Brain Blood Vessel Segmentation based on Region Growing and U-net Neural Network

Lingsong Huang*, Haoquan Wang
School of Information and Communication Engineering, North University of China, Taiyuan, Shanxi, China
**Corresponding Author.*

Abstract: Aiming at the problems of insufficient feature extraction in existing deep learning-based cerebrovascular segmentation methods and uneven segmentation results when the original imaging quality is poor, a cerebrovascular segmentation method that integrates region growing and an improved U-net neural network is proposed. Based on the deep learning segmentation results, automatic seed point selection for region growing is performed and fused to improve the segmentation accuracy at the pixel level. In this work, the integrated segmentation method improves the Dice coefficient from 0.805 to 0.878 and the Average Hausdorff Distance (AHD) from 3.949 to 0.903 compared to the deep learning segmentation method.

Keywords: Cerebrovascular Segmentation; U-net Neural Network; Region Growing; Fusion Method

1. Introduction

Cerebrovascular disease is one of the serious health problems worldwide. For example, stroke and aneurysm are often related to structural abnormalities of cerebrovascular vessels. Accurate analysis and identification of the morphology and structure of cerebrovascular vessels are of great significance for the early diagnosis and treatment of diseases. Magnetic resonance angiography (MRA) is a widely used imaging technology that can non-invasively observe blood flow in blood vessels and provide important imaging information for the evaluation of cerebrovascular vessels.

However, manual segmentation of cerebrovascular vessels from MRA images is a time-consuming task that requires professionals. Moreover, manual segmentation of cerebrovascular vessels depends on the operator's experience, which may lead to subjectivity in the segmentation results. In recent years, with the development of computer hardware and medical image processing technology, the improvement of computing power has made automatic or semi-automatic image segmentation methods more and more outstanding. Among them, deep learning technology has been widely studied and applied due to its outstanding performance in image recognition and analysis.

In recent years, deep learning has been increasingly widely used in the field of medical image segmentation. In particular, the U-net architecture, due to its unique symmetric structure and jump connection, performs well in small sample learning and undertakes various medical image segmentation tasks, including accurate segmentation of cerebrovascular vessels. U-net can accurately segment cerebral blood vessels from complex MRA images. Using deep learning models such as U-net for cerebral blood vessel segmentation can not only improve the accuracy of segmentation, but also significantly improve the efficiency of segmentation and reduce the workload of doctors. However, the accuracy of deep learning segmentation depends largely on the accuracy of the training and annotation data set. Therefore, a cerebral blood vessel segmentation method that combines traditional segmentation and deep learning is proposed, which has the accuracy of deep learning cerebral blood vessel segmentation and the objectivity of traditional segmentation methods based on the characteristics of the data itself. In this work, the cerebral blood vessel segmentation that combines the two segmentation methods is significantly better than the cerebral blood vessel segmentation that only uses deep learning in the final dice value performance.

2. Related Work

2.1 Traditional Cerebral Vascular Segmentation Method

Before the emergence of deep learning methods, researchers have developed various traditional cerebrovascular segmentation techniques. These methods can be mainly divided into threshold-based, region growing-based and model-based methods [1].

Although the threshold-based method is simple and efficient, the quality of the segmentation result depends heavily on the choice of threshold size. Setting the threshold too high will lead to under-segmentation, while setting the threshold too low will introduce more non-vascular regions and produce over-segmentation. In addition, due to image noise, intensity inhomogeneity and the contrast variation between blood vessels and background, a single threshold is often difficult to meet the segmentation requirements. To solve these problems, some improved methods have been proposed, such as adaptive threshold, multi-threshold [2] and threshold selection based on histogram analysis [3].

The performance of the region growing method depends largely on the selection of seed points and the design of the growing criterion. Improper seed points may lead to the omission of vascular regions or the overgrowth of non-vascular regions. The setting of similarity criteria, such as grayscale threshold and shape constraint, also has an important influence on the segmentation results. In order to improve the robustness of region growing, some studies have introduced strategies such as automatic seed point selection [4] and adaptive growing criterion [5].

Model-based methods describe blood vessels by fitting parameterized geometric models, such as cylinders, tubular structure tensors, and central axis models [6]. Such methods can integrate prior knowledge of blood vessels and have certain robustness to image noise and local anomalies. However, it is still challenging to accurately fit complex and irregular vascular structures. In addition, the initialization and optimization calculation of model parameters are also relatively complex. In order to improve the expressiveness and adaptability of the model, some studies have proposed deformable models based on shape priors, statistical shape models [7], and vascular shape representation based on deep learning.

Although traditional methods have achieved brain vascular segmentation to a certain extent, factors such as complex vascular networks, low contrast, and image artifacts limit their performance. In addition, traditional methods usually rely on manually designed features and heuristic rules, and their generalization ability is limited. In order to further improve segmentation accuracy and robustness, some studies have tried to combine different traditional methods, such as combining thresholds with region growing [8] and combining thresholds with morphological operations [9], to give full play to their respective advantages. However, how to effectively integrate different methods is still a problem worth exploring.

2.2 Application of Deep Learning in Medical Imaging

Convolutional Neural Networks (CNNs) are a commonly used network structure that extracts hierarchical features of images by stacking convolutional layers and pooling layers. CNNs have demonstrated excellent performance in medical image detection, classification, and segmentation tasks [10]. For example, Gulshan et al. [11] used CNN to detect diabetic retinopathy in fundus images, achieving a level comparable to that of professional ophthalmologists. Esteva et al. trained a deep CNN model for skin cancer diagnosis, and its performance was comparable to that of 21 professional dermatologists [12].

In addition to CNNs, some other deep learning architectures such as Generative Adversarial Networks (GANs) have also been applied in medical image processing [13]. For example, Amran Dor used adversarial networks for cerebrovascular vessel segmentation in BV-GAN: 3D time-of-flight magnetic resonance angiography cerebrovascular vessel segmentation using adversarial CNNs, reducing the requirement for image resolution [14].

Among the many deep learning medical image segmentation fields, the U-Net proposed by Ronneberger et al. [15] is also widely used in medical image processing. Its encoder-decoder structure and skip connection design enable it to achieve good segmentation performance even with small samples. U-Net and its variants have mature solutions for the segmentation of various medical images, such as tumors, organs, and blood vessels. For example, Guo et al. used multiple U-net networks to train and infer the 3D slices of the image separately in Cerebrovascular segmentation from TOF-MRA based on multiple-U-net with focal loss function, and then determined the final result based on voting [16].

In addition, some researchers have also explored combining deep learning with traditional methods such as graph theory and morphology to further improve the quality of image segmentation. For example, Liskowski et al. [17] combined deep neural networks with graph cut algorithms to achieve high-quality segmentation of retinal vascular images.

2.3 The Choice between Deep Learning and Traditional Segmentation Methods

At present, U-net has become the first choice or optimized model for more scholars in cerebrovascular segmentation due to its superior performance. As mentioned above, region growing starts from a predefined seed point and continuously merges adjacent pixels into the region according to the similarity criterion between pixels.

The segmented image inferred by the deep learning method is very similar to the annotated image participating in the training. At this time, the coordinate points in the predicted image are selected as the predefined seed points for region growing, which can optimize the point selection process and no longer require manual selection. It can also use region growing to annotate the cerebrovascular parts that may not be inferred by deep learning according to the characteristics of the image itself. In addition, the results inferred by the deep learning model are more inclined to the style of the annotated data set participating in the training. The brain segmentation method integrated with region growing also helps the final result to tend to the cerebrovascular characteristics presented by the original MRA image to a certain extent.

3. Brain Blood Vessel Segmentation Method based on Region Growing and U-net Network

3.1 Dataset Preparation

Since cerebrovascular annotation requires a lot of manpower and resources, open-source cerebrovascular annotation data is very rare. This article uses the time-of-flight (TOF) MRA data provided by the 2023 Cerebral Artery Segmentation Challenge (CAS). The organizer pointed out in the challenge that the challenge task is mainly to segment cerebral arteries from 3D TOF-MRA images obtained from patients with symptomatic intracranial artery stenosis. The main purpose of using this dataset for training and verification in this work is to verify whether the cerebrovascular segmentation method that integrates region growing and deep learning is better than the cerebrovascular segmentation method that uses the U-net neural network alone.

3.2 Model Architecture Design

The neural network framework used in this work uses an improved U-net framework. The model adds a residual network and a Dropout layer to the original structure.

The encoder part consists of four levels, each of which includes two 3D convolutional layers with ReLU activation, followed by a pooling layer with a stride of 2. A Dropout layer is applied after the first convolutional layer. As the encoder goes deeper, the spatial resolution of the feature map is halved, and the number of feature channels is doubled. The number of feature channels at each level is 16, 32, 64, 128, and 256, respectively, and the downsampling stride of each level is 2.

The decoder part gradually restores the original resolution of the image by upsampling the feature map and splicing it with the feature map of the corresponding level of the encoder. Each level includes an upsampling operation, followed by two 3D convolutional layers, the first convolutional layer is followed by a ReLU activation and a Dropout layer, and the second convolutional layer is followed by a ReLU activation.

Between the encoder and the decoder, the bottom layer of the model includes two 3D convolutional layers without pooling operations. Two residual units are used in each encoder and decoder level. Finally, the model uses a 1x1 convolutional layer to map the feature map to binary predictions (i.e., blood vessels and non-blood vessels).

This U-Net model architecture utilizes the encoder-decoder structure to achieve accurate image segmentation through downsampling and upsampling operations and combines multi-scale feature information. The use of dropout layers and residual units helps improve the training stability of the model. The architecture is shown in Figure 1

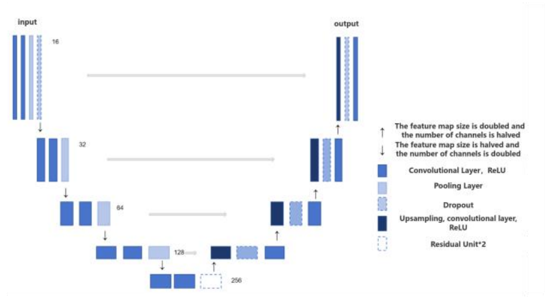

Figure 1. Improved U-net

3.3 Implementation Details

The input image is intensity-scaled and normalized to [0.0, 1.0] to reduce the intensity difference between different images, making the model easier to learn and optimize. Random cropping and random rotation are used to enhance the image data. The cropping space size is [96,96,96]. Five random cropping blocks are generated for each sample. The angle of random rotation does not exceed 90 degrees, the probability of rotation is 50%, and rotation is only performed in two dimensions to improve the generalization ability of the model.

The model is trained on NVIDIA GeForce RTX 4090. The environment dependencies include pytorch, monai, etc. U-net is implemented using monai of Adam optimizer.

The Dice loss function is used for model training. The Dice loss function is a metric specifically used to evaluate the performance of models in image segmentation tasks. It can effectively deal with the problem of class imbalance. The Dice coefficient measures the similarity of two sample sets and is defined as:

$$Dice(P,G)=\frac{2|P\cap G|}{|P|+|G|} \tag{1}$$

In the actual implementation, this paper uses the continuous value version of the Dice loss function to facilitate backpropagation and gradient optimization. Let P_i and G_i represent the predicted value and true label of the th pixel, respectively, it is defined as:

$$L_{Dice}=1-\frac{2\sum_{i=1}^{N}p_i g_i}{\sum_{i=1}^{N}p_i^2+\sum_{i=1}^{N}g_i^2} \tag{2}$$

In this formula, N represents the sum of the number of pixels contained in the image. By minimizing the Dice loss function, the model can better learn segmentation results that are more consistent with the true label, especially when dealing with unbalanced data.

When integrating the region growing segmentation method, the selected seed points are based on the initial segmentation results of deep learning or the boundaries of the binary image, and the indexes of these boundary points are converted into a list of seed points:

$$\{(x_1,y_1,z_1),(x_2,y_2,z_2),\ldots,(x_N,y_N,z_N)\} \tag{3}$$

Where (x_i,y_i,z_i) represents the coordinates of the i seed point, and N is the total number of seed points. In order to avoid the destruction of the deep learning segmentation results by region growing, this paper sets a higher grayscale threshold, performs region growing on all the seed points found, and expands to the neighboring pixels that meet the conditions.

The evaluation method selected is the dice value and AHD (Average Hausdorff Distance). In the context of medical image segmentation, given two-point sets A and B, point sets A and B represent the boundary or surface of the segmentation result and the reference standard. AHD measures the average distance between the two surfaces and provides a geometric similarity measure between the two.

A lower AHD value indicates that the segmentation result is closer in space to the reference standard, thus indicating better segmentation performance. Compared with the traditional Hausdorff distance, AHD is more robust to outliers because it considers the average distance between all point pairs. The calculation method of AHD is:

$$AHD(A,B)=\frac{1}{|A|+|B|}\left(\sum_{a\in A}\min_{b\in B}|a-b|+\sum_{b\in B}\min_{a\in A}|b-a|\right) \tag{4}$$

Where |A| and |B| represent the number of points in point sets A and B.

4. Experiment and Result Analysis

4.1 Experimental Setup

Since the 2023 Cerebral Artery Segmentation Challenge (CAS) has ended, this work failed to obtain all the datasets used in the competition.

Instead, 99 images were used. Images numbered 90 to 99 were not used for training and were used for model evaluation.

Epoch was set to 100 (rounds), and the dice value of the evaluation dataset was calculated every 5 rounds. The experimental process is shown in Figure 2:

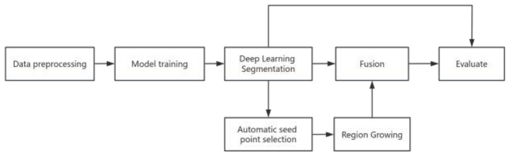

Figure 2. Low Chart

4.2 Experimental Results and Analysis

Using the deep learning method, the Dice coefficient of the deep learning fusion region growing segmentation method (hereinafter referred to as the fusion segmentation method), Figure 3 is the AHD comparison result.

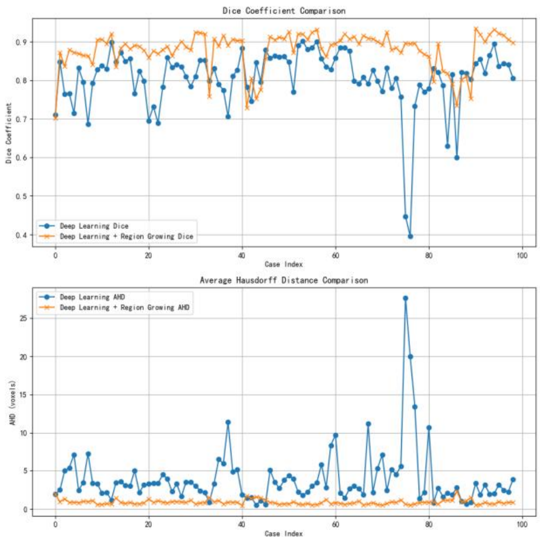

Figure 3. Comparison of Segmentation Indicators for all Datasets

The above is the evaluation comparison chart of all data. The performance of the validation set that did not participate in the training is shown in Figure 4.

The effects before and after the fusion segmentation method are shown in Figure 5 and Figure 6. These two pictures are the comparison of the cerebrovascular region segmented by the U-net neural network and the cerebrovascular region segmented by the fusion segmentation method in the cross section and coronal plane of the same MRA image. The green one is the deep learning segmentation result, and the yellow one is the segmentation result after region growing based on the automatically selected seed points.

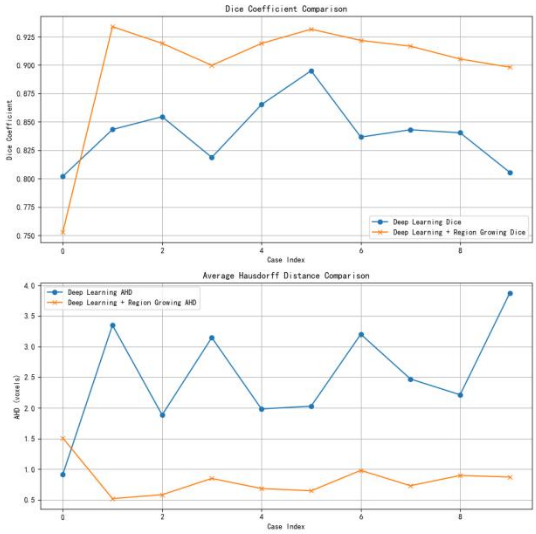

Figure 4. Comparison of Validation Set Segmentation Indicators

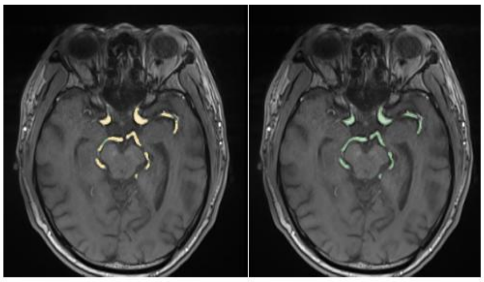

Figure 5. Axial Segmentation Comparison

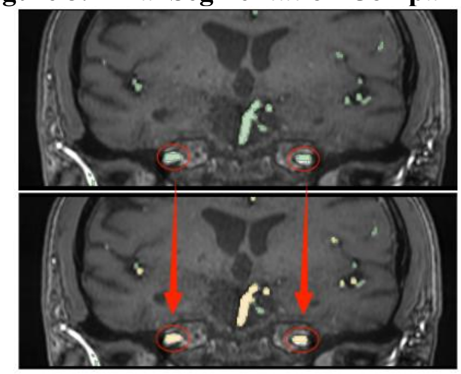

Figure 6. Coronal Segmentation Comparison

It can be seen that the region growing segmentation method using automatic seed point selection is roughly consistent with the deep learning method in the segmented cerebrovascular area. Although the overall segmentation effect is still not as good as that of the deep learning segmentation method, in some pixel-level segmentation results, the region growing segmentation method can break through the areas that the deep learning segmentation method fails to segment.

In fact, morphological post-processing is used in the fusion of deep learning segmentation results and region growing segmentation results to deal with redundancy in the segmentation results. Two main methods are used, opening and closing operations. The opening operation is to perform an erosion operation first, followed by a dilation operation, and the closing operation is to perform a dilation operation first, followed by an erosion operation, to fill small holes in the segmentation results, eliminate depressions on the boundaries, make the boundaries smoother, and eliminate small protruding areas in the segmentation results, and remove small, connected components. In order to verify whether the morphological post-processing has an impact on the deep learning method, which makes the fusion segmentation method outperform the deep learning segmentation method, the following comparative experiments are conducted:

Compare the deep learning segmentation results, the deep learning segmentation results that have used the same morphological post-processing as the fusion segmentation method, and the results of the fusion segmentation method. Here, the Dice coefficient and the average Hausdorff distance are still compared. The results are shown in Table 1.

Table 1. Comparison of Segmentation Results using Morphological Post-processing

method	dice	AHD
Deep Learning	0.805	3.949
Deep learning + post-processing	0.763	3.960
Deep Learning + Region Growing	0.878	0.903

The experimental results in Table 1 show that using morphological post-processing alone in deep learning results does not have a positive impact on deep learning segmentation results. Using the same morphological post-processing here will reduce the original segmentation precision. Therefore, it can be ruled out that morphological post-processing causes the fusion segmentation method to be better than the deep learning segmentation method used in this work. This may be because the feature capture ability of deep learning is strong enough. In the case where most cerebrovascular image features have been captured, simple morphological post-processing cannot better beautify or help optimize the deep learning segmentation results.In the result evaluation, it is difficult not to notice that two MRA data have low Dice values when doing deep learning segmentation. According to the observation of the data and segmentation results, the segmentation results directly inferred by the deep model have a large number of non-annotated segmentations, which may be due to the fact that a large number of annotated features appear in the original image outside the annotated part. For these two sets of data, if morphological post-processing is performed directly on the deep learning segmentation results, the Dice coefficient will only increase by less than 0.05. Fortunately, after using the fusion region growing segmentation method, both the Dice coefficient and AHD have been significantly improved and are leveled to the general level of the fusion segmentation method, which fully demonstrates the advantages of the fusion segmentation method in dealing with extreme cases.

5. Conclusion and Outlook

Although this paper uses a more advanced improved U-net neural network for fusion, there are still many excellent neural networks that have not been used for reference experiments. It cannot be concluded that the segmentation method after fusion region growth must be better than before fusion. However, according to some data in this experiment, the segmentation effect of the fusion segmentation method is indeed worse than before fusion, but most images have been significantly improved after using the fusion segmentation method, not only in the case where the deep learning segmentation results themselves are not good. However, based on the sample improvement data after the fusion segmentation algorithm is used, the samples with higher accuracy of the original segmentation results have generally improved less than those with lower segmentation accuracy after using the fusion segmentation method. Therefore, there is reason to suspect that using models whose original segmentation accuracy is close to perfect may not get a certain improvement by using the fusion segmentation method. However, in the actual cerebrovascular segmentation, it is difficult for a model to perfectly process most of the data. When facing the segmentation results of those with poor segmentation quality, the fusion segmentation algorithm is still useful.

With the rapid development of artificial intelligence today, various black box models have achieved more and more excellent results, and more and more efficient network models are constantly being born. However, we always have certain doubts about these unexplainable and even uncontrollable models. Although the results produced by these models seem so close to reality or what we hope to get, they are closer to the results told to us by a child who has not grown up and has superior intelligence. We enjoy its convenience and worry about its uncontrollability after growing up. However, I prefer to compare it to a source of inspiration, just like the results produced by the deep learning segmentation method in this work are used to select seed points for regional growth of controllable traditional segmentation algorithms, and secondary segmentation is performed by merging pixels. The results produced by deep learning are also used as a source of inspiration to be erupted. It is bound by a framework to obtain more ideal results. I think the same may be true for artificial intelligence. Guiding these inspirations to be erupted not only makes the generated results more controllable, but also closer to the results people want.

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