Formula-Driven Data Augmentation and Partial Retinal Layer Copying for Retinal Layer Segmentation

Tsubasa Konno[1], Takahiro Ninomiya[2], Kanta Miura[1], Koichi Ito[1], Noriko Himori[2], Parmanand Sharma[2], Toru Nakazawa[2], and Takafumi Aoki[1]

1 Graduate School of Information Sciences,

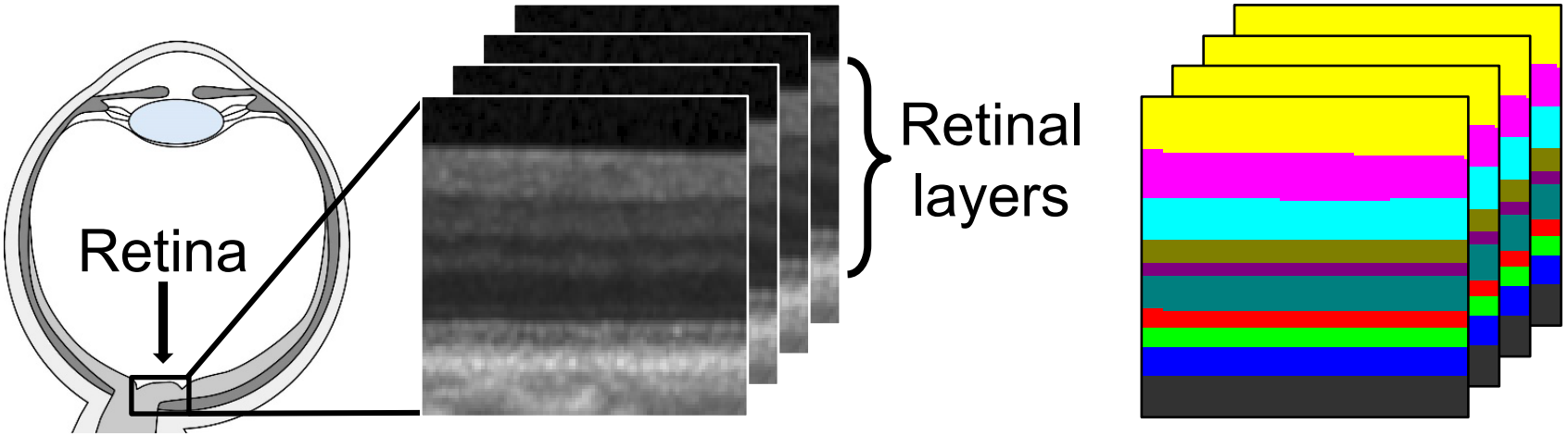
Tohoku University, Japan

2 Department of Ophthalmology,

Graduate School of Medicine, Tohoku University, Japan

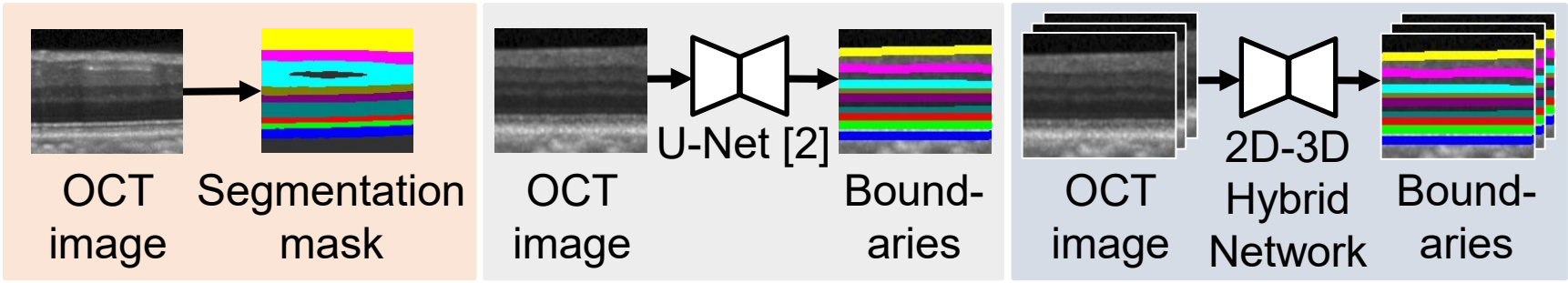
Optical Coherence Tomography (OCT)

- Visualize the internal structure of retina noninvasively in three dimensions
- Use OCT images to evaluate the thickness of retinal layers for diagnosis of diseases that cause structural changes in the retina
- Measure the thickness of retinal layers by segmenting retinal layers



Conventional Methods

- Standard image segmentation: Pixel-wise labeling
  - Cannot consider the anatomical order of retinal layers
- Boundary detection: Detect the boundaries between retinal layers according to the anatomical order of the retinal layers
  - FCBR [1]: 2D U-Net [2]
  - SASR [3]: 2D-3D hybrid network



Standard image segmentation | FCBR [1] | SASR [3]

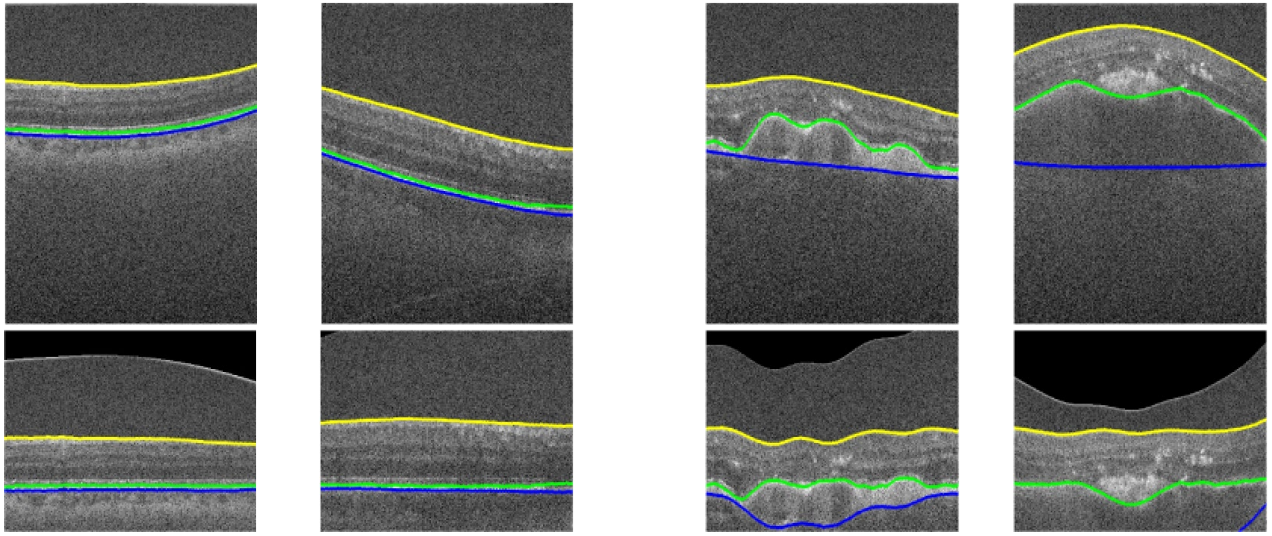
[1] Y. He et al., "Fully convolutional boundary regression for retina OCT segmentation," MICCAI, 2019.
[2] O. Ronneberger et al., "U-Net: Convolutional networks for biomedical image segmentation," MICCAI, 2015.
[3] H. Liu et al., "Simultaneous alignment and surface regression using hybrid 2D-3D networks for 3D coherent layer segmentation of retina OCT images," MICCAI, 2021.

Problems of Boundary Detection

- Simplify the boundary detection by applying flattening [4] to the OCT images
- Flattening may fail, if the quality of the OCT image is low or the shape of retinal layers changes significantly due to diseases
- Consider a boundary detection method without flattening

Before flattening

After flattening



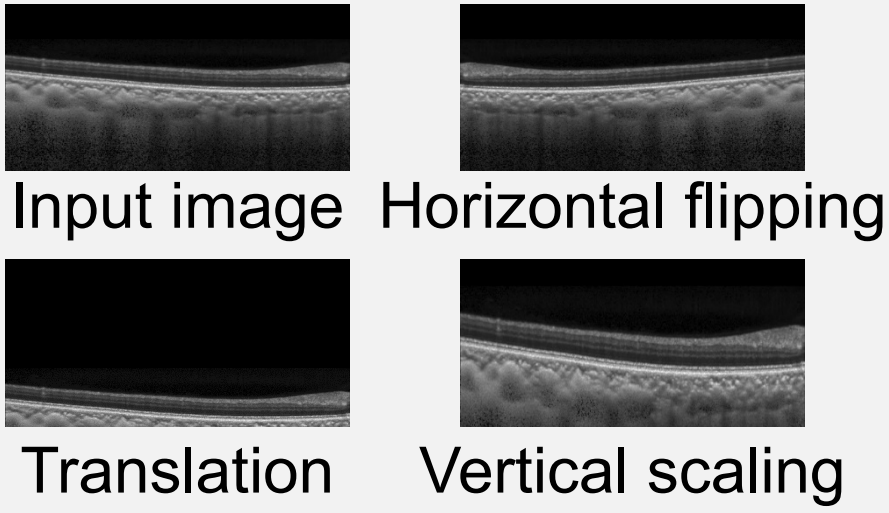
Success cases

Failure cases

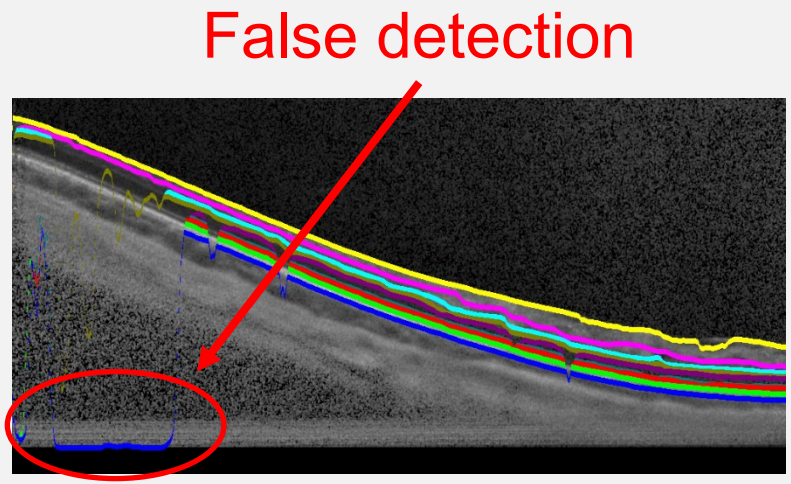
[4] A. Lang et al., “Retinal layer segmentation of macular OCT images using boundary classification,” Biomedical Optics Express, 2013.

Data Augmentation for OCT Images

- To detect the boundaries without flattening, we need to train the network with a variety of OCT images
- Retinal layer segmentation methods use standard data augmentation to increase the variability of OCT images
  - Cannot increase the variability of retinal shapes
  - Cannot reproduce background noise of OCT images that may be falsely detected as retinal layers



Standard data augmentation



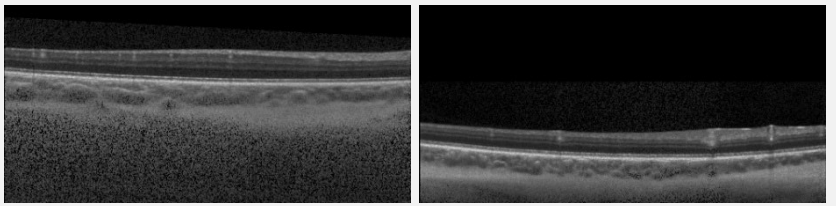
An example of false detection

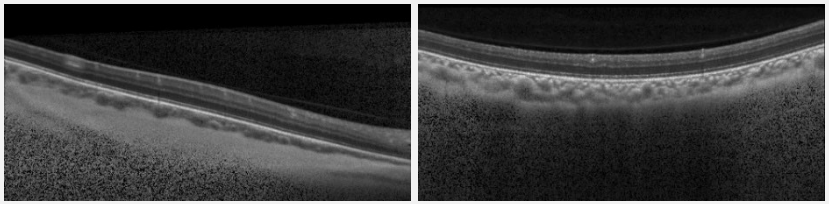
Objective

- Improve the accuracy of ophthalmic diagnostic support systems that use retinal layer thickness
- Propose two novel data augmentation methods for retinal layer segmentation
  1. Formula-Driven Data Augmentation (FDDA)
     Emulate a variety of retinal shapes, and increase the variability of retinal shapes in the training data
  2. Partial Retinal Layer Copying (PRLC)
     Reproduce the background noise of OCT images, and reduce false detection in the background region
- Evaluate the accuracy of boundary detection by introducing FDDA and PRLC to existing segmentation methods (FCBR [1], SASR [3])

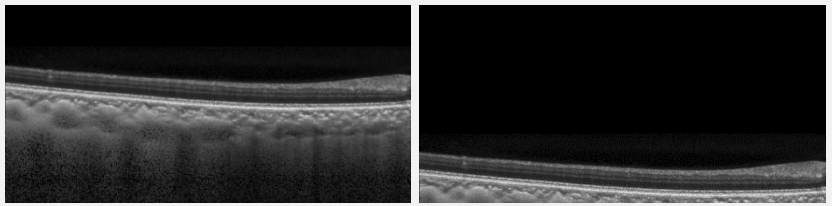
Formula-Driven Data Augmentation (FDDA)

- Emulate a variety of retinal shapes based on mathematical formulas
- Change the position, the tilt, and the curvature of the retina by shifting vertically each column of OCT images
- Increase the variability of retinal shapes

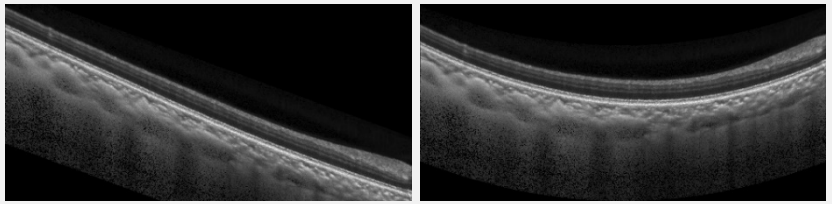




Examples of actual OCT images



Before FDDA After FDDA

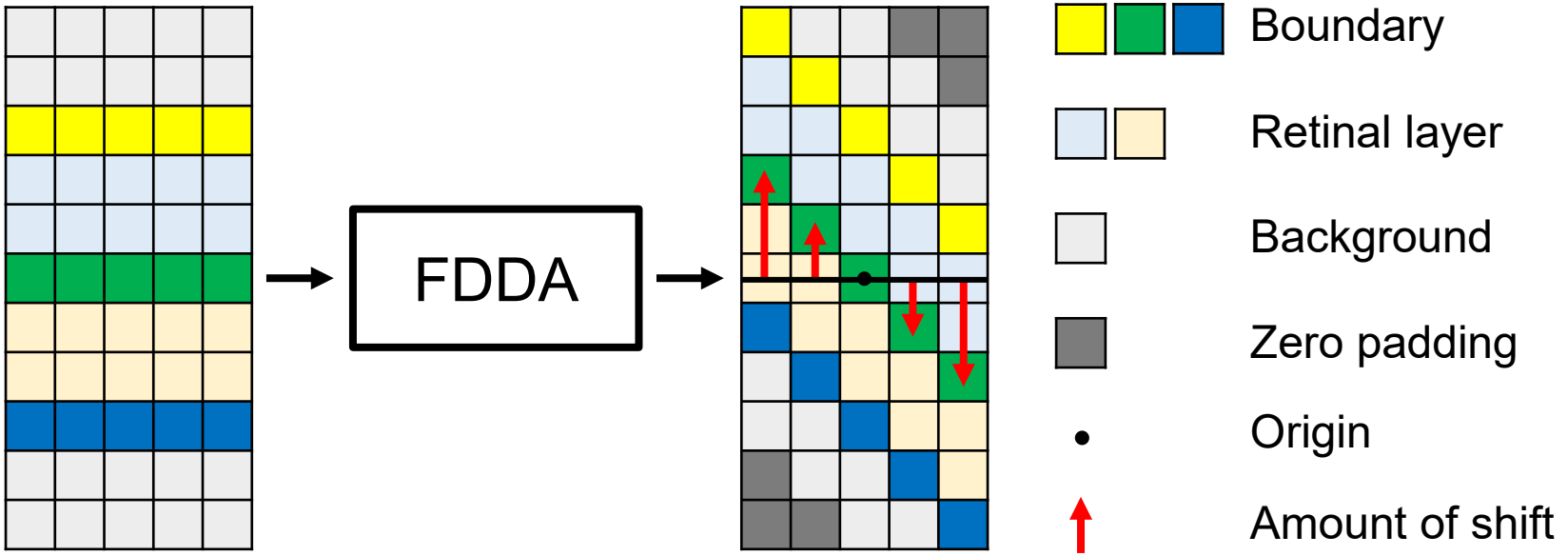


After FDDA After FDDA

Examples of applying FDDA

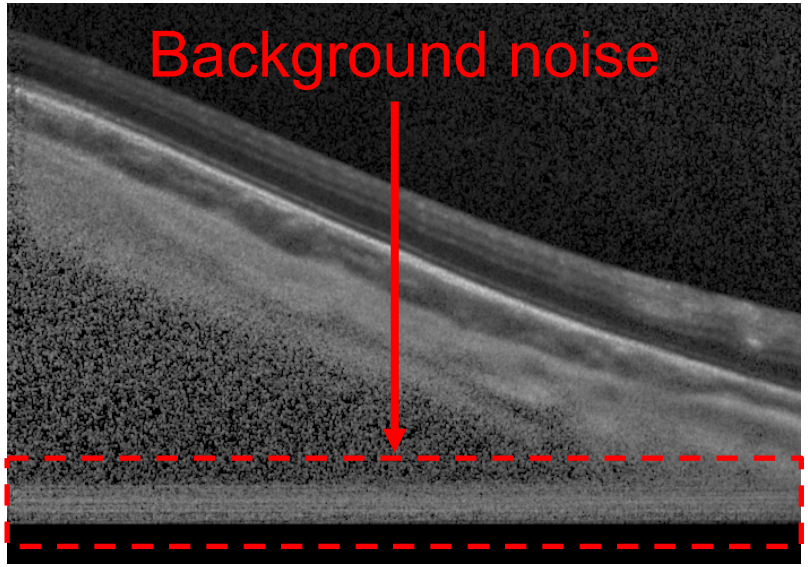
The Details of FDDA

- Shift each column of an OCT image according to a simple combination of 0~2nd-order functions
- Zeroth-order, first-order, and second-order functions change the position, the tilt, and the curvature of retinas respectively
- The labels after data augmentation can be obtained by shifting the labels in the same way

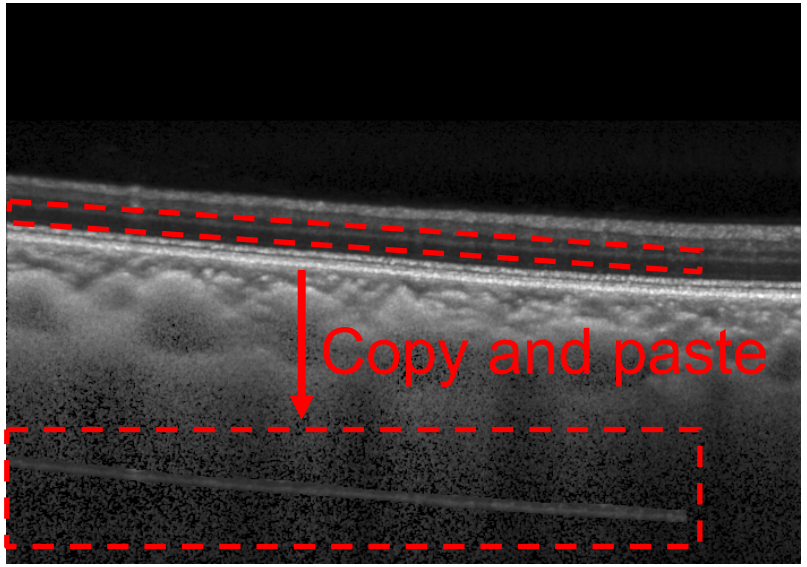


Partial Retinal Layer Copying (PRLC)

- Copy a part of retinal layers and paste it on the background region to reproduce background noise
- The segmentation network is trained to detect the pasted retinal layers as the background
- Reduce false detection in the background region



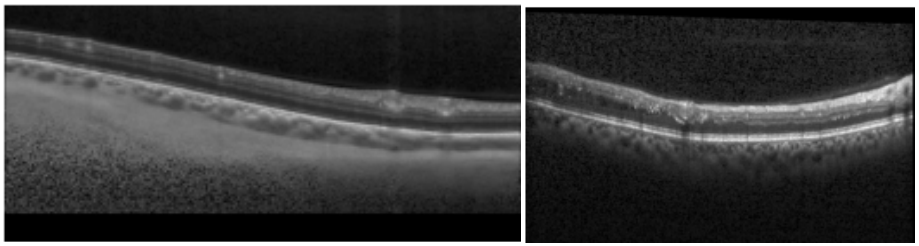
An example of OCT image



An example of applying PRLC

Experiments

- Evaluate the accuracy of boundary detection by introducing FDDA and PRLC to existing segmentation methods (FCBR [1], SASR [3])
- Compare FDDA and PRLC with similar data augmentation methods (RandomAffine, CutMix [5])
- Evaluate the mean absolute distance (MAD) between the detected boundary and the ground truth
- Use two public OCT datasets
  - OCT MS and Healthy Control (MSHC) [6]
  - Duke Cyst DME (Duke DME) [7]



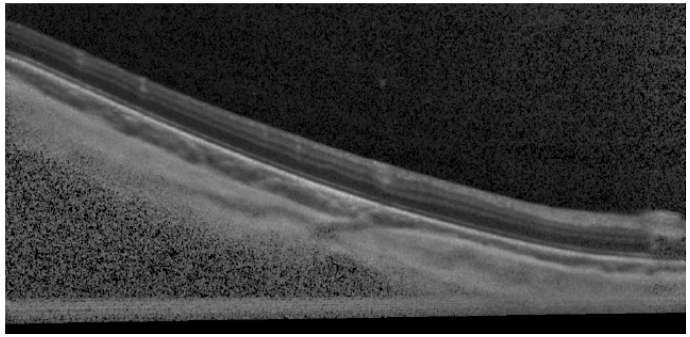
MSHC Duke DME

[5] S. Yun et al., “CutMix: Regularization strategy to train strong classifiers with localizable features,” ICCV, 2019.
[6] Y. He et al., “Retinal layer parcellation of optical coherence tomography images: data resource for multiple sclerosis and healthy controls,” Data Brief, 2018.
[7] S.J. Chiu et al., “Kernel regression based segmentation of optical coherence tomography images with diabetic macular edema,” Biomed. Opt. Express, 2015.

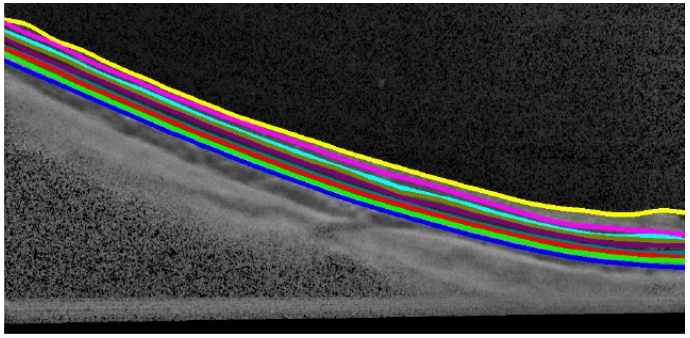
MAD [μm] of Each Method

Method	Flattening	MSHC	Duke DME
FCBR [1]	O	2.92	6.59
FCBR [1]		3.87	6.94
w/ RandomAffine		3.76	6.44
w/ CutMix [5]		3.52	6.68
w/ FDDA		2.92	6.04
w/ PRLC		3.16	6.32
w/ FDDA and PRLC		2.84	5.97
SASR [3]	O	2.87	6.54
SASR [3]		3.05	6.34
w/ FDDA		2.92	5.84
w/ PRLC		2.99	6.10
w/ FDDA and PRLC		2.90	5.83

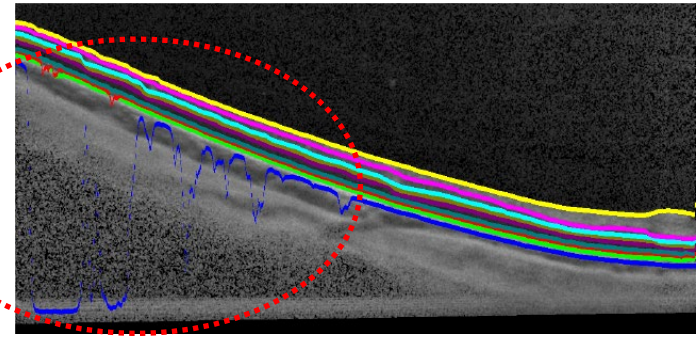
Examples of Detected Boundaries



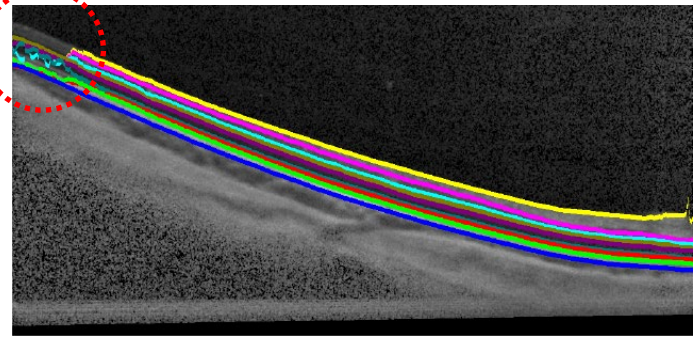
Input image



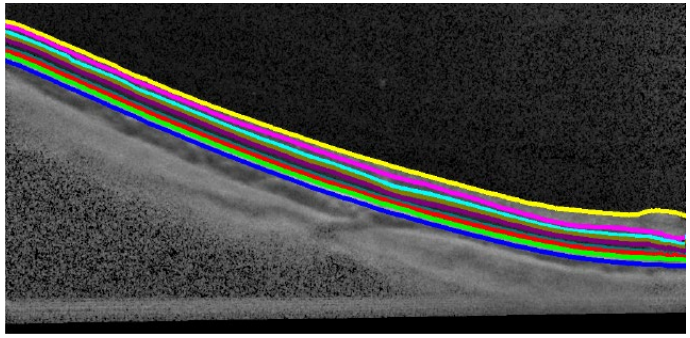
Ground truth



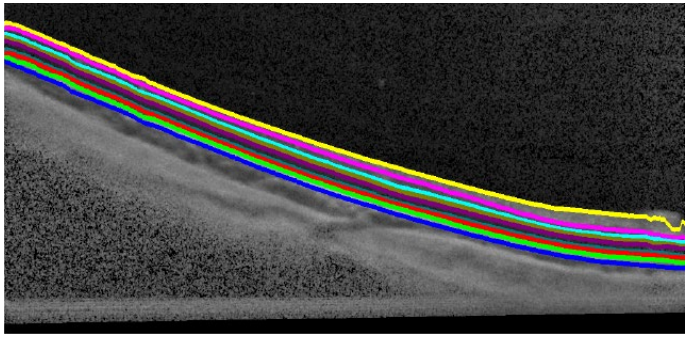
FCBR [1]



SASR [3]



FCBR w/ FDDA and PRLC



SASR w/ FDDA and PRLC

Conclusion and Future Work

- Conclusion
  - Proposed two novel data augmentation methods for retinal layer segmentation: FDDA and PRLC
  - Through the experiments, the use of FDDA and PRLC makes it possible to detect the boundaries with the same or higher accuracy than when flattening is performed

- Future work
  - Investigate the further improvement of segmentation accuracy by emulating retinas with myopia and/or structural disorders from retinas of healthy subjects