Deep-learning based Significant Stenosis detection from Multiplanar reformatted Images of traced Intracranial arteries

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Synopsis

Intracranial stenosis is one of the most common causes of stroke worldwide. We presented a novel framework for automatic significant intracranial artery stenosis detection for both CTA and MRA images. We improved an artery tracing technique so that the combined CTA/MRA dataset can be used to train a more robust stenosis detection model. We utilized Multi-Planar Reformation (MPR) view for arteries to improve the performance in stenosis detection. Our experiments demonstrate the generalization of our model in a limited dataset containing 30 patients.

Introduction

intracranial atherosclerosis and stenosis is one of the most common causes of stroke worldwide[1]. Clinically, both Magnetic Resonance Angiography (MRA) and Computed Tomography (CTA) can be used to detect stenosis in the arteries. However, it is time-consuming for a radiologist to manually analyze the MRA/CTA images because of the usually large 3D dataset, complex arterial anatomy and the potential of having multiple sites of stenosis.. An automated method capable of identifying intracranial stenosis would help to facilitate clinical evaluation.

To date, there is a paucity of literature on automated intracranial stenosis detection algorithms. A challenge unique to this task is that intracranial arteries (ICA) are tortuous and have variable anatomy. We propose to extract the artery centerline to narrow down the search region for stenosis detection using intracranial artery tracing methods. Furthermore, tracing methods[3] exist for arteries from MRA, but for its adaptation to CTA data, additional steps are required such as skull-stripping.

In this study, we present a deep-learning based framework for automatic ICA stenosis detection using Multi-planar reformatted (MPR) MRA images. We further expand the framework on CTA to better leverage the multi-modality data for developing a more generalized and robust model for stenosis detection.

Methods

Figure. 1 shows our overall pipeline.

Arteries of interest are traced using an ICA tracing method[4]. For tracing on CTA, several steps are additionally required. We adopted a skull-striping method[5] to extract brain region from CTA images, which is based on the contour evolution technique.
To reduce spurious branches or fragments after artery tracing, we introduced an optimizing algorithm which is described as following:
(1) A vessel centerline is considered to be spurious when the weighted sum of its average intensity and length is less than a threshold.
(2) The short segment with dramatic direction change (>= 60 degrees) at the end of the vessel is removed.
(3) The centerline stretches forward when the intensity decrease is below a specific ratio and connects to another if a collision with another vessel happens.
Manual editing is then performed to ensure the tracing quality.

Stenosis Classification Network

With the centerline extracted by iCafe, the artery is partitioned into segments with a length of 40XX pixels, and a set of MPR views of the segments are generated by 3D Curved Multi-Planar reformation[6].
We build a deep-learning network to classify a single MPR view into significant stenosis (luminal narrowing ≥ 50%) or non-significant stenosis (narrowing <50%). Figure 3 shows an overview of our network. This network is trained on single MPR views.
Then, for each vessel segment, we classify each of the six MPR views with this trained network. A voting mechanism is used to decide if the stenosis exists: if equal or more than N MPR views of the artery was classified as stenosis (N as voting number), this segment is considered stenotic. Figure 4 shows our artery segment classification framework. (five is chosen according to the experiment results in Figure 5, Tab2)

Evaluation

Dataset

We evaluated our method with a dataset of clinical intracranial MRA scans of 15 patients (23 significant stenoses) and CTA scans of 15 patients (20 significant stenosis). We focused on the non-calcified stenosis in the main arteries (MCA, ACA, BA, and PCA) due to imaging resolution. Data augmentation is performed by vertical and horizontal flipping. After the centerline extraction and MPR generation, our training dataset contains a total of 5784 MPR views (64% MRA, 36% CTA, 50% with stenosis) from 964 artery segments. Each slice of the MPR volume was provided an annotation by two experienced radiologists. We adopted the cross-validation strategy, in which 20 percent of arteries were randomly selected for evaluation while the rest were used for training.

We trained the stenosis detection model using CTA, or MRA data alone and combined CTA/MRA data. The following metrics were used in evaluation: sensitivity, specificity, and accuracy. We considered MPR view with stenosis as positive, without stenosis as negative.

We also evaluated the detection performance with voting number from 1 to 6.

Results

The results are shown in Figure. 5.
Table 1 illustrates the classification performance of our proposed network, where we test with different data settings. The best result is achieved when CTA and MRA images are combined.
Table 2 provides an indication of the performance of our framework for recognizing a single vessel segment under different voting number.

Discussion

In this work, we have several contributions, (1) We improved an artery tracing technique for centerline generation for both CTA and MRA images, so that the combined dataset can be used to train a more robust stenosis detection model. (2) We utilized the Multi-Planar Reformation(MPR) view for arteries to improve the performance in stenosis detection. The results in Figure 5 Table 1 demonstrate the generalization ability of our model.

Conclusion

A deep-learning based framework for automatic intracranial artery stenosis detection was developed for both CTA and MRA. It is a promising technique to provide diagnosis assistance for radiologists to reduce their workload in artery review.

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Figures

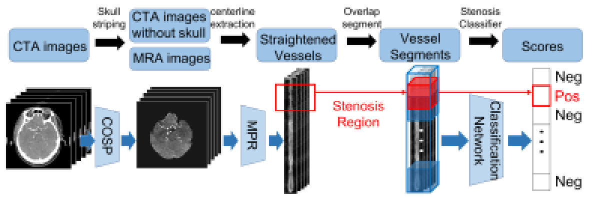

Fig 1. Overview of our proposed pipeline.

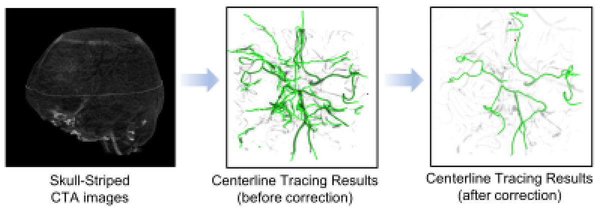

Fig. 2 Centerline tracing results of skull-striped CTA. This figure shows the results of our automatic optimizing algorithm. (Correction includes both the automatic optimizing algorithm and necessary manual adjustments).

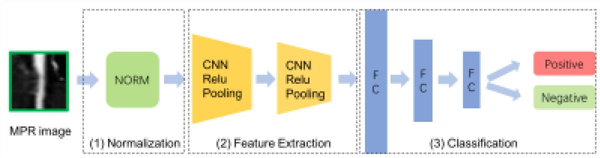

Fig. 3 The stenosis classification network. (1) normalize the input image with mean and standard deviation, (2) extract features by the convolutional network, (3) classify the stenosis with three fully connected networks.

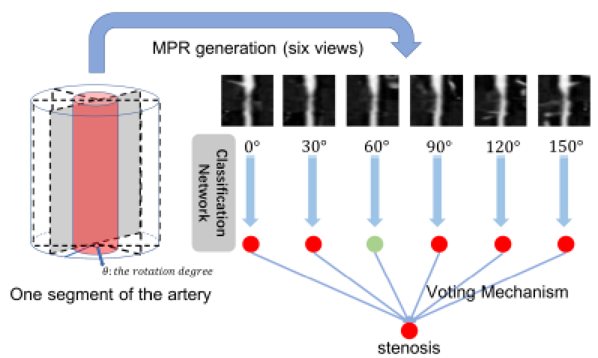

Fig. 4 Artery segment classification framework: six MPR views with different degrees are generated. Each view is classified by one shared classification network to be stenosis (red dot) or non-stenosis (red dot). Voting mechanism: If five or more images are classified as stenosis, this artery segment is considered having stenosis.

Table 1. Performance of classification model on different data setting.

Method	*Se*	*Sp*	*Acc*	Dataset
MRA+AUG	37.68	85.42	62.29	15 patients
CTA+AUG	35.51	83.33	60.86	15 patients
MRA+CTA	62.86	71.53	66.44	30 patients
MRA+CTA+AUG	**68.21**	**71.70**	**70.51**	30 patients

Table 2. Performance of framework under different voting number.

Voting number	*Se*	*Sp*	*Acc*
1	**85.71**	41.67	67.80
2	80.00	54.17	69.49
3	77.14	58.33	69.49
4	71.43	70.83	71.19
5	71.43	79.17	**74.58**
6	62.86	**87.50**	72.88

Fig. 5 Tab1 shows the performance of our model, trained separately on MRA, CTA, MRA + CTA, MRA + CTA + data augmentation. Tab2 shows the performance of our pipeline on different voting numbers. (voting number is the threshold to determine whether the stenosis exist in the segment from multiple angles of MPR)