



Precise Segmentation of Choroid Layer in Diabetic Retinopathy Fundus OCT Images by Using SEC-UNet*

XU Xiang-Cong^{1,2,3**}, CHEN Jun-Yan^{1,2**}, WANG Xue-Hua^{1,2***}, LI Rui^{1,2,3}, XIONG Hong-Lian^{1,2},
 WANG Ming-Yi^{1,2}, ZHONG Jun-Ping^{1,2}, TAN Hai-Shu^{1,2}, ZHENG Yi-Xu⁴,
 XIONG Ke^{4***}, HAN Ding-An^{1,2***}

⁽¹⁾*School of Physics and Optoelectronic Engineering, Foshan University, Foshan 528225, China;*

⁽²⁾*Guangdong-Hong Kong-Macao Joint Laboratory for Intelligent Micro-Nano Optoelectronic, Foshan University, Foshan 528225, China;*

⁽³⁾*School of Mechatronic Engineering and Automation, Foshan University, Foshan 528225, China;*

⁽⁴⁾*Department of Ophthalmology, Nanfang Hospital, Southern Medical University, Guangzhou 510515, China)*

Abstract Objective Diabetic retinopathy (DR) is a serious complication of diabetes that may cause vision loss or even blindness in patients. Early examination of the choroid plays an essential role in the diagnosis of DR. However, owing to the fuzzy choroid-sclera interface (CSI) and shadow of retinopathy in the optical coherence tomography (OCT) images of DR, most existing algorithms cannot segment the choroid layer precisely. The present paper aims to improve the accuracy of choroid segmentation in DR OCT images. **Methods** In this paper, we propose an optimized squeeze-excitation-connection (SEC) module integrated with the UNet, called the SEC-UNet, which not only focuses on the target but also jumps out of the local optimum to enhance the overall expressive ability. **Results** The experimental results show that the area under the ROC curve (*AUC*) of the SEC-UNet reaches up to 0.993 0, which outperforms that obtained for conventional UNet and SE-UNet models. It indicates that the SEC-UNet can obtain accurate and complete segmentation results of the choroid layer. Statistical analysis of choroid parameter changes indicated that compared with normal eyes, the 1 mm adjacent area of choroid fovea increased in 87.1% of DR patients. It proved that DR is likely to cause choroid layer thickening. **Conclusion** Our method may become a useful diagnostic tool for doctors to explore the function of the choroid in the prevention, pathogenesis, and prognosis of diabetic eye disease.

Key words diabetic retinopathy, choroid segmentation, optical coherence tomography, squeeze-excitation-connection UNet

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Diabetic retinopathy (DR) is a serious complication of diabetes and has become one of the main causes of blindness worldwide^[1]. Early detection of eye diseases and appropriate treatment can greatly reduce the number of patients with DR^[2]. The choroid is a vascular plexus layer that lies between the sclera and retina, providing oxygen and nourishment to the eye^[3]. It performs critical physiological functions and plays a crucial role in determining various diseased conditions^[4-8]. Studies have shown that changes in the shape and anatomical structure of the choroid are strongly related to the incidence and severity of DR^[9-11]. Figure 1 illustrates the manually segmented boundaries in a fundus optical coherence tomography

(OCT) B-scan image of DR. This process is time-consuming and depends on the experience and

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** These authors contributed equally to this work.

*** Corresponding author.

WANG Xue-Hua. Tel: 86-18718560259,

E-mail: xhwang10000@163.com

XIONG Ke. Tel: 86-13760811213, E-mail: shinco1223@163.com

HAN Ding-An. Tel: 86-15118799767, E-mail: handingan@163.com

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subjective judgment of the doctor. Therefore, an automatic and precise segmentation method is urgently needed for future clinical applications.

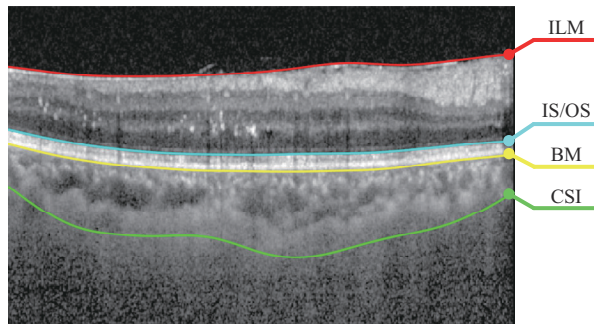


Fig. 1 Illustration of a manually labeled OCT B-scan of a patient with DR

Four boundaries consist of internal limiting membrane (ILM; red curve), inner segment/out segment (IS/OS; blue curve), Bruch's membrane (BM; yellow curve), and choroid-sclera interface (CSI; green curve).

In the past, many algorithms for choroid segmentation have been developed^[12-18], such as graph search^[19], active contours and Markov random fields^[20], and support vector machines (SVM)^[21]. However, these have not been adopted into the real clinical environment; this is primarily because a. there are too many super parameters that need to be adjusted in the segmentation program, and b. the segmentation results need to be manually corrected and processed. In recent years, deep learning has been widely used in medical image processing. Masood *et al.*^[17] used a convolutional neural network (CNN) Cifar-10 architecture to extract the choroid part of OCT images into patches with or without CSI. However, it needs to deal with a large number of overlapping windows, which can be computationally redundant. George *et al.*^[22] used SegNet to obtain the choroid region and used the morphology for edge detection. Segmentation of pathological choroid images is not ideal because of the inadequate use of shallow features. UNet may be one of the most popular and successful architectures for medical image segmentation to date^[23] because its fully CNN structure requires only a small number of samples, the encoding path of coarse-grained context detection, and the decoding path of fine-grained location. However, because the shape, size, or light of the target affects the accuracy of the segmentation results, a

single UNet may not perform well. Therefore, multiple UNets are cascaded to increase the model performance. Oktay *et al.*^[24] proposed attention gates, which automatically learn to focus on the target, and integrating them into the conventional UNet model can increase the prediction accuracy without adding additional networks. Another excellent attention mechanism is the squeeze-and-excitation (SE) module^[25], which can focus on the target, highlight useful features by channel, and suppress irrelevant features. Rundo *et al.*^[26] incorporated SE modules into UNet to segment the prostate zonal and achieved excellent results.

However, the SE module in the network can easily fall into the local optimum while ignoring the global features of the target, which results in a decreased accuracy in the DR choroid boundary segmentation task. In this paper, we propose an optimized SE module, namely the squeeze-excitation-connection (SEC) module, in which a skip connection between the feature mapping layer and the conversion output was inserted. The SEC module not only retains the attention ability of the original SE module but also enables the current layer to pass its own feature maps to the subsequent layer, thereby enhancing the overall expressive ability of the network. We integrated the SEC module with UNet and compared it with conventional UNet and SE-UNet models for segmentation of the choroid boundary in DR OCT images. The results indicated that SEC-UNet achieved the best performance (*i. e.*, an area under the ROC curve (*AUC*) value of 0.993 0). The qualitative and quantitative comparisons demonstrated that the SEC module is effective and that the proposed model can achieve precise segmentation of DR choroid images. In this paper, we measure the foveal choroidal thickness and the volume of the adjacent area. In the future, it may become a useful diagnostic tool for doctors to explore the mechanism for the pathogenesis of DR.

1 Methods

In this study, the SEC-UNet was developed to segment the choroid boundaries in OCT images of DR, where the UNet structure serves as the backbone and the SEC module serves as an attention mechanism to strengthen the discriminative representation ability, thereby making the network more adaptive to DR

choroid segmentation tasks.

1.1 Network architecture

SEC-UNet combines an encoder and a decoder path, as shown in Figure 2. The network starts with an input image with dimensions $320 \times 320 \times 3$. The first layer of the encoder path is a convolutional layer with a stride of 1. The second layer is the SEC module with a channel size of 128. The third layer comprises maxpooling layers with a stride of 2. We repeated the

same steps 3 times, and the channel sizes of these modules were 256, 512, and 1 024, respectively. The decoder path takes the output of the encoder path as the input; the two paths are similar except that the maxpooling layers are replaced by upsampling layers with a stride of 2 in the decoder path. The features obtained through the encoder and decoder paths are combined by the skip connection. At the end of the net, the choroid and background areas are segmented using the SoftMax activation function.

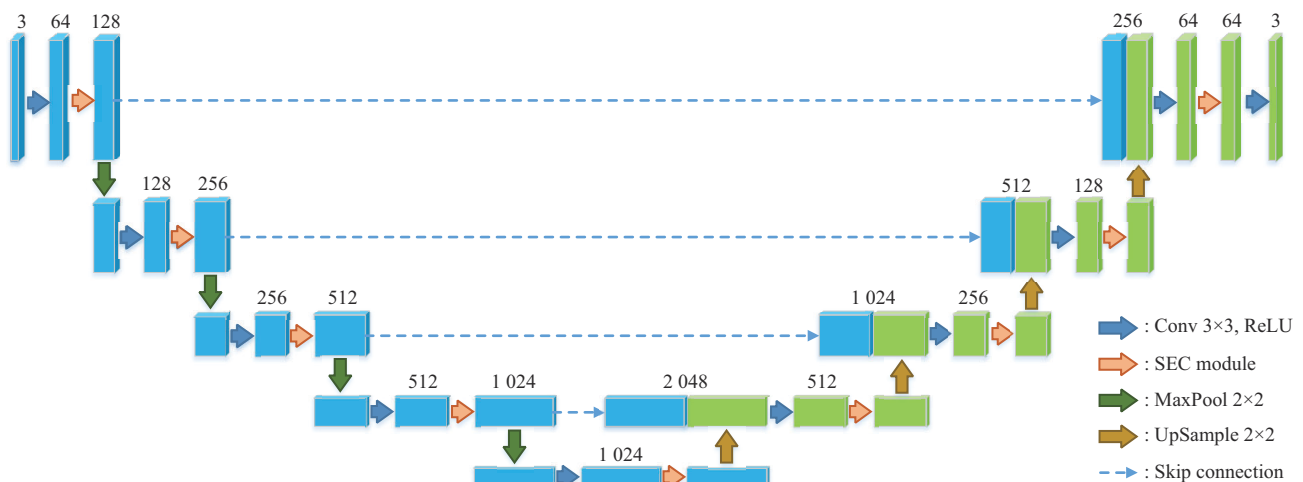


Fig. 2 Architecture of the proposed SEC-UNet model

1.2 SEC module

The SEC module is an optimized version of the SE module, as shown in Figure 3. The SE module is a

lightweight gating mechanism^[25]. It can enhance the representational power of the network by modeling channel-wise relationships.

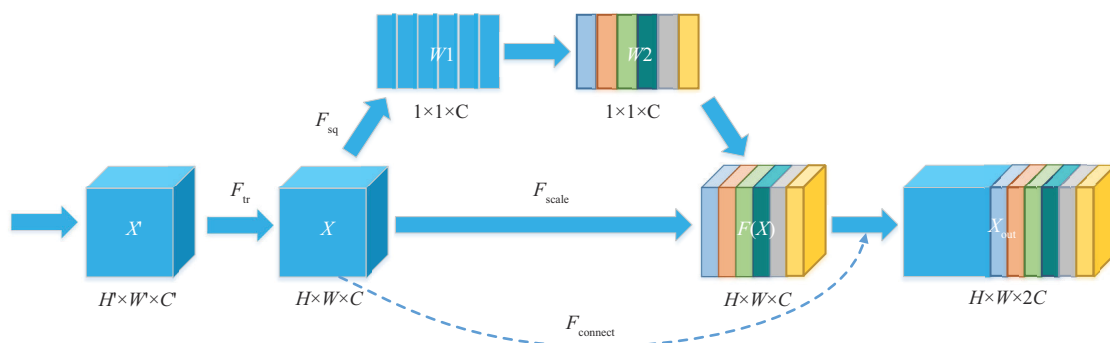


Fig. 3 Squeeze-excitation-connection module

In the SE module, the input maps $X' \in \mathbb{R}^{H' \times W' \times C'}$ are transformed (F_{tr}) to feature maps $X \in \mathbb{R}^{H \times W \times C}$. Before feeding X into the next transformation, it

undergoes 3 successive steps: squeeze, excitation, and connection. The global spatial information is squeezed (F_{sq}) into a channel descriptor by global average

pooling, and the gating mechanism is employed to tackle the issue of exploiting channel dependencies:

$$F(X) = \sigma(W2\delta(W1)) \quad (1)$$

where σ denotes the Sigmoid function, δ refers to the rectified linear unit (ReLU)^[27] function, $W1 \in R^{\frac{C}{r} \times C}$ and $W2 \in R^{C \times \frac{C}{r}}$ are fully connected layers, and r is the reduction rate in the dimensionality reduction layer (set as 16). The transformation output of the SE module is obtained by rescaling (F_{scale}) of $F(X)$.

The SE module recalibrates the features through the internal gating structure to focus the attention of the network on the target. However, it easily falls into the local optimum, ignoring the global features of the target, which results in inaccurate boundary segmentation in the choroid segmentation task. In this study, we modified the original structure of the SE module. We took inspiration from the dense connectivity in DenseNet, which takes a feed-forward mode to connect the current layer to the subsequent layer, thus encouraging feature reuse and enhancing feature expression capabilities^[28]. We inserted a skip connection ($F_{connect}$) between the feature mapping layer and the transform output:

$$X_{out} = F_{connect}(X, F(X)) \quad (2)$$

This feed-forward connection mode can take advantage of the context information and can effectively enhance the global and local expression capabilities at the same time. It also encourages feature reuse throughout the network and makes the module more compact.

2 Experiments and results

In this section, we introduced the database used to evaluate networks followed by detailed network parameters and training details and displayed the segmentation results and comparison among different networks.

2.1 Dataset

The collection and analysis of image data were approved by the Human Research Ethics Committee of Nanfang Hospital of Southern Medical University and adhered to the tenets of the Declaration of Helsinki. The dataset was acquired using Heidelberg OCTSPECTRALIS S200 and consisted of EDI-OCT images from 40 DR eyes (25 patients). Each EDI-OCT cube has 128 B-scans, and a given B-scan contains 512 A-scans, each of which comprises 596

pixels. We randomly selected 30 B-scans from each volume and manually annotated them by experienced doctors. For each B-scan, we used the graph search method^[29] to obtain the IS/OS boundary, removed the region above it to retain region of interest (ROI) for reducing the choroid-independent information, and then cropped it into 10 patches (320×320) in the horizontal direction to expand the data. The new dataset was divided into training set, validation set, and test set in the ratio 7 : 2 : 1.

2.2 Implementation

The proposed method was built on Keras with TensorFlow as the backend^[30]. The experiments were run on a single GPU (NVIDIA GeForce GTX 2080Ti). The model was trained for 100 epochs. Each convolution layer in the model had a kernel size of 3×3. The weights and biases of SEC-UNet were initialized using the He_normal scheme. We used the Adam optimizer with a mini-batch size of 8 to update the network weights and biases. The learning rate for training the model was 10^{-5} . In the training stage, we placed a dropout layer with a probability of 0.2 after the convolution layer to prevent the network from overfitting.

2.3 Evaluation metrics

The choroid segmentation results can be evaluated by accuracy (ACC), sensitivity (SE), specificity (SP), and $F1$ -score ($F1$)^[31], which are defined as

$$ACC = \frac{TP + TN}{TP + FP + TN + FN} \quad (3)$$

$$SE = \frac{TP}{TP + FN} \quad (4)$$

$$SP = \frac{TN}{TN + FP} \quad (5)$$

$$F1 = \frac{2 \times TP}{2 \times TP + FP + FN} \quad (6)$$

where TP , TN , FP , and FN represent the number of true positive, true negative, false positive, and false negative pixels, respectively. Other evaluation metrics, such as receiver operating characteristic (ROC) curve and AUC , were also used in this study.

2.4 Comparison between different networks

To validate the performance of the proposed algorithm, we tested SEC-UNet for DR choroid segmentation and compared it with the conventional UNet^[23] and SE-UNet^[26] models. These networks were trained on the same parameter settings, including the Adam optimizer, initial learning rate, and

maximum epoch number, to ensure a fair comparison. As shown in Figure 4, the ROC curve of the proposed model reaches the upper left corner, and the *AUC* is (a value of 0.993 0) larger than that of the other two models. In contrast, the ROC curves of the UNet and SE-UNet were entangled, which reveals that SE-UNet cannot improve the performance of UNet in this segmentation task. For the complex features of DR choroid images, the SE module overfocuses on the boundary and falls into the local optimum, while ignoring the overall expression of the target.

Table 1 lists the evaluation metrics of the models. The highlighted numbers represent the best performance. It can be observed that despite an *SE* value lower than the SE-UNet model, the *ACC*, *SP*, and *F1* values of the proposed model are higher than those of the other two, indicating its superiority in the segmentation performance. SEC-UNet has the slowest training and prediction speed, which trades computational cost for superior segmentation performance. The higher *SE* value but lower *SP* value

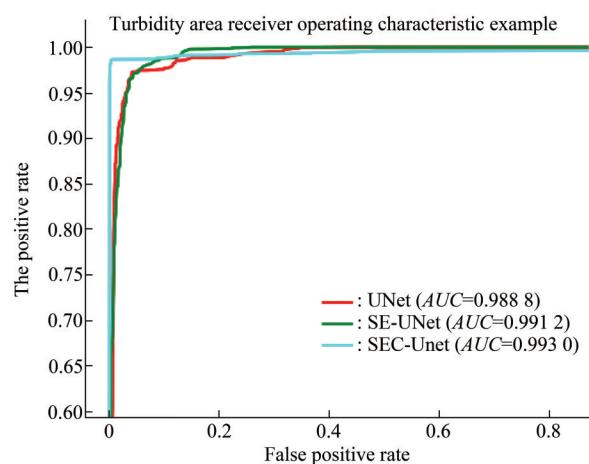


Fig. 4 ROC curve and AUC analysis of different models

of the SE-UNet model indicates that it tends to oversegment the choroid region. The *F1* values of UNet and SE-UNet are similar, which verifies the drawbacks of over-focus on the boundary in the SE module.

Table 1 Comparison with different models

Method	Result						
	<i>ACC</i> /%	<i>SE</i> /%	<i>SP</i> /%	<i>F1</i> /%	Training speed/(img·s ⁻¹)	Testing speed/(img·s ⁻¹)	Parameters
UNet [23]	92.38	83.67	92.74	68.49	5.92	5.50	29.90 M
SE-UNet [26]	91.80	86.63	91.75	67.13	5.12	3.67	30.76 M
SEC-UNet	94.06	85.85	94.27	73.02	3.47	2.75	45.70 M

Figure 5 shows 4 sample results to visually compare our method with other models. The original images, choroid ROI images, and ground-truth masks are presented in Figure 5a–c. The segmentation results obtained by UNet, SE-UNet, and SEC-UNet are shown in Figure 5d–f. It can be observed that BM is better than CSI in the segmentation results of each model because of the fuzzy gradient feature of CSI. The shadow of retinopathy in the DR choroid image is projected into the choroid, which makes it difficult to distinguish the features of the choroid internal vessels and the sclera. This leads to the UNet and SE-UNet mistaking the internal vessel pixels as scleral pixels, as shown in Figure 5d, e. Moreover, the CSI in UNet's segmentation results deviate greatly from the correct one; this is because its main purpose is to recover the global information of the target object,

ignoring detailed features such as boundaries. The segmentation results of SE-UNet are slightly better compared with UNet's, but the accuracy of boundary segmentation is lower because of its tendency to easily fall into the local optimum, ignoring the global features of the target. SEC-UNet obtained the most accurate and complete segmentation results (Figure 5f) compared with the ground-truth masks (Figure 5c), which proves that the SEC module can not only focus on the target object but also jump out the local optimum to take advantage of the global feature information. The qualitative and quantitative results demonstrate that the proposed SEC module is effective and the SEC-UNet can achieve automatic and precise segmentation of choroid layer in DR OCT images.

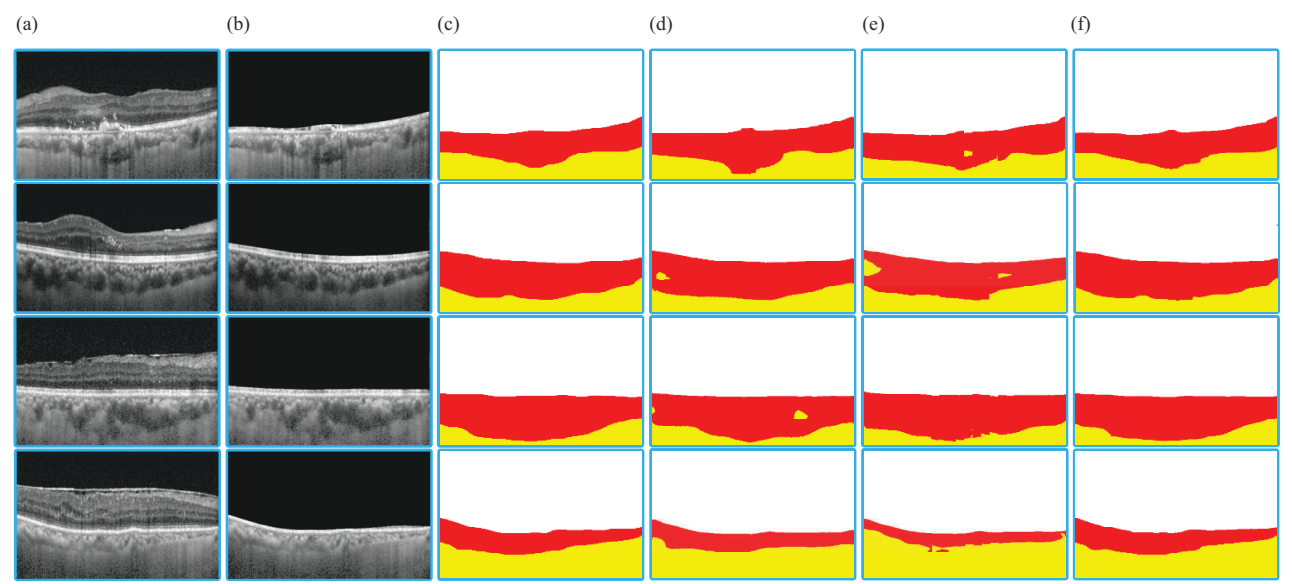


Fig. 5 Sample results

From left to right: (a) original choroid OCT images; (b) choroid ROI images: removed the region above choroid to reduce independent information; (c) ground-truth masks; (d–f) results obtained by UNet, SE-UNet, and our proposed method.

2.5 Statistical analyses of the choroidal parameters variation

According to clinical findings, DR may cause choroidal changes^[10]. Thus the quantitative measurement of choroidal parameters is of great significance for the diagnosis and preventive treatment of DR. This paper calculated 38 sets of choroid foveal thickness (*CFT*) and volume of adjacent area (*CFV*) within 1 mm diameter, respectively, from 28 DR patients. The average values of 7 normal people served as the threshold to judge choroidal change. Results showed in Table 2 indicated that most *CFT*, 1 mm *CFV* increased in DR eyes compared with normal eyes. And the 1 mm *CFV* performed the highest correlation with DR. So it can be used to characterize the choroidal changes caused by DR more accurately and comprehensively.

Statistical analysis of choroid parameter changes indicated that compared with normal eyes, the 1 mm adjacent area of choroid fovea increased in 87.1% of

DR patients. It proved that DR is likely to cause choroid layer thickening.

3 Conclusion

In this paper, we presented a new SEC-UNet model to improve the accuracy of choroid segmentation in DR OCT images. Compared with the conventional UNet and SE-UNet models, this model achieved the best performance (*AUC* value of 0.993 0). Our algorithm can obtain automatic and precise segmentation of the choroid layer in DR images, which may be helpful for doctors in diagnosing fundus diseases related to the choroid state. The statistical analysis of choroid parameter presented the 1 mm adjacent area of choroid fovea increased in 87.1% of DR patients, which means DR may thicken the choroid layer. In addition, the proposed SEC module can also be incorporated into other network frameworks, such as VGG^[32], ResNet^[33], and DenseNet^[28], to accomplish tasks such as image classification, scene classification, and object detection.

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Table 2 The performance of <i>CFT</i> , 1 mm <i>CFV</i> ($\bar{x} \pm s$)		
Group	<i>CFT</i> /μm	1 mm <i>CFV</i> /mm ³
Normal	288±59.968	0.283±0.056
DR	297±68.256	0.388±0.138
Ratio	83.90%	87.10%

Ratio: the ratio of choroidal reduction number to the total.

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通过SEC-UNet精准分割糖尿病视网膜病变眼底OCT图像脉络膜层*

许祥丛^{1,2,3)**} 陈俊彦^{1,2)**} 王雪花^{1,2)***} 李睿^{1,2,3)} 熊红莲^{1,2)} 王茗祎^{1,2)} 钟俊平^{1,2)}
谭海曙^{1,2)} 郑毅旭⁴⁾ 熊柯^{4)***} 韩定安^{1,2)***}

(¹⁾ 佛山科学技术学院物理与光电工程学院, 佛山 528225; (²⁾ 佛山科学技术学院粤港澳智能微纳光电技术联合实验室, 佛山 528225;

(³⁾ 佛山科学技术学院机电工程与自动化学院, 佛山 528225; (⁴⁾ 南方医科大学南方医院眼科, 广州 510515)

摘要 目的 糖尿病视网膜病变(DR)是糖尿病的严重并发症,可导致患者视力下降甚至失明。脉络膜的早期检查在DR诊断中起着至关重要的作用。然而,由于DR患者的光学相干层析成像(OCT)中存在脉络膜和巩膜边界模糊、视网膜病变阴影等问题,导致大多数现有算法无法精准分割脉络膜层。本文目的在于提高DR患者OCT图像中脉络膜层分割的精准度。**方法** 本文提出了一种结合挤压激励连接(SEC)模块和UNet的网络,简称SEC-UNet,不仅增强Unet的局部细节目标关注能力,且能跳出局部最优来增强整体表达能力。**结果** SEC-UNet模型的ROC曲线下面积(AUC)达到0.993 0,优于传统UNet模型和SE-UNet模型。这表明SEC-UNet能够获得准确、完整的脉络膜层分割结果。统计分析脉络膜参数变化发现,与正常眼相比,87.1%的DR患者脉络膜中央凹1 mm内体积增加,这证明了DR很可能导致脉络膜增厚。**结论** 该技术有望成为一种新的辅助诊断工具,帮助医生研究脉络膜在糖尿病眼病的预防、发病机制和预后中的作用。

关键词 糖尿病视网膜病变, 脉络膜分割, 光学相干层析成像, 挤压激励连接UNet

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** 并列第一作者。

*** 通讯联系人。

王雪花 Tel: 18718560259, E-mail: xhwang10000@163.com

熊柯 Tel: 13760811213, E-mail: shinco1223@163.com

韩定安 Tel: 15118799767, E-mail: handingan@163.com

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