified right and left lateral ventricle contours. Liu et al. [6] proposed to delineate the midline by automatically localizing the anatomical points. However, in severe cases (see Fig 1), the predefined anatomical points or parts of the human brain may not be visible which limits the above methods. Besides, the detected midline referring to anatomical points is usually not smooth and decreases the quantification quality for an accurate diagnosis.

To address such issues, we formulate the brain midline
delineation as a segmentation task and propose a novel three-stage framework. By modeling the midline in a pixel-wise way, our method can accurately quantify the pathology features which are essential for clinical applications. Besides, based on the UNet [7], we propose to inject a CoordConv Layer to leverage the spatial information of brain midline and a Cascade AtrousConv Module to enlarge the receptive field for the further refinement. Moreover, we formulate the optimal midline selection as a pathfinding problem to solve the problem of the brain midline discontinuity. This strategy can be applied to other segmentation tasks with geometric constraints. Experimental results show that our proposed framework achieves superior performance and promising generalization ability on automatic midline delineation.

2. METHOD

Our proposed framework is illustrated in Fig. 2. It comprises three stages: image alignment, midline segmentation and pathfinding. In the following sections, we will introduce each stage in detail.

2.1. Alignment

Due to the variations of patients’ head positions during CT scanning, the relative position of the brain in the CT image is usually not consistent. As the midline delineation is sensitive to the location information, we attempt to align the image to the standard space. We first use a standard UNet [7] to estimate the initial midline structure. Consequently, the two endpoints (S and E in Fig. 2) of the midline can be located to calculate the offset angle and the brain center. We can align the original CT image by an affine transformation of translation and rotation so that the semantics of pixels in CT of different directions can be aligned.

2.2. Midline Detection Network

Our proposed midline detection network (MD-Net) is based on the UNet. We adopt the CoordConv Layer for spatial information modeling, which is set as the first layer of the encoder. Besides, a Cascade AtrousConv Module is added to the highest semantic level feature, which can enlarge the receptive field remarkably.

CoordConv Layer. The midline is the junction of the two hemispheres, which is highly correlated to position information. In this part, we adopt the coordination-guided convolutional layers (CoordConv Layer) [8] to model the spatial information. The CoordConv is a simple extension to the classic convolutional layer, which integrates position information by concatenating extra coordinate channels. Two extra channels are added respectively to represent x, y coordinates of the input. The values of coordination channels are normalized to the range from -1 to 1.

Cascade AtrousConv Module. Atrous convolutions are widely used for semantic segmentation [9], which increase the receptive field while keeping the feature map resolution unchanged. The receptive field of the encoder in the standard UNet is 140×140, only covering part of the input CT image, which may neglect the importance of global context information on midline segmentation. Therefore, we propose a Cascade AtrousConv Module to explore a larger receptive field (620×620, covering the full image 512×512), as shown in Fig. 3.

Loss Function. Cross entropy is a classic loss function in semantic segmentation tasks. Dice coefficient loss can alleviate the problem of sample imbalance to a certain extent. So we combine the weighted cross-entropy and dice loss as the
3. EXPERIMENTS

3.1. Datasets and Evaluation Metrics

Datasets. The proposed models are evaluated on one in-house dataset and one public dataset CQ500\footnote{http://headctstudy.qure.ai/dataset}. For the in-house dataset, we collected 877 non-contrast head CT scans with 5-mm slice thickness from three hospitals. The dataset is randomly split into a train/val/test set of 708/87/82 stacks and the number of scans with midline shift is 207/44/42 respectively. For the public dataset CQ500, we choose 235 CT scans (53 midline shift) with around 5-mm slice thickness. One senior radiologist marks all the CT scans as the gold standard.

Evaluation Metrics. The Dice coefficient, Hausdorff Distance (HD) and average symmetric surface distance (ASD) are the three most commonly used evaluation metrics in medical image segmentation\cite{10, 11}. In the midline delineation task, we need to measure the distance between the predicted midline and the actual midline which can not be well gauged by the Dice coefficient. Therefore, we choose the HD and ASD as the evaluation metrics.

3.2. Implementation details

For image preprocessing, three adjacent slices are stacked as the input to model the inter-slice information and the image densities are normalized using the brain window. The midline ground truth is expanded to a band with 5-pixel width. We use Adam to train the model by setting $\beta_1 = 0.9$, $\beta_2 = 0.99$ for 100 epochs. The initial learning rate is 0.001. The poly learning rate policy is employed where the initial learning rate is multiplied by $(1 - \frac{iter}{total_{iter}})^{power}$ with power = 0.9. Our implementation is based on Pytorch package.

3.3. Results

Table 1: Comparison of the alignment and pathfinding stage in the proposed framework.

| Method  | Alignment | Pathfinding | HD          | ASD         |
|---------|-----------|-------------|-------------|-------------|
| UNet    | ✓         | ✓           | 4.62(6.29)  | 1.45(1.07)  |
| UNet    | ✓         | ✓           | 3.54(4.18)  | 1.60(0.77)  |
| UNet    | ✓         | ✓           | 2.44(2.88)  | 0.83(0.68)  |

Ablation study. In this section, we set the UNet\cite{21} as the baseline method, which is widely used in the medical image segmentation. The quantitative performance is in terms of mean \pm std of HD (mm) and ASD (mm) index. We conduct ablation experiments to investigate the proposed three components: alignment, segmentation and pathfinding. All ablation experiments are evaluated on the in-house test set.

Firstly, we verify the effectiveness of the alignment and pathfinding stage. As shown in Table\footnote{1} the alignment of input...
images can greatly improve the performance. In the pathfinding phase, the performance can be further improved by post-processing the probability map with dynamic programming. Secondly, we add each of the proposed modules to baseline independently. Meanwhile, the input images are aligned. As shown in Table 2, the modules we proposed can improve the performance to a certain extent. Combining all modules, our proposed MD-Net achieves the best results.

As shown in Fig. 4(b), baseline methods suffer two major issues to correctly delineate brain midline: 1) inaccurate position of the midline and 2) discontinuity of the midline. To address the first issue, we propose the MD-Net with the CoordConv layer and the Cascade AtrousConv module, which can enhance the position discrimination ability and guarantee that segmented midlines are around correct location (see Fig. 4(d)). For the second issue, we propose the pathfinding stage to guarantee the continuity of the midline which is essential in severe cases (see Fig. 4(e)).

**Comparison to the State-of-the-Art Methods.** The encoder-decoder architecture like U-Net [7] and UNet++ [12] has achieved state-of-the-arts in many medical image segmentation tasks. In this section, we compare the proposed MD-Net with the above two methods. As shown in Table 3, our proposed method can achieve superior performance on both the in-house dataset and CQ500 dataset. Finally, our proposed method achieves an average HD of 2.26 (mm) and ASD of 0.81 (mm) in our in-house dataset and an average HD of 2.58 (mm) and ASD of 0.72 (mm) in our in-house dataset.

**Table 3: Performance comparison of our method with other methods.** "*" means the output probability map is post-processed during pathfinding stage.

| Method          | In-house     | CQ-500       |
|-----------------|--------------|--------------|
|                 | HD           | ASD          | HD            | ASD            |
| UNet [7]        | 3.54(4.18)   | 1.60(0.77)   | 3.26(3.26)    | 1.67(0.66)     |
| UNet++[12]      | 3.46(3.86)   | 1.57(0.75)   | 3.59(4.82)    | 1.68(0.76)     |
| Ours(MD-Net)    | 2.93(1.68)   | 1.49(0.65)   | 3.08(2.72)    | 1.58(0.63)     |
| Ours(MD-Net*)   | 2.26(1.71)   | 0.81(0.57)   | 2.58(2.54)    | 0.72(0.53)     |

**4. CONCLUSION**

We propose a novel framework of midline delineation on non-contrast head CT scans, which consists of three stages: alignment, segmentation and pathfinding. Firstly, we align an input CT image into the standard space. Secondly, the MD-Net is proposed to enhance the position discrimination ability. Thirdly, the output probability map is post-processed to guarantee the continuity of the midline by using dynamic programming. Finally, experimental results demonstrate the superior performance of proposed method on both the in-house dataset and the CQ500 dataset.
5. REFERENCES

[1] Po-Hsun Tu, Zhuo-Hao Liu, Chi-Cheng Chuang, Tao-Chieh Yang, Chieh-Tsai Wu, and Shih-Tseng Lee, “Postoperative midline shift as secondary screening for the long-term outcomes of surgical decompression of malignant middle cerebral artery infarcts,” Journal of Clinical Neuroscience, vol. 19, no. 5, pp. 661–664, 2012.

[2] Ali Arhami Dolatabadi, Alireza Baratloo, Alaleh Rouhipour, Ali Abdalvand, Hamidreza Hatamabadi, Mohammadmehdi Forouzanfar, Majid Shojaee, and Behrooz Hashemi, “Interpretation of computed tomography of the head: emergency physicians versus radiologists,” Trauma monthly, vol. 18, no. 2, pp. 86, 2013.

[3] Chun-Chih Liao, I-Jen Chiang, Furen Xiao, and Jau-Min Wong, “Tracing the deformed midline on brain ct,” Biomedical Engineering: Applications, Basis and Communications, vol. 18, no. 06, pp. 305–311, 2006.

[4] Wenan Chen, Kayvan Najarian, and Kevin Ward, “Actual midline estimation from brain ct scan using multiple regions shape matching,” in 2010 20th International Conference on Pattern Recognition. IEEE, 2010, pp. 2552–2555.

[5] Xuguang Qi, Automated midline shift detection on brain CT images for computer-aided clinical decision support, Virginia Commonwealth University, 2013.

[6] Ruizhe Liu, Shimiao Li, Bolan Su, Chew Lim Tan, Tze-Yun Leong, Boon Chuan Pang, CC Tchoyoson Lim, and Cheng Kiang Lee, “Automatic detection and quantification of brain midline shift using anatomical marker model,” Computerized Medical Imaging and Graphics, vol. 38, no. 1, pp. 1–14, 2014.

[7] Olaf Ronneberger, Philipp Fischer, and Thomas Brox, “U-net: Convolutional networks for biomedical image segmentation,” in International Conference on Medical image computing and computer-assisted intervention. Springer, 2015, pp. 234–241.

[8] Rosanne Liu, Joel Lehman, Piero Molino, Felipe Petroski Such, Eric Frank, Alex Sergeev, and Jason Yosinski, “An intriguing failing of convolutional neural networks and the coordconv solution,” in Advances in Neural Information Processing Systems, 2018, pp. 9628–9639.

[9] Liang-Chieh Chen, George Papandreou, Iasonas Kokkinos, Kevin Murphy, and Alan L Yuille, “Semantic image segmentation with deep convolutional nets and fully connected crfs,” arXiv preprint arXiv:1412.7062, 2014.

[10] Bjoern H Menze, Andras Jakab, Stefan Bauer, Jayashree Kalpathy-Cramer, Keyvan Farahani, Justin Kirby, Yuliya Burren, Nicole Porz, Johannes Slotboom, Roland Wiest, et al., “The multimodal brain tumor image segmentation benchmark (brats),” IEEE transactions on medical imaging, vol. 34, no. 10, pp. 1993–2024, 2014.

[11] Qian Yue, Xinzhe Luo, Qing Ye, Lingchao Xu, and Xiahai Zhuang, “Cardiac segmentation from lge mri using deep neural network incorporating shape and spatial priors,” arXiv preprint arXiv:1906.07347, 2019.

[12] Zongwei Zhou, Md Mahfuzur Rahman Siddiquee, Nima Tajbakhsh, and Jianming Liang, “Unet++: A nested u-net architecture for medical image segmentation,” in Deep Learning in Medical Image Analysis and Multimodal Learning for Clinical Decision Support, pp. 3–11. Springer, 2018.