Eliminating Shadow Artifacts via Generative Inpainting Networks to Quantify Vascular Changes of the Choroid

Huihong Zhang\textsuperscript{1,4}, Jianlong Yang\textsuperscript{1,*}, Kang Zhou\textsuperscript{1,5}, Fei Li\textsuperscript{2}, Yan Hu\textsuperscript{1}, Shenghua Gao\textsuperscript{5}, Jun Cheng\textsuperscript{1}, Yanwu Xu\textsuperscript{6}, Xiulan Zhang\textsuperscript{2}, and Jiang Liu\textsuperscript{1,3}

\textsuperscript{1} Ningbo Institute of Industrial Technology, Chinese Academy of Sciences, China\textsuperscript{*yangjianlong@nimte.ac.cn}
\textsuperscript{2} State Key Laboratory of Ophthalmology, Zhongshan Ophthalmic Center, Sun Yat-sen University, China
\textsuperscript{3} Southern University of Science and Technology
\textsuperscript{4} University of Chinese Academy of Sciences
\textsuperscript{5} ShanghaiTech University
\textsuperscript{6} Baidu Inc

Abstract. Shadow artifacts from retinal vessels hinder the development of quantitative choroidal biomarkers in Optical Coherence Tomography (OCT), which limits the clinical applications of the choroidal OCT to the measures of layer thickness. In this paper, we present a novel framework that could eliminate the retinal shadows and realize the quantification of choroidal vasculature. Different from existing methods, we convert the shadow elimination into an object removal task, which can be handled by image inpainting techniques. We adopt and finetune a two-stage generative inpainting network which connects the edges of the vessels ahead of refilling the shadow-contaminated areas. It shows surpassing performance in repairing the choroidal vasculature compared with traditional inpainting algorithms. We further verify the feasibility of the proposed frame using a prospective observational study, which detects the choroidal vascular changes related to the Intra-Ocular Pressure (IOP) elevation of 34 healthy volunteers. As the average IOP increases from 15.84±1.99 mmHg to 34.48±5.35 mmHg, we achieve the decreases of the choroidal vessel density and flow index from 0.3491±0.020 to 0.463±0.019 and from 0.336±0.025 to 0.300±0.019, respectively.

Keywords: Optical coherence tomography · Choroidal vasculature · Generative inpainting networks.

1 Introduction

The choroid, lying between the retina and the sclera, is the vascular layer which provides oxygen and nourishment to the outer retina \cite{2}. Traditional imaging modalities like fundus camera and ophthalmoscope acquire 2D overlapping information of the retina and the choroid, form which choroidal vascular information
cannot be extracted separately so that the vascular changes of the choroid could not be precisely retrieved and evaluated. Optical Coherence Tomography (OCT) is a non-invasive 3D imaging modality that could separate the information of the underlying choroid from the retina, thus has been becoming a powerful tool to understand the role of the choroid in various ocular diseases \cite{10}. It has been shown that the thickness of the choroid layer extracted from OCT, especially the subfoveal choroid thickness, is directly related to the incidence and severity of predominate ocular diseases, such as pathologic myopia \cite{17}, Diabetic Retinopathy (DR) \cite{13}, Age-related Macular Degeneration (AMD) \cite{18}, and glaucoma \cite{14}.

On the other hand, the choroidal vasculature, which could also be acquired from volumetric OCT data, has relatively limited applications in the study and diagnosis of ocular diseases \cite{19,16}. The contamination induced by the vessel shadows from the superficial layers of the retina is the primary reason that limits the extraction of quantitative vascular biomarkers from the underneath layers \cite{7}. As shown in the left of Fig. 1, the vessels locating at the superficial retina cause strong attenuation of the OCT probe light, thus bring shadow-like dark tails to the underneath layers extending to the choroid and the sclera (inside the dashed red boxes). The center part of Fig. 1 is a layer-segmented OCT volume, which could further be used to generate the \textit{en face} images of each layer as shown in the right of Fig. 1. Inside the green box is the Ganglion Cell Layer (GCL) which possesses the retinal vessels with high light reflectance. While the depth-projected vessel positions turn dark on the vessel-absent Retinal Pigment Epithelium (RPE) layer (inside the red box) and the choroid layer (inside the orange box). It is evident that the shadows bring difficulties to the extraction of the choroidal vasculature.

Very recently, several methods have been proposed to minimize or eliminate
the shadow artifacts from the choroidal OCT. Maruko et al. directly subtracted the en face choriocapillary image from the en face choroidal image to get rid of the shadow-projection artifacts. An Attenuation Compensation (AC) algorithm was also employed to deal with the retinal vessel shadows. In this paper, we present a framework for quantitative analysis of choroidal blood flow, where the core task is shadow elimination. We propose to convert the shadow elimination problem into the object removal task in the field of computer vision and process it with Generative Inpainting Network (GIN). GIN was adopted and finetuned to repair the shadow-contaminated areas. The proposed method shows superior accuracy in the quantification of the vascular changes of the choroid related to high Intra-Ocular Pressure (IOP).

The main contributions of this work are as follows: (1) We propose to convert the shadow elimination problem into the object removal task, thus can be handled by image inpainting techniques. (2) A two-stage inpainting GIN was adopted for the shadow removal task and achieved better performance than traditional inpainting methods. (3) The small changes in the choroidal blood flow were observed for the first time by the framework we present for quantitative analysis of choroidal blood flow.

2 Method

The proposed framework is composed of three stages to process the volumetric OCT data, as shown in Fig. 2.

**Preprocessing:** The boundary between the choroid and the sclera in the OCT data was firstly enhanced via the AC algorithm, which also has the functions of improving choroidal vessel contrast and minimizing the retinal shadow. This boundary together with the boundaries of the RPE and Bruch’s membrane were automatically segmented with a graph search algorithm. Then the OCT volume was flatten based on the RPE. We obtained the en face RPE and choroid by calculating axial mean projection value among these boundaries. Finally, the vessel shadows on the avascular RPE image was used to extract the mask and the choroid image was used to extract the edge using the Canny method.

**Generative Inpainting Network:** Recently, Generative Adversarial Networks (GAN) shows the powerful force for image inpainting problem compared with traditional algorithms. The adopted Generative Inpainting Network (GIN) is a two-stage GAN. The first stage termed Edge-GAN takes masked canny edge as input, while the second stage termed Choroid-GAN takes masked choroid as input. Let \( E_{gt} \) and \( C_{gt} \) be ground-truth of Canny edge and choroid respectively, while \( E_{pred} \) and \( C_{pred} \) denote output prediction of Edge GAN and Choroid GAN respectively. Edge-GAN takes \( E_m \) as input and eliminates mask with edge generator \( G_e \), \( E_{pred} = G_e(E_m) \). It is trained with an edge adversarial
Fig. 2. Graphic illustration of the proposed framework, which is composed of three stages. 1) The framework processes raw OCT volume to RPE mask and Canny edge. 2) The framework eliminates retinal vessels shadow via Generative Inpainting Network. 3) The framework quantifies vascular changes of the choroid. (Best viewed with colors.)

loss and Mean Absolute Error (MAE) loss as follows:

\[
\min_{G_e} \max_{D_e} \mathcal{L}_{G_e} = \min_{G_e} (\lambda_{adv,1} \max_{D_e} \mathcal{L}_{adv,1} + \lambda_{mae,1} \| G_e(E_m) - E_{gt} \|_1),
\]

\[
\mathcal{L}_{adv,1} = E[\log D_e(E_{gt})] + E[\log(1 - D_e(G_e(E_m)))],
\]

where \(\lambda_{adv,1}\) and \(\lambda_{mae,1}\) are regularization parameters.

The Choroid-GAN takes \(C_m\) with \(E_{pred}\) as input and eliminates mask with choroid generator \(G_c, C_{pred} = G_c(C_m, E_{pred})\). It is trained with a choroid adversarial loss and MAE loss as follows:

\[
\min_{G_c} \max_{D_c} \mathcal{L}_{G_c} = \min_{G_c} (\lambda_{adv,2} \max_{D_c} \mathcal{L}_{adv,2} + \lambda_{mae,2} \| G_c(C_m, E_{pred}) - C_{gt} \|_1),
\]

\[
\mathcal{L}_{adv,2} = E[\log D_c(C_{gt})] + E[\log(1 - D_c(G_c(C_m, E_{pred})))],
\]

where \(\lambda_{adv,2}\) and \(\lambda_{mae,2}\) are regularization parameters. For our experiments, we empirically choose \(\lambda_{adv,1} = 1, \lambda_{mae,1} = 10, \lambda_{adv,2} = 0.1\) and \(\lambda_{mae,2} = 1\).

The GIN is different from the pretrained GAN [12] in two aspects. 1) The pretrained GAN is not optimized with the choroid dataset and we improve the adaptive capacity with a choroid dataset. 2) To reduce the computation cost and speed up the training of the GIN, we adopt the pretrained GAN as the initialization and finetune the model based on it.

Quantification: After eliminating retinal vessels shadow, we segmented choroidal vasculature by thresholding and binarizing. The generated vessel map was used
for calculating the vessel density [8]. We inverted the intensity value in the \textit{en face} choroid. Then it was combined with the vessel map to get the flow map, which could be further used to calculate the flow index [8].

3 Experiments

\textbf{Data Collection:} We use 34 healthy volunteers with the ages ranging from 18 to 30 years old recruited in a local hospital. A swept-source OCT system with the A-line rate of 100 kHz (DRI OCT-1 Atlantis, Topcon, Japan) was employed to collect data from both of their eyes. We used the $6 \times 6 \text{mm}^2$ Field Of View (FOV) volumetric scan protocol centered at the fovea. Each of the volumes contains 256 B-scans and each of the B-scans has 512 A-lines. Each A-line contains 992 data points uniformly distributed in a depth range of $\sim 3 \text{mm}$. To simulate the state of high IOP, after taking the baseline scans in a normal sitting position, each of the volunteers was asked to take scans in the upside-down position. The average IOP was increased to $34.48 \pm 5.35 \text{mmHg}$ because of the upside-down, compared with the average IOP of $15.84 \pm 1.99 \text{mmHg}$ at the normal position.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{comparison.png}
\caption{Comparison of the proposed method with the prior arts. AC: attenuation compensation. CTI: coherence transport inpainting. (Best viewed with colors.)}
\end{figure}

\textbf{Comparison of Shadow Removal Approaches:} The results using the proposed framework were compared with the existing shadow-removal approaches, Attenuation Compensation (AC) algorithm. We also included another inpainting-based approach using traditional Coherence Transport Inpainting (CTI) [9] for comparison. As shown in Fig 3, the original choroidal vasculature is contaminated by the retinal vessel shadows at the locations shown in the shadow mask. Inside the green and/or yellow boxes are two selected zoom-in regions. The AC could enhance the contrast of the choroidal vessels and minimize faint shadows as
shown in the yellow box. However, it cannot get rid of the dark shadows as shown in the green box. With the assistance of the inpainting-based approach, both the faint and dark shadows could be thoroughly eliminated. However, the CTI introduces unnatural artifacts compared with the proposed method, as shown in the zoom in boxes.

![Fig. 4. Quantitative comparison of different inpainting algorithms. EBI: exemplar-based inpainting. CTI: coherence transport inpainting. ROI: region of interest.](image)

**Quantitative Comparison of Inpainting Algorithms:** Due to the absence of the ground-truth choroidal vasculature, we created the artificial retinal vessel mask with the vessel widths slightly wider than the real shadows (the retinal vessels in the dataset are less than 8 pixels in a $512 \times 512$ pixels en face image, we used the vessel widths of 10 to 15 pixels). The artificial mask combining with the repaired choroid images were used as the input to evaluate the inpainting algorithms. Besides the CTI and the proposed GIN, we also included the classical Exemplar-Based Inpainting (EBI) algorithm in the evaluation. Structure

| Metrics  | Methods | Masked | EBI | CTI | Proposed Pre-trained | Proposed Fine-tuned |
|----------|---------|--------|-----|-----|----------------------|---------------------|
| SSIM ↑   |         | 0.778  | 0.901 | 0.931 | 0.918 ±0.039          | 0.946 ±0.013        |
|          |         | ±0.085 | ±0.043 | ±0.015 |                        |                     |
| PSNR ↑   |         | 11.851 | 25.988 | 29.352 | 29.990 ±3.253          | 30.615 ±3.824       |
|          |         | ±2.605 | ±3.117 | ±3.712 |                        |                     |
| MSE ($\times10^3$) ↓ | | 3.464  | 0.165 | 0.109 | 0.105 ±0.079          | 0.091 ±0.071        |
|          |         | ±1.805 | ±0.092 | ±0.082 |                        |                     |

Table 1. Quantitative comparison of different inpainting algorithms.
Similarity Index (SSIM), Peak Signal to Noise Ratio (PSNR), and Mean Squared Error (MSE) were employed as quantitative metrics. We used the masked images as the baseline. The results were summarized in Table 1. We tested these metrics using the corresponding functions in MATLAB. The SSIM measurements in Table 1 suggest the good feasibility of the proposed inpainting-based method in this task. All of the testing methods have the SSIMs of > 0.9, which implies a realistic restoration of the choroidal vasculature. We got high MSE values because the images were not normalized to [0 1], which would not influence the conclusion of the comparison. In accordance with the experimental results above, the finetuned GIN has the best performances in the quantitative of all the metrics. The CTI outperformed the pre-trained GIN, which suggests the specificity of the en face choroidal images compared with the natural scene images used in the pre-trained model. Figure 4 illustrates some sample inpainting results using different algorithms. Six Region Of Interests (ROIs) from two en face choroid images are used for demonstration. Based on visual inspection, the traditional algorithms tend to induce more inpainting artifacts than the GIN. But all of them could repair the missing areas with good visual similarity with the ground truth.

Fig. 5. Application of the proposed method in the quantitative measurement of choroidal vasculature changes related to high IOP. (Best viewed with colors.)

**Application to Quantify Vascular Changes:** After removing the retinal shadows, the choroidal vasculature can be clearly visualized and used in the quantitative analysis. Figure 5 demonstrates the calculated vessel and flow maps before and during the upside down of two subjects in the datasets. Obvious decrease in vessels and blood flow could be observed in the images of the high IOP state, which further induces the reduction in mean values. In the datasets, the choroidal vessel density changes from 0.491 ± 0.020 at the normal state to 0.463 ± 0.019 during the high IOP state. Their corresponding flow indexes are 0.336 ± 0.025 and 0.300 ± 0.019, respectively.
4 Conclusions

Eliminating the retinal shadow artifacts in volumetric OCT data is an important precondition for the quantitative analysis of the choroidal vasculature. In this paper, we have proposed a novel framework of OCT data processing for this task. The shadow removal was converted into an inpainting task and handled with a two-stage generative adversarial network. With the specially-designed data set and experiments, we have evaluated the feasibility and performance of the proposed framework. The results show that this work is promising in paving the road to apply quantitative vascular biomarkers of the choroid in the study and diagnosis of various ocular diseases.

References

1. Canny, J.: Computational approach to edge detection. TPAMI 13, 679–698 (1986)
2. Cox, M.J.: Optics of the human eye. Ophthalmic & Physiological Optics 21(5), 426–426 (2010)
3. Criminisi A, P., et al.: Region filling and object removal by exemplar-based image inpainting. TIP 13(9), 1200–1212 (2004)
4. Garvin, M.K., et al.: Automated 3-d intraretinal layer segmentation of macular spectral-domain optical coherence tomography images. TMI 28(9), 1436–1447 (2009)
5. Girard, M., et al.: Shadow removal and contrast enhancement in optical coherence tomography images of the human optic nerve head. Investigative Ophthalmology & Visual Science 52(10), 7738 (2011)
6. Goodfellow, I., et al.: Generative adversarial nets. In: NIPS. pp. 2672–2680 (2014)
7. Huang, D., et al.: Projection-resolved optical coherence tomographic angiography. BOE 7(3), 816 (2016)
8. Jia, Y., et al.: Quantitative oct angiography of optic nerve head blood flow. BOE 3(12), 3127–3137 (2012)
9. Jianlong, Y., et al.: Enhancing visibility of choroidal vasculature in oct via attenuation compensation and coherence transport inpainting. Accepted by ARVO (2019)
10. Laviers, H., et al.: Enhanced depth imaging-oct of the choroid: a review of the current literature. Graefes archive 252(12), 1871–83 (2014)
11. Maruko, I., et al.: Open visualizing large choroidal blood flow by subtraction of the choriocapillaris projection artifacts in swept source optical coherence tomography angiography in normal eyes. Sci Rep 8(1)
12. Nazeri, K., et al.: Edgeconnect: Generative image inpainting with adversarial edge learning (2019)
13. Regatieri, C.V., et al.: Choroidal thickness in patients with diabetic retinopathy analyzed by spectral-domain optical coherence tomography. Retina 32(3), 563–8 (2012)
14. Shida, C., et al.: Changes in choroidal thickness after trabeculectomy in primary angle closure glaucoma. Investigative Ophthalmology & Visual Science 55(4), 2608 (2014)
15. Vupparaboina, K.K., et al.: Quantitative shadow compensated optical coherence tomography of choroidal vasculature. Sci Rep 8(1) (2018)
16. Wang, J.C., et al.: Diabetic choroidopathy: Choroidal vascular density and volume in diabetic retinopathy with swept-source optical coherence tomography. American Journal of Ophthalmology 184 (2017)

17. Wang, S., et al.: Choroidal thickness and high myopia: a cross-sectional study and meta-analysis. Bmc Ophthalmology 15(1), 1–10 (2015)

18. Yiu, G., et al.: Relationship of central choroidal thickness with age-related macular degeneration status. American Journal of Ophthalmology 159(4), 617–626.e2 (2015)

19. Zheng, F., et al.: Choroidal thickness and choroidal vessel density in nonexudative age-related macular degeneration using swept-source optical coherence tomography imaging. Investigative Ophthalmology & Visual Science 57(14), 6256–6264 (2016)

20. Zhou, H., et al.: Attenuation correction assisted automatic segmentation for assessing choroidal thickness and vasculature with swept-source oct. BOE 9(12), 6067–6080 (2018)