AAR-Unet: Blood vessels segmentation in ultra-wide-angle fundus images

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Abstract. The structural information of blood vessels in ultra-wide-angle fundus images has important guiding significance for diagnosing ophthalmic diseases. Besides, efficient and correct segmentation of ultra-wide-angle fundus vascular images has become an urgent clinical need. However, manual diagnosis is a time-consuming and laborious work. Because of the limitation of primary medical resources, the situation of missed diagnosis and misdiagnosis would probably appear in the diagnosis of artificial experience. In this paper, we proposed an automatic vascular segmentation algorithm based on attention gate based atrous residual (AAR) Unet combined with Top-Hat transform vascular enhancement. In AAR-Unet, we integrated atrous convolution into Res-Unet to expand the receptive field and improve the correlation between objects. To improve the segmentation effect of small blood vessels under low contrast, the attention gate module is introduced. The experimental results show the overall accuracy, sensitivity, specificity and DSC of the proposed algorithm are 0.988, 0.890, 0.993 and 0.875 respectively. The results indicate the algorithm can segment the blood vessels of ultra-wide-angle fundus images accurately.

1. Introduction
Color fundus retinal vascular segmentation is an important part of computer-aided diagnosis of retinal diseases, such as arteriosclerosis, vein occlusion, diabetic retinopathy. Regular accurate measurement of the width, curvature and proliferation of blood vessels can reliably evaluate these diseases[1]. If vascular abnormalities are found, patients can be treated in time to prevent the deterioration of the disease. Due to the particularity of retinal vessels, such as thin blood vessels, manual segmentation of retinal vessels will be very tedious and may make mistakes, which requires experienced ophthalmologists to manually annotate a large number of retinal images. This such as is not feasible for large-scale research and clinical applications. Therefore, it is particularly important to study an accurate and fast retinal blood vessel segmentation algorithm.
In traditional methods in the past, Zhao Y Q et al.[2] used anisotropic diffusion filters to smooth images and maintain vascular boundaries, and then used region growth method and level set method to segment retinal vessels. Chang C C et al.[3] make use of the obvious attribute changes at the junction of different regions of the image to segment the blood vessels of the image. Zhao Y et al.[4] proposed a new infinite active contour model, which uses the mixed region information of the image to segment blood vessels.

In recent years, deep learning has made a breakthrough in the field of image processing[5]. In the aspect of fundus retinal image segmentation, Fu et al.[6] proposed a retinal blood vessel segmentation method based on convolution neural network and fully connected conditional random domain. Ronneberger et al.[7] proposed U-Net based on FCN, which uses skip connection technology to perform blood vessel segmentation. Feng et al.[8] proposed a cross-connected convolutional neural network (CcNet) for automatic segmentation of retinal vessels.

In this paper, we proposed an automatic vascular segmentation algorithm based on attention gate based atrous residual (AAR) Unet combined with Top-Hat transform vascular enhancement. In AAR-Unet, we integrated atrous convolution into Res-Un et to expand the receptive field and improve the correlation between objects. To improve the segmentation effect of small blood vessels under low contrast, the attention gate module is introduced. Comparing the experimental results with ground-truth, the AAR-Unet model proposed in this paper and the method based on Top-Hat transform preprocessing can correctly segment the blood vessels of the wide-angle fundus image.

2. Method

2.1. Preprocessing
The acquired wide-angle fundus vascular image has the phenomenon of uneven illumination, low contrast between microvessels and the background, which makes the algorithm low in robustness, so it is necessary to preprocess the fundus retinal image for further processing. In order to reduce the influence of the upper and lower eyelids, the resolution of 3900×3072 is cut to 3754×2480. The central area of the image is extracted from the green channel and then cut. After the image is normalized, bilateral filtering is used for denoising. Limited contrast histogram equalization is adopted to suppress noise and improve the contrast between blood vessels and background. Using Gamma transform to suppress the uneven illumination and centerline reflection. Finally, the microvascular information of retinal image is further improved by Top-Hat transform.

2.2. Network structure
In order to accelerate the speed of network training, the image is cut to 128 × 128 before network training. U-Net[9] is a semantic segmentation network based on pixel level, which shows good segmentation performance for small image data sets such as medical images. Therefore, using U-Net as the basic framework can solve the small sample problem well. U-Net consists of an encoding module and a decoding module. The encoding module gradually reduces the spatial dimension of the image and extracts the main features through downsampling operation. The decoding module gradually repairs the details and spatial dimensions of the object through the up-sampling operation. Therefore, after convoluting and downsampling, there will be some problems, such as the disappearance of gradient, the loss of structural information. In order to solve the problems, this paper introduces residual network, atrous convolution and attention gate module and then integrates them into U-Net network, which proposes a new network structure called attention atrous residual U-shaped network (AAR-Unet). The network architecture is shown in figure 1. AAR-Unet can further expand the receptive field and improve the correlation between objects without losing information, which can improve the segmentation effect of small blood vessels at low contrast, so as to improve the performance of vascular segmentation.
AAR-Unet is divided into two parts: encoding module and decoding module, and each part is composed of four small modules. To reduce the loss of structural information and accelerate the convergence of the network, the residual module is introduced into each small module in each part, and the residual module is defined as shown in figure 2. The convolution in the residual module is replaced by atrous convolution, which expands the receptive field and improves the correlation between objects. The attention gate module is introduced into the decoder to deal with the features propagated by the jump connection in the encoder to improve the segmentation effect of small blood vessels at low contrast. The attention gate module is an application of flexible attention mechanism. The specific internal structure is shown in figure 3.

3. Experiment

3.1. Dataset

This data set was collected by Optos 200Tx instrument. The resolution of each image is 3900 × 3072. The data labels are marked by two doctors with more than 10 years of clinical experience. The algorithm is implemented in the Keras library of Python3.6 and TensorFlow. In order to solve the problem of limited data, data expansion (such as flipping, cutting, rotation, translation) is used for training to enhance the invariance and robustness of the network. The experiment was carried out on the NVIDIA GeForce GTX 1660Ti GPU, 2.60GHz CPU and 16GB RAM. AAR-Unet is trained by back propagation algorithm and ADAM optimizer. The learning rate is set to 0.0001 and the learning stops after 100.
iterations. Due to GPU memory limitations, the batch of training datasets is set to 2 and the validation dataset is set to 2.

3.2. Evaluation strategy
In this experiment, sensitivity, specificity, overall accuracy[11] and DSC[12] are used to evaluate the segmentation performance of the network. All evaluation indicators are defined as follows:

Sensitivity $= \frac{TP}{TP+FN}$ (1)

Specificity $= \frac{TN}{TN+FP}$ (2)

Overall accuracy $= \frac{TP+TN}{2 \times TP+FN+FP}$ (3)

DSC $= \frac{2 \times TP}{2 \times TP+FN+FP}$ (4)

Where TP is true positive (the correct segmented vascular area); TN is true negative (the correct segmented background area); FP is false positive (the wrong segmented vascular area); FN is false negative (the wrong segmented background area).

4. Result
The proposed algorithm is tested on the ultra-wide-angle fundus data set, and compared with Res-Unet segmentation, the result of retinal blood vessel segmentation is shown in figure 4. From the effect of the segmentation map, the segmentation of small blood vessels by Res-Unet is not complete, but the segmentation results obtained by the proposed algorithm are basically consistent with the standard map of expert segmentation especially in the segmentation of small blood vessels.

![Figure 4. Results of wide-angle fundus vascular segmentation, (a) is the pre-processing image of the original image, (b) is Ground-Truth, (c) is the result of Res-Unet segmentation, (d) is the result of AAR-Unet segmentation.](image)

Table 1 shows the average results of Res-Unet and AAR-Unet segmentation in terms of sensitivity, specificity, overall accuracy and DSC. In various evaluation indicators, AAR-Unet is better than Res-Unet. Among them, the sensitivity of AAR-Unet is 0.890, which shows that the algorithm can effectively reduce vascular wrong segmentation. The specificity reached 0.993, which indicates that most of the background regions were segmented correctly. The overall accuracy is as high as 0.988, which indicates that the sum of the target pixels and background area pixels correctly determined by the model accounts for a high percentage of the total number of pixels. The DSC is as high as 0.875, which indicates that the similarity between the target area determined by the model and the target area of the label is high. From the point of view of the comprehensive index, this algorithm can segment the fundus vessels of ultra-wide angle accurately and effectively.

|                | sensitivity | specificity | overall accuracy | DSC   |
|----------------|-------------|-------------|------------------|-------|
| Res-Unet       | 0.805       | 0.989       | 0.981            | 0.792 |
| AAR-Unet       | 0.890       | 0.993       | 0.988            | 0.875 |

5. Conclusion
In this paper, we proposed an automatic vascular segmentation algorithm based on attention gate based atrous residual (AAR) Unet combined with Top-Hat transform vascular enhancement. In AAR-Unet, we integrated atrous convolution into Res-Unet to expand the receptive field and improve the correlation
between objects. To improve the segmentation effect of small blood vessels under low contrast, the attention gate module is introduced. According to the results of the evaluation index, the AAR-Unet model can segment the blood vessels of the ultra-wide-angle fundus image accurately. The proposed method provides a new idea for vascular segmentation of ultra-wide-angle fundus images and an effective quantitative reference tool for clinical diagnosis and treatment.

Reference

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