EasyChair Preprint

№ 13710

Deep Learning-Based Approaches for Ciliary Muscle Segmentation and Biomarker Extraction

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June 19, 2024

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***Abstract*—This paper highlights our recently published work [1] that involves the application of deep learning techniques to perform the segmentation of the ciliary muscle in Anterior Segment Optical Coherence Tomography (AS-OCT) images. The ciliary muscle is vital for various anterior segment of the eye functions, including intraocular pressure regulation and lens shape maintenance. To advance research, we propose a fully automatic method for segmenting and measuring ciliary muscle biomarkers in $6\ mm$ and $16\ mm$ scan depths, commonly used in clinical analysis. Our approach ensures repeatable and immediate results through thorough exploration of artificial intelligence approaches combining different network architectures, encoders, data augmentation and transfer learning strategies. Additionally, we extract relevant biomarkers, aiding in diagnoses and monitoring of ocular diseases such as glaucoma, myopia, and presbyopia, and facilitating the development of new therapeutic strategies. With high accuracy values (0.9665 ± 0.1280 and 0.9772 ± 0.0873 for the best $6\ mm$ and $16\ mm$ combinations, respectively), our system provides clinicians and researchers with a valuable, automatic tool for ciliary muscle segmentation and analysis in AS-OCT images.**

***Index Terms*—CAD system; AS-OCT; Ciliary Muscle; Segmentation; Biomarkers; Deep Learning**

I. Introduction

The ciliary muscle, critical for vision clarity by adjusting lens shape, is extensively studied for its role in accommodation-related conditions. Anterior Segment Optical Coherence Tomography (AS-OCT) enables detailed ciliary muscle analysis, facilitating a fully automatic methodology for biomarker extraction, enhancing diagnosis and monitoring of ocular diseases with valuable clinical implications.

In [1], we presented a fully automatic methodology for ciliary muscle segmentation and analysis in AS-OCT images at commonly used scan depths, employing deep learning-based approaches to extract relevant biomarkers. These biomarkers, including ciliary muscle length, area, and thickness, offer comprehensive evaluation of ciliary muscle morphology and behavior, aiding in diagnosing and monitoring ocular diseases. The methodology reduces variability, ensures repeatable analysis, and provides valuable insights for ophthalmology research.

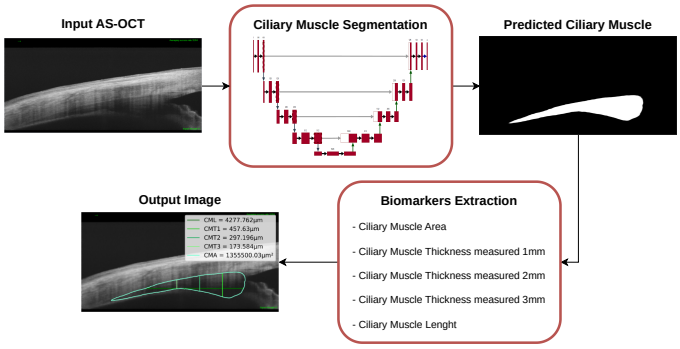

Fig. 1: General scheme of the methodology.

II. Materials

To carry out the study [1], we have utilized a custom dataset comprising 1035 AS-OCT images and its corresponding ciliary muscle labels, divided into subsets based on scan depth. The images were acquired as part of a cross-sectional study at the International Centre for Advanced Ophthalmology in Madrid, Spain, adhering to ethical guidelines. Ciliary muscle analyses were conducted using the DRI-Triton device, ensuring high-quality scans under uniform lighting conditions.

III. Methodology

Fig. 1 shows an overview of the methodology presented in [1]. It involves automatic segmentation of the ciliary muscle using state of the art deep learning techniques and extraction of biomarkers from AS-OCT images. Two network architectures, U-Net and Feature Pyramid Network (FPN), combined with ResNet-18 and ResNet-34 encoders, are employed for segmentation. Training involves 200 epochs and 5 repetitions with random data splits into training (60%), validation (20%), and test sets (20%). The Adam optimizer is used with Dice loss for training, and data augmentation techniques are applied to increase dataset size and diversity. Transfer learning from ImageNet is also explored. The extracted biomarkers include

Scan Depth	*Architecture*	*Encoder*	*Transfer Learning*	*Accuracy*	*Jaccard*	*Dice*	*Precision*	*Recall*
$6\ mm$	**U-Net**	**ResNet-18**		0.9657 ± 0.1278	0.8106 ± 0.1320	0.8867 ± 0.1200	0.9032 ± 0.0725	0.8937 ± 0.1378
		ResNet-34		0.9662 ± 0.1278	0.8150 ± 0.1332	0.8891 ± 0.1219	0.9089 ± 0.0724	0.8930 ± 0.1411
		ResNet-18	•	0.9662 ± 0.1277	0.8151 ± 0.1313	0.8895 ± 0.1197	0.9081 ± 0.0695	0.8943 ± 0.1386
		ResNet-34	•	0.9665 ± 0.1280	0.8194 ± 0.1306	0.8923 ± 0.1194	0.9109 ± 0.0690	0.8969 ± 0.1364
	FPN	**ResNet-18**		0.9660 ± 0.1279	0.8136 ± 0.1299	0.8887 ± 0.1190	0.9066 ± 0.0700	0.8938 ± 0.1361
		ResNet-34		0.9663 ± 0.1279	0.8170 ± 0.1323	0.8906 ± 0.1207	0.9109 ± 0.0711	0.8940 ± 0.1383
		ResNet-18	•	0.9661 ± 0.1277	0.8148 ± 0.1303	0.8895 ± 0.1189	0.9102 ± 0.0709	0.8916 ± 0.1351
		ResNet-34	•	0.9640 ± 0.1352	0.8183 ± 0.1338	0.8907 ± 0.1248	0.9060 ± 0.0852	0.8983 ± 0.1403
$16\ mm$	**U-Net**	**ResNet-18**		0.9508 ± 0.2086	0.6411 ± 0.2053	0.7492 ± 0.2198	0.8325 ± 0.1858	0.7340 ± 0.2395
		ResNet-34		0.9586 ± 0.1680	0.6120 ± 0.2190	0.7240 ± 0.2289	0.8164 ± 0.1854	0.7285 ± 0.2573
		ResNet-18	•	0.9604 ± 0.1677	0.7119 ± 0.1613	0.8133 ± 0.1599	0.8485 ± 0.1680	0.8015 ± 0.1797
		ResNet-34	•	0.9521 ± 0.2091	0.7131 ± 0.1740	0.8110 ± 0.1850	0.8544 ± 0.1879	0.7928 ± 0.1931
	FPN	**ResNet-18**		0.9758 ± 0.0883	0.6546 ± 0.1973	0.7653 ± 0.1976	0.8541 ± 0.1067	0.7647 ± 0.2330
		ResNet-34		0.9759 ± 0.0877	0.6544 ± 0.1985	0.7632 ± 0.2070	0.8619 ± 0.1062	0.7554 ± 0.2336
		ResNet-18	•	0.9767 ± 0.0875	0.7049 ± 0.1332	0.8146 ± 0.1199	0.8808 ± 0.0963	0.7885 ± 0.1467
		ResNet-34	•	0.9772 ± 0.0873	0.7326 ± 0.1215	0.8362 ± 0.1101	0.8787 ± 0.0890	0.8273 ± 0.1373

TABLE I: Test results in terms of mean $\pm$ standard deviation for 5 randomised repetitions for 6 mm and 16 mm configurations.

ciliary muscle length, area, and thickness at different distances from the scleral spur, along with the complete ciliary muscle thickness profile. Evaluation includes statistical analysis and qualitative comparison with expert measurements using box plots and Bland-Altman analysis to ensure reliability and accuracy.

IV. Results and Discussion

Regarding the performance of the segmentation part, different neural network configurations were evaluated, including those trained from scratch and those using transfer learning. The stability and performance of these configurations were assessed for both 6 mm and 16 mm images. Results show that all configurations perform well for automatic segmentation, achieving stability before epoch 30. The test results demonstrate high values for all the segmentation metrics, with certain configurations outperforming others (see Table I). Qualitative results further support the effectiveness of the proposed methodology, showing accurate and consistent segmentation of the ciliary muscle (Fig. 2).

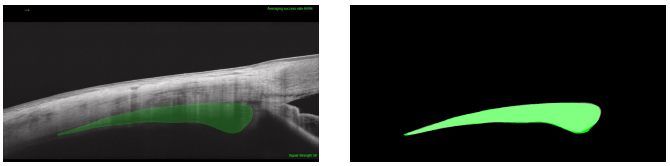

Fig. 2: Example of the resulting segmented region (green) overlapped with: the input image and the manual label (grey).

Regarding the biomarker extraction, quantitative analyses including box plots and Bland-Altman analyses compare automatic with manual measurements by clinical experts. The results indicate the effectiveness of the approach, providing reliable and accurate results consistent with expert assessments. Qualitative analysis of biomarker extraction also demonstrates visually accurate and clinically interpretative results (Fig. 3).

Overall, the study presents a comprehensive evaluation of the proposed approach for automatic segmentation and biomarker extraction in AS-OCT images of the ciliary muscle, showing promising results for clinical applications.

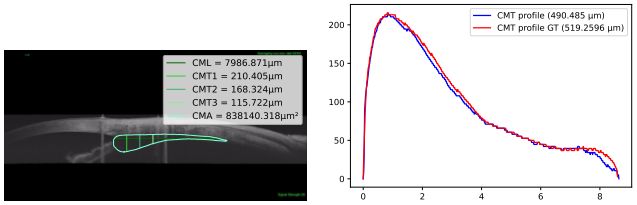

Fig. 3: Representative output example of biomarkers extraction (left) and its CMT profile representation (right).

V. Conclusion

Our study [1] introduced a deep learning-based method for automating the segmentation and biomarker extraction from AS-OCT images of the ciliary muscle. Results indicate accurate segmentation and biomarker extraction, offering potential workload reduction for clinical experts. The adaptable nature of our approach suggests applicability to various AS-OCT images and biomarkers, broadening its clinical utility. Future plans include refining the method, validating it against more labeled datasets, integrating into a user-friendly platform, and conducting comparative clinical evaluations to strengthen its clinical relevance.

Acknowledgment

This work was supported by Ministerio de Ciencia e Innovación, Government of Spain through the research project with [grant numbers RTI2018-095894-B-I00, PID2019-108435RB-I00, TED2021-131201B-I00, and PDC2022-133132-I00]; Consellería de Educación, Universidade, e Formación Profesional, Xunta de Galicia, Grupos de Referencia Competitiva, [grant number ED431C 2020/24], predoctoral grant [grant number ED481A-2023-152].

References

[1] Goyanes, E., de Moura, J., Fernández-Vigo, J. I., Fernández-Vigo, J. A., Novo, J., Ortega, M. (2024). Automatic simultaneous ciliary muscle segmentation and biomarker extraction in AS-OCT images using deep learning-based approaches. Biomedical Signal Processing and Control, 90, 105851.