

Universal Wavelet Units in 3D Retinal Layer Segmentation

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- Proposed Method
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Motivation

Motivation

- Optical Coherence Tomography (OCT) provides high-resolution visualization of retinal structures and supports the diagnosis and monitoring of age-related macular degeneration (AMD), diabetic macular edema (DME), glaucoma, and other retinal diseases.
- Accurate retinal layer segmentation is essential for quantitative assessment of disease progression and treatment response.
- OCT segmentation is further complicated by motion artifacts, pathological deformations, weak layer boundaries, and variations in retinal anatomy.
- Standard max-pooling operations may discard fine spatial details and high-frequency features that are important for precise boundary localization.
- A more structure-preserving downsampling strategy is therefore needed for robust 3D retinal OCT segmentation.

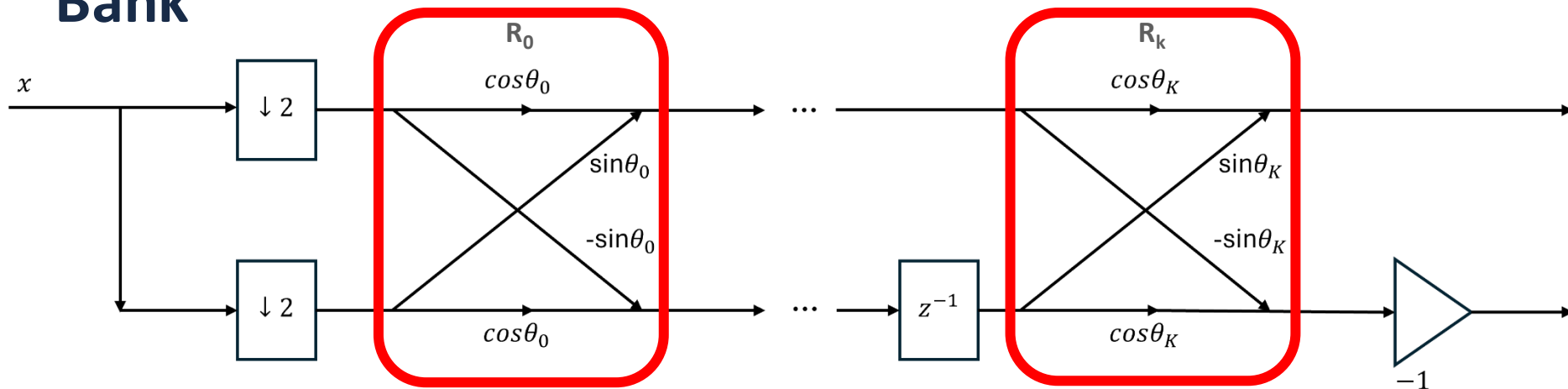
Proposed Method

Proposed Method

- We propose **UwU-MGUNet**, an enhanced MGU-Net-based framework for motion-corrected 3D retinal OCT segmentation.
- Conventional max-pooling or static wavelet downsampling layers are replaced with tunable wavelet-inspired downsampling modules:
 - **OrthLatt-UwU**
 - **BiorthLatt-UwU**
 - **LS-Biorth-UwU**
- These modules use learnable lattice filter banks to preserve anatomical structures, spatial details, and high-frequency information during downsampling.
- Experiments on the JRC and PPS datasets demonstrate consistent Dice-score improvements over the standard max-pooling-based model.

Universal Wavelet Unit: Orthogonal Lattice Structure based Wavelet Unit

Orthogonal Lattice Structure of The Filter Bank



- Orthogonal Lattice Structure for the Analysis Bank:

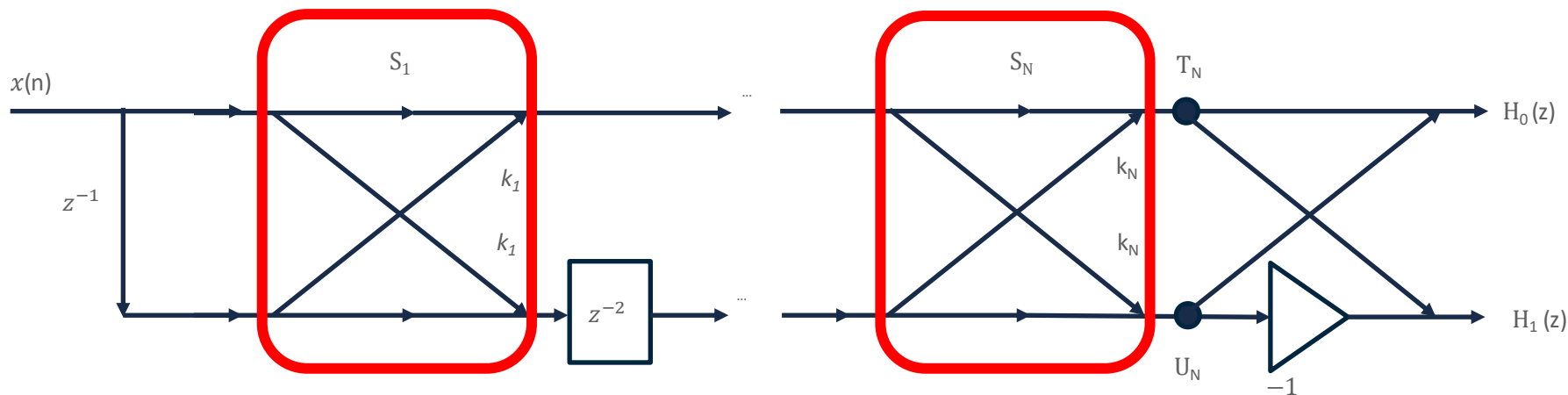
$$\begin{pmatrix} \mathbf{H}_{0,K}(z) \\ \mathbf{H}_{1,K}(z) \end{pmatrix} = \begin{pmatrix} \mathbf{H}_{0,K}(z) \\ -z^{-L}\mathbf{H}_{0,K}(-z^{-1}) \end{pmatrix} = \mathbf{H}_{P,K}(z^2) \begin{pmatrix} 1 \\ z^{-1} \end{pmatrix}$$

$$= \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \underbrace{\begin{bmatrix} \cos\theta_K & \sin\theta_K \\ -\sin\theta_K & \cos\theta_K \end{bmatrix}}_{\mathbf{R}} \begin{bmatrix} 1 & 0 \\ 0 & z^{-2} \end{bmatrix} \cdots \begin{bmatrix} \cos\theta_0 & \sin\theta_0 \\ -\sin\theta_0 & \cos\theta_0 \end{bmatrix} \begin{pmatrix} 1 \\ z^{-1} \end{pmatrix}$$

The Orthogonal Lattice structure satisfies the Perfect Reconstruction Condition.

Universal Wavelet Unit: Biorthogonal Lattice Tunable Wavelet Unit

Biorthogonal Lattice Structure



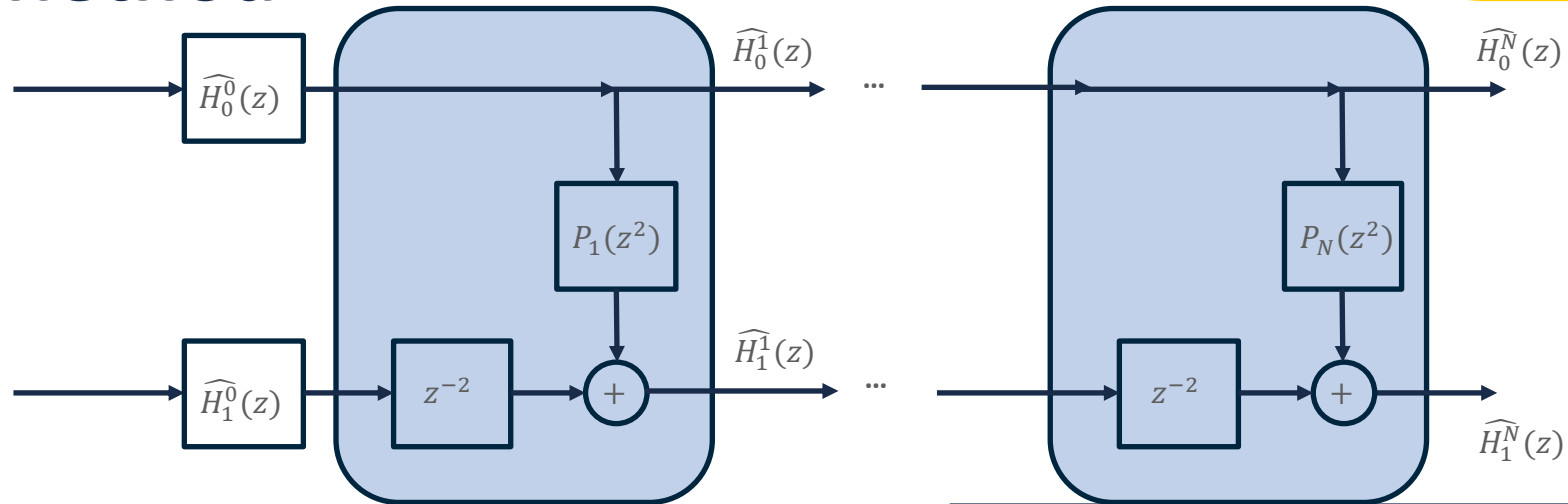
Biorthogonal Lattice Structure for the Analysis Bank:

$$\begin{aligned}
 \begin{bmatrix} H_0(z) \\ H_1(z) \end{bmatrix} &= \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} T_N(z) \\ U_N(z) \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} S_N \Lambda(z^{-2}) S_{N-1} \Lambda(z^{-2}) \dots S_2 \Lambda(z^{-2}) S_1 \begin{bmatrix} 1 \\ z^{-1} \end{bmatrix} \\
 &= \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} 1 & k_N \\ k_N & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & z^{-2} \end{bmatrix} \begin{bmatrix} 1 & k_{N-1} \\ k_{N-1} & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & z^{-2} \end{bmatrix} \dots \begin{bmatrix} 1 & k_2 \\ k_2 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & z^{-2} \end{bmatrix} \begin{bmatrix} 1 & k_1 \\ k_1 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ z^{-1} \end{bmatrix}
 \end{aligned}$$

- k can be used as tunable lattice coefficients for H_0 and H_1 .
- Biorthogonal Lattice structure keeps the perfect reconstruction constraint in the filter bank.

Universal Wavelet Unit: Biorthogonal Tunable Wavelet Unit With Lifting Scheme

Method



With:

$$\begin{bmatrix} \widehat{H}_0^0 \\ \widehat{H}_1^0 \end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 + z^{-1} \\ 1 - z^{-1} \end{bmatrix}$$

For $P_k(z) = -a_k + a_k z^{-2k}$ (k is from 1 to N) we have:

$$\begin{bmatrix} H_0 \\ H_1 \end{bmatrix} = \begin{bmatrix} \widehat{H}_0^N \\ \widehat{H}_1^N \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ P_N(z^2) & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & z^{-2} \end{bmatrix} \cdots \begin{bmatrix} 1 & 0 \\ P_1(z^2) & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & z^{-2} \end{bmatrix} \begin{bmatrix} \widehat{H}_0^0 \\ \widehat{H}_1^0 \end{bmatrix}$$

Recursive Algorithm

$\begin{bmatrix} \widehat{H}_0^N \\ \widehat{H}_1^N \end{bmatrix}$ can be found with the following recursive form for k is from 1 to N :

$$\begin{bmatrix} \widehat{H}_0^k \\ \widehat{H}_1^k \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ P_k(z^2) & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & z^{-2} \end{bmatrix} \begin{bmatrix} \widehat{H}_0^{k-1} \\ \widehat{H}_1^{k-1} \end{bmatrix}$$

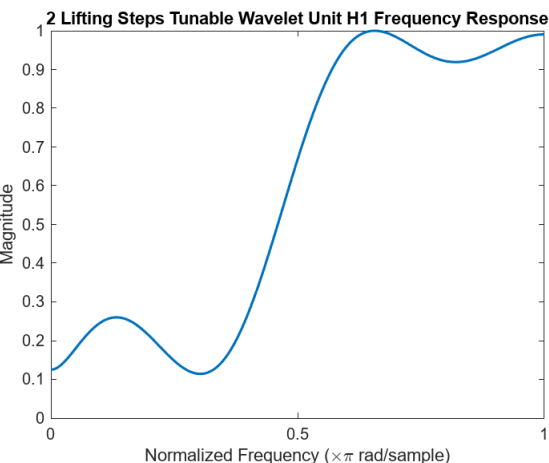
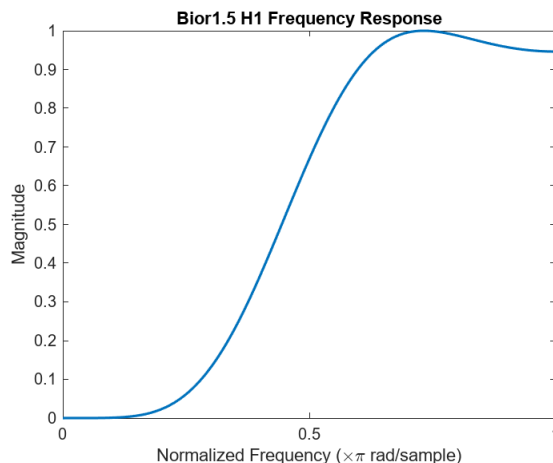
$$\begin{bmatrix} \widehat{H}_0^k \\ \widehat{H}_1^k \end{bmatrix} = \begin{bmatrix} \widehat{H}_0^{k-1} \\ -a_k \widehat{H}_0^{k-1} + z^{-2} \widehat{H}_1^{k-1} + a_k z^{-4k} \widehat{H}_0^{k-1} \end{bmatrix}$$

With $\begin{bmatrix} \widehat{H}_0^0 \\ \widehat{H}_1^0 \end{bmatrix} = \begin{bmatrix} H_0 \\ H_1 \end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 + z^{-1} \\ 1 - z^{-1} \end{bmatrix}$

Lifting Step Implementation Analysis

Initializing Coefficients		Groundtruth Coefficients	
1 Lifting Step	0.7071, 0.7071	Bior1.3	0.7071, 0.7071
	-0.0880, -0.0880, 0.7071, -0.7071, 0.0880, 0.0880		-0.0884, -0.0884, 0.7071, -0.7071, 0.0884, 0.0884
2 Lifting Steps	0.7071, 0.7071	Bior1.5	0.7071, 0.7071
	0.0166, 0.0166, -0.1215, -0.1215, 0.7071, -0.7071, 0.1215, 0.1215, -0.0166, -0.0166		0.0166, 0.0166, -0.1215, -0.1215, 0.7071, -0.7071, 0.1215, 0.1215, -0.0166, -0.0166

Original



Tuned

Discrete Wavelet Decomposition

Filters: $\mathbf{L} = \begin{bmatrix} \dots & \dots & \dots & & \\ \dots & l_{-1} & l_0 & l_1 & \\ & & \dots & l_{-1} & l_0 & l_1 & \dots \\ & & & & \dots & \dots & \end{bmatrix}$ $\mathbf{H} = \begin{bmatrix} \dots & \dots & \dots & & \\ \dots & h_{-1} & h_0 & h_1 & \\ & & \dots & h_{-1} & h_0 & h_1 & \dots \\ & & & & \dots & \dots & \end{bmatrix}$

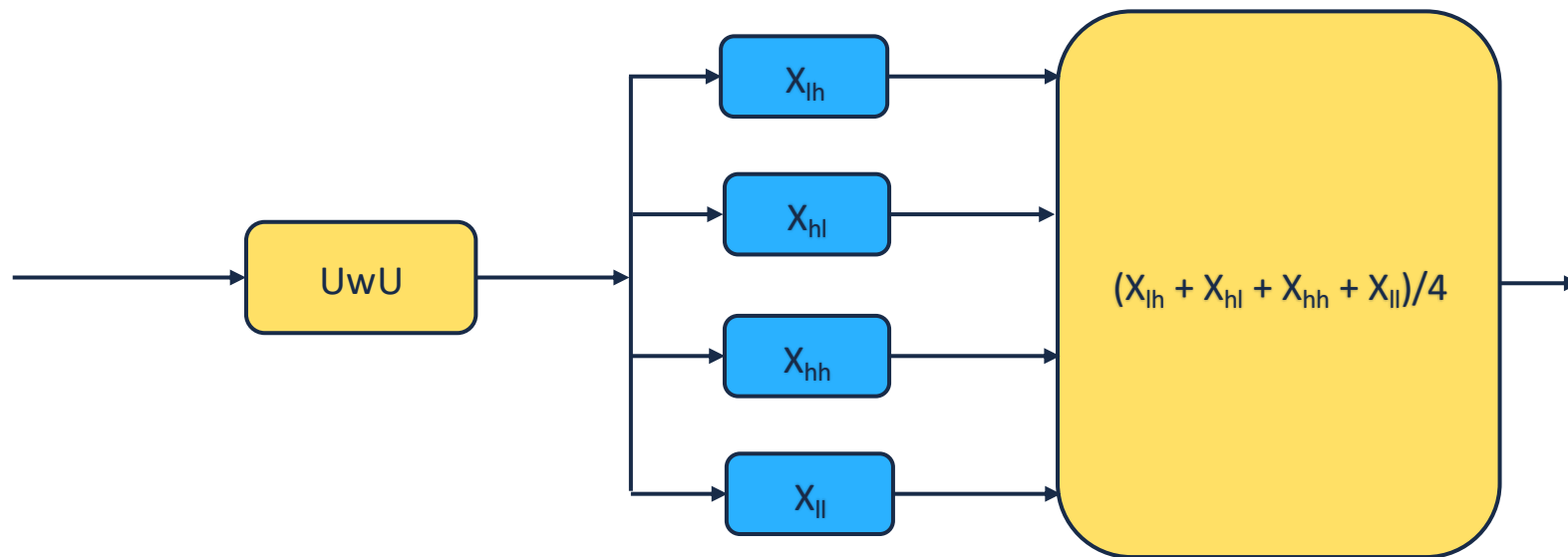
Analysis:

$$\begin{aligned} \mathbf{X}_{ll} &= \mathbf{L}\mathbf{X}\mathbf{L}^T, & \mathbf{X}_{lh} &= \mathbf{H}\mathbf{X}\mathbf{L}^T \\ \mathbf{X}_{hl} &= \mathbf{L}\mathbf{X}\mathbf{H}^T, & \mathbf{X}_{hh} &= \mathbf{H}\mathbf{X}\mathbf{H}^T \end{aligned}$$

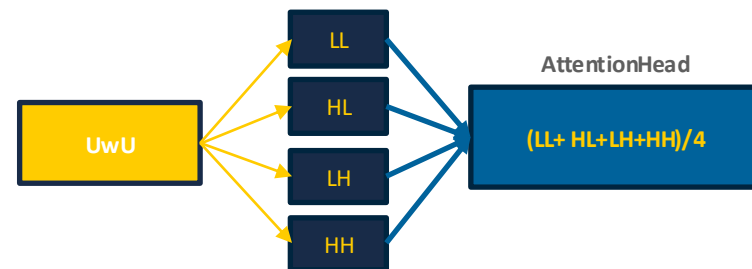
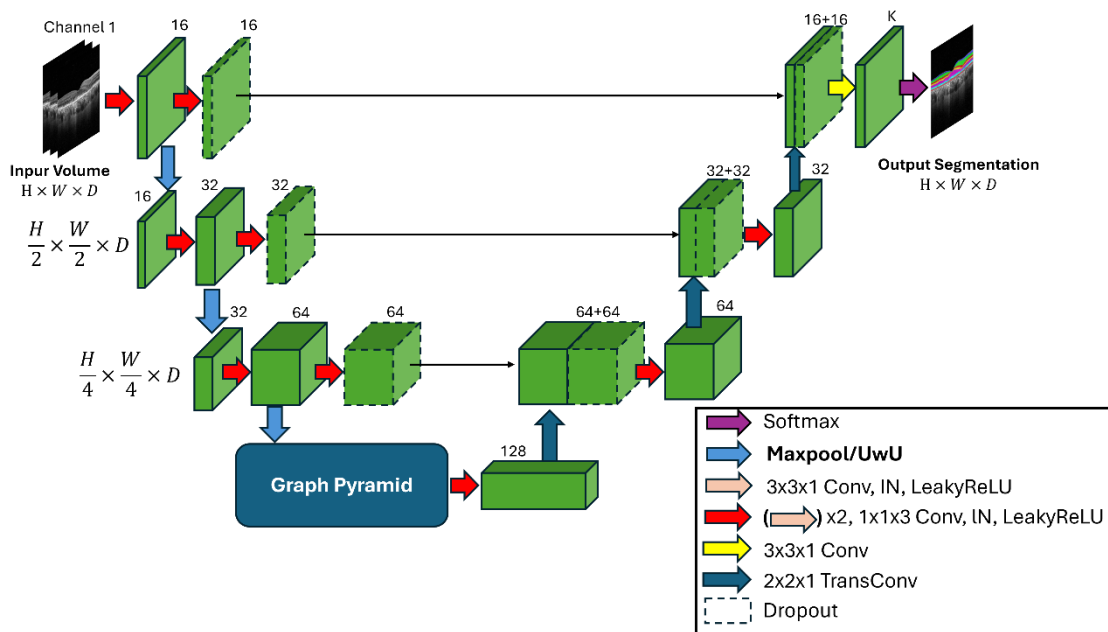
Synthesis:

$$\mathbf{X} = \mathbf{L}^T \mathbf{X}_{ll} \mathbf{L} + \mathbf{L}^T \mathbf{X}_{lh} \mathbf{H} + \mathbf{H}^T \mathbf{X}_{hl} \mathbf{L} + \mathbf{H}^T \mathbf{X}_{hh} \mathbf{H}$$

Sub-band Component Fusion



3D Segmentation Model



Experiment setup:

- Learning Rate: 0.0005
- Epochs: 40

UwU Implementation:

- Replace pooling/downsampling in MGUnet (kernel size: [1,2,2])

Experiments and Results

JRC Retina Layer Segmentation Dataset

Dataset: 30 OCT volumes acquired using the Heidelberg Spectralis system.

Data split: 15 volumes for training and 15 for validation.

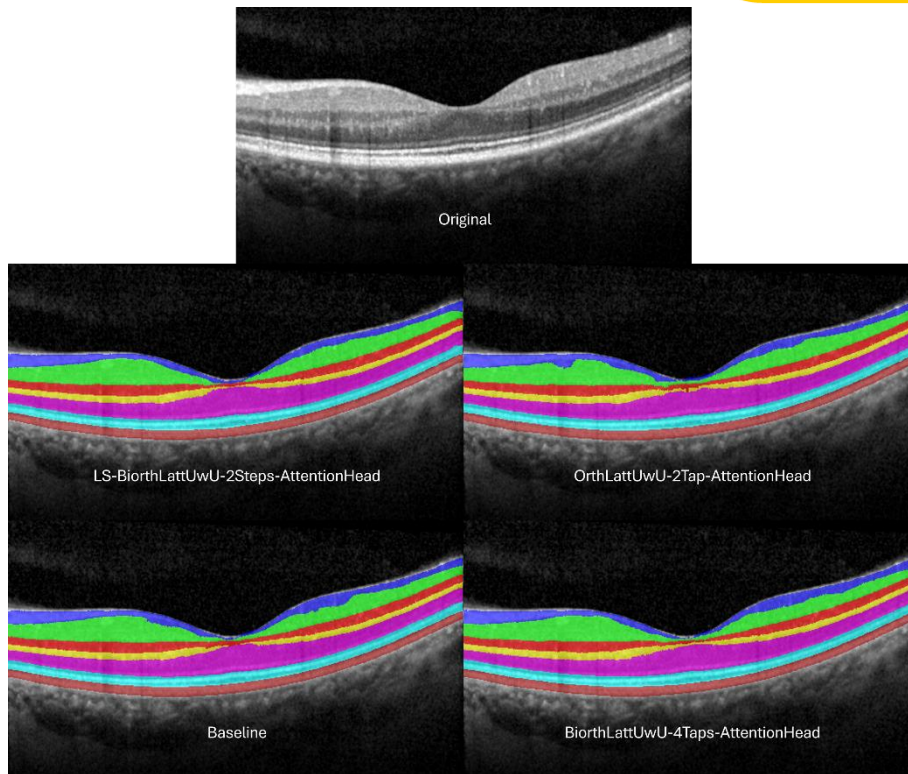
Volume size: $496 \times 512 \times 49$ voxels.

Physical dimensions: $1.9 \times 5.8 \times 5.8$ mm³.

Annotations: Eight retinal boundaries—ILM, RNFL, IPL, INL, OPL, ELM, PR2, and BM.

Annotation process: Manually corrected in Heidelberg HEYEX by six trained retinal MD fellows and reviewed by ophthalmologists at the Jacobs Retina Center.

Clinical diversity: Normal eyes and multiple retinal diseases, including wet/dry AMD, NPDR, ERM, CRVO, retinal detachment, macular hole, and chorioretinopathy.



JRC [ILM, RNFL, IPL, INL, OPL, ELM, PR2, BM]

Baseline	Avg: 0.9066		ILM-RNFL: 0.9145		RNFL-IPL: 0.9250		IPL-INL: 0.8767		INL-OPL: 0.8618		OPL-ELM: 0.9266		ELM-PR2: 0.9170		PR2-BM: 0.9249	
WaveCNet	Avg: 0.9077		ILM-RNFL: 0.9140		RNFL-IPL: 0.9245		IPL-INL: 0.8819		INL-OPL: 0.8647		OPL-ELM: 0.9296		ELM-PR2: 0.9149		PR2-BM: 0.9241	
	OrthLattUwU								BiorthLattUwU							
nTap	Avg	ILM-RNFL	RNFL-IPL	IPL-INL	INL-OPL	OPL-ELM	ELM-PR2	PR2-BM	Avg	ILM-RNFL	RNFL-IPL	IPL-INL	INL-OPL	OPL-ELM	ELM-PR2	PR2-BM
2-Tap	0.9083	0.9152	0.9265	0.8821	0.8643	0.9303	0.9152	0.9247	0.9080	0.9146	0.9257	0.8818	0.8654	0.9305	0.9156	0.9224
4-Tap	0.9087	0.9146	0.9259	0.8833	0.8665	0.9309	0.9155	0.9238	0.9089	0.9155	0.9260	0.8823	0.8655	0.9309	0.9168	0.9255
6-Tap	0.9085	0.9146	0.9258	0.8835	0.8654	0.9308	0.9153	0.9242	0.9079	0.9137	0.9254	0.8821	0.8659	0.9305	0.9147	0.9232
8-Tap	0.9077	0.9134	0.9237	0.8815	0.8655	0.9308	0.9145	0.9246	0.9076	0.9138	0.9238	0.8809	0.8647	0.9303	0.9154	0.9242
LS-BiorthUwU	Avg		ILM-RNFL		RNFL-IPL		IPL-INL		INL-OPL		OPL-ELM		ELM-PR2		PR2-BM	
1 Step	0.9086		0.9149		0.9264		0.8833		0.8652		0.9314		0.9156		0.9233	
2 Step	0.9079		0.9136		0.9250		0.8819		0.8643		0.9313		0.9164		0.9229	
3 Step	0.9083		0.9143		0.9255		0.8829		0.8657		0.9310		0.9162		0.9223	
4 Step	0.9083		0.9150		0.9261		0.8825		0.8647		0.9310		0.9165		0.9226	
5 Step	0.9085		0.9141		0.9247		0.8822		0.8656		0.9314		0.9168		0.9244	
6 Step	0.9046		0.9084		0.9235		0.8748		0.8605		0.9279		0.9156		0.9214	
7 Step	0.9082		0.9149		0.9255		0.8819		0.8646		0.9309		0.9160		0.9235	
8 Step	0.9087		0.9138		0.9250		0.8827		0.8661		0.9310		0.9168		0.9254	

PPS (OPL and ELM)

Clinical condition: Pentosan polysulfate maculopathy, associated with reduced visual acuity and nyctalopia

Dataset size: 31 OCT volumes

Training set: 23 volumes, including normal and PPS maculopathy cases

Test set: 8 volumes from PPS maculopathy cases

Annotations: Two retinal layer boundaries—outer plexiform layer (OPL) and external limiting membrane (ELM)

Annotation process: All layer boundaries were manually corrected

PPS	Dice OPL-ELM
MGUNet	0.9144
OrthLattUwU-AttentionHead-MGUNet	0.9196
BiorthLattUwU-AttentionHead-MGUNet	0.9172
LiftingScheme-BiorthUwU-LS5-AttentionHead-MGUNet	0.9234

Conclusion

- **First study** to evaluate tunable wavelet-based pooling for 3D retinal OCT segmentation
- Replaced conventional pooling with **OrthLatt-UwU**, **BiorthLatt-UwU**, and **LS-Biorth-UwU** modules
- Learnable wavelet filters improved preservation of **anatomical details** and **volumetric spatial coherence**
- Provides a principled framework for integrating wavelet theory into high-precision 3D medical image segmentation

Thank you

Reference

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