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Retinal layer segmentation in OCT with a curvature prior and uncertainty estimation using deep learning

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Objective

- Age-related Macular Degeneration (AMD) is a serious retinal condition characterized by fluid or fibrous tissues between the retinal pigment epithelium (RPE) and the Bruch's membrane (BM) layers:
  - Segmenting these layers is crucial for detecting and monitoring AMD
  - Automated methods exist, but they:
    - Do not account for anatomical coherence considerations
    - Do not provide feedback about the prediction's confidence
    - Are often bound to a device vendor or disease stage
- Our contributions:
  - A new deep learning method for a robust layer segmentation of BM in OCT images with uncertainty feedback
  - A large scale evaluation on all AMD stages

Datasets

- Trained and evaluated on a private dataset:
  - 1,449 volumetric OCT scans of 478 eyes from 386 patients
  - Heidelberg Spectralis and Zeiss Cirrus scans
  - Covers all major AMD stages: intermediate AMD (iAMD), neovascular AMD (nAMD), and geographic atrophy (GA)
  - Contains (semi-)manual annotations of the BM;
- External validation on the openly available Duke SD-OCT nAMD dataset

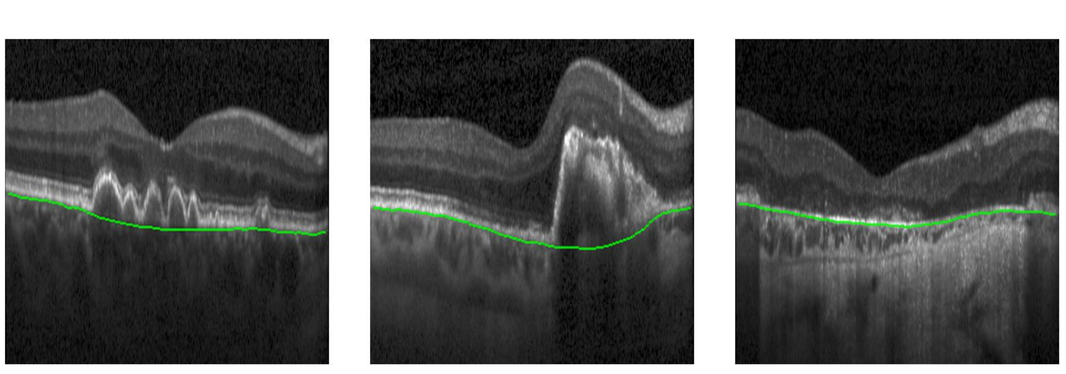


Figure 1: Typical examples for the three stages of the AMD in order: iAMD, nAMD and GA. The BM is marked with a green line.

Methods

- A backbone fully convolutional neural network produces a probability map for the position of the BM:
  - Each column of the probability map is a probability distribution
  - The predicted position of the BM is the expected value of the distribution
  - The network is optimized to match the curvature of the predicted layer with a novel loss term
- The uncertainty of the position is quantified
  - Standard deviation of the probability distribution
- Uncertain positions are 3D interpolated using Thin Plate Splines (TPS)

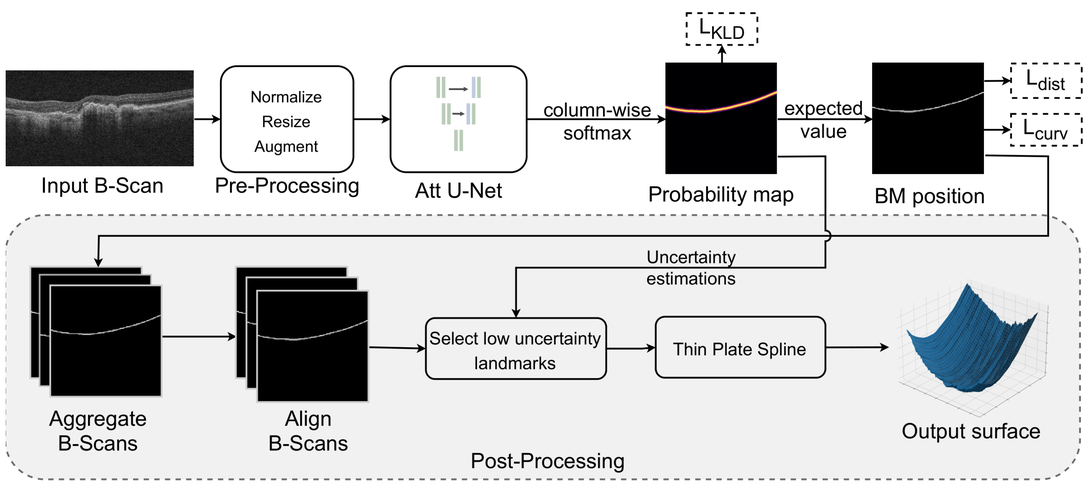


Figure 2: An overview of the proposed method. The input is a single B-scan, which is pre-processed. The Att U-Net predicts a probability map of equal size as the input. Each column contains a probability distribution of the possible BM location. The actual BM position is calculated from the expected value. Besides matching the correct position, a curvature constraint is imposed to learn the expected shape of the layer. During inference, the calculated probability maps from a volumetric scan are aggregated, aligned, and using random control points with low uncertainty a Thin Plate Spline surface is calculated to replace the highly uncertain values.

Results

- When compared to a baseline without anatomical priors
  - 8% improvement in Mean Average Error (MAE)
  - 20% improvement in Root Mean Squared Error
  - The number of outliers are reduced
- 5% improvement in MAE over the SOTA [1] on the external dataset
- The uncertainty measurement positively correlates with the error rate

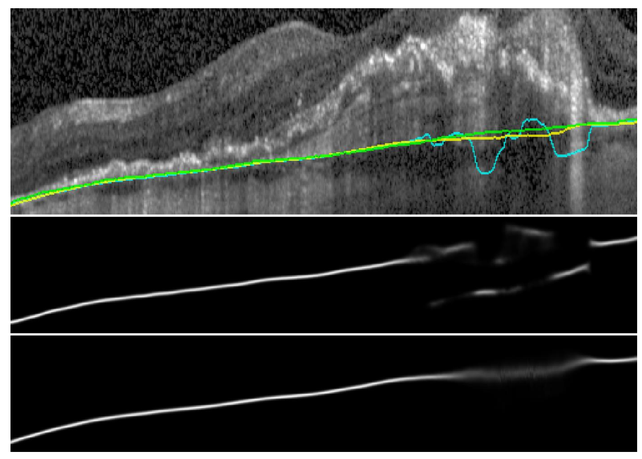
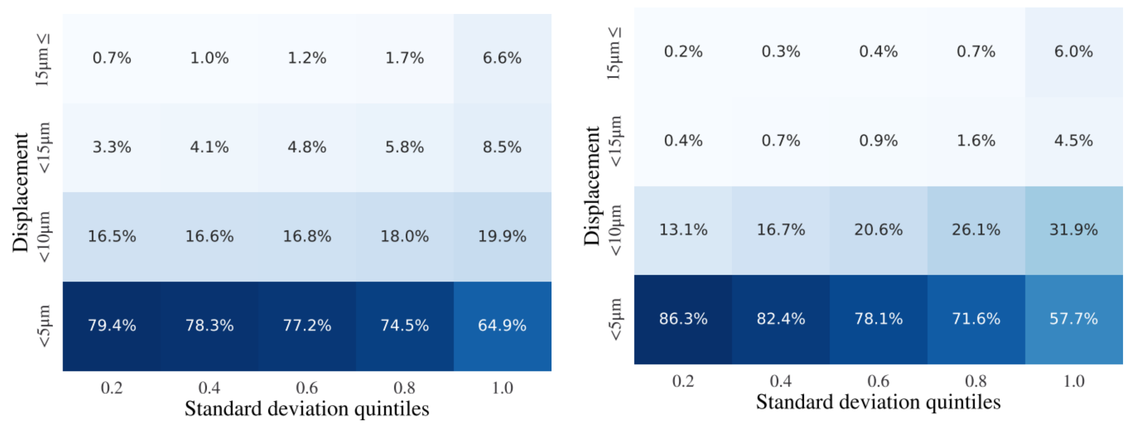


Figure 3: A sample segmentation. The relevant part of the B-scan is seen on the top image, with the baseline (green), the prediction without the curvature term (blue) and the prediction with the curvature term (yellow). The middle image is the output density function of the prediction without the curvature term, the bottom image is using the curvature term.

	Method	MAE	Std
AMD	DexiNed[1]	**0.70**	**0.13**
	Ours	**0.70**	0.24
Control	DexiNed[1]	0.59	**0.08**
	Ours	**0.47**	0.11
All	DeepForest[2]	1.24	0.52
	CapsNet[3]	1.09	2.49
	BFC-DN[4]	0.97	0.86
	DexiNed[1]	0.66	**0.12**
	Ours	**0.63**	0.23

Table 1: Comparison with the state-of-the-art methods on the Duke dataset. Depending on the task, our method performs similarly or better than the current solutions.



(a) Internal dataset **(b)** Duke dataset

Figure 4: The distribution of the displacement of the predicted BM positions against the quintiles of the predicted uncertainty. The lower is the uncertainty, the more accurate is the prediction.

Conclusion

- To our knowledge, this is the first work which:
  - Focuses on the segmentation of BM
  - Includes the especially challenging late AMD stages
  - Was evaluated on a large-scale dataset with all AMD stages and different disease vendors
- Key findings:
  - Anatomical priors improve the segmentation performance
  - The proposed uncertainty measurement can be used to detect wrong segmentations, which can be corrected using TPS

References

[1] J. A. Sousa, A. Paiva, A. Silva, J. D. Almeida, G. B. Junior, J. O. Diniz, W. K. Figueredo, and M. Gattass, ''Automatic segmentation of retinal layers in OCT images with intermediate age-related macular degeneration using U-Net and DexiNed,'' *PLOS ONE*, vol. 16, no. 5, p. e0251591, May 2021.
[2] Z. Chen, D. Li, H. Shen, Y. Mo, H. Wei, and P. Ouyang, ''Automated retinal layer segmentation in OCT images of age-related macular degeneration,'' *IET Image Processing*, vol. 13, no. 11, pp. 1824--1834, 2019.
[3] A. M. Santos, ''Diagnosis of age-related macular degeneration from optical coherence tomography using geostatistics and capsule network,'' Ph.D. dissertation, Universidade Federal do Maranh˜ ao, 2019.
[4] S. Sedai, B. Antony, D. Mahapatra, and R. Garnavi, ''Joint segmentation and uncertainty visualization of retinal layers in optical coherence tomography images using bayesian deep learning,'' in *Computational Pathology and Ophthalmic Medical Image Analysis*. Springer International Publishing, 2018, pp. 219--227.