Wavelet-Based Filter for Noise and Background Removal in Extended Depth of Field Microscopy

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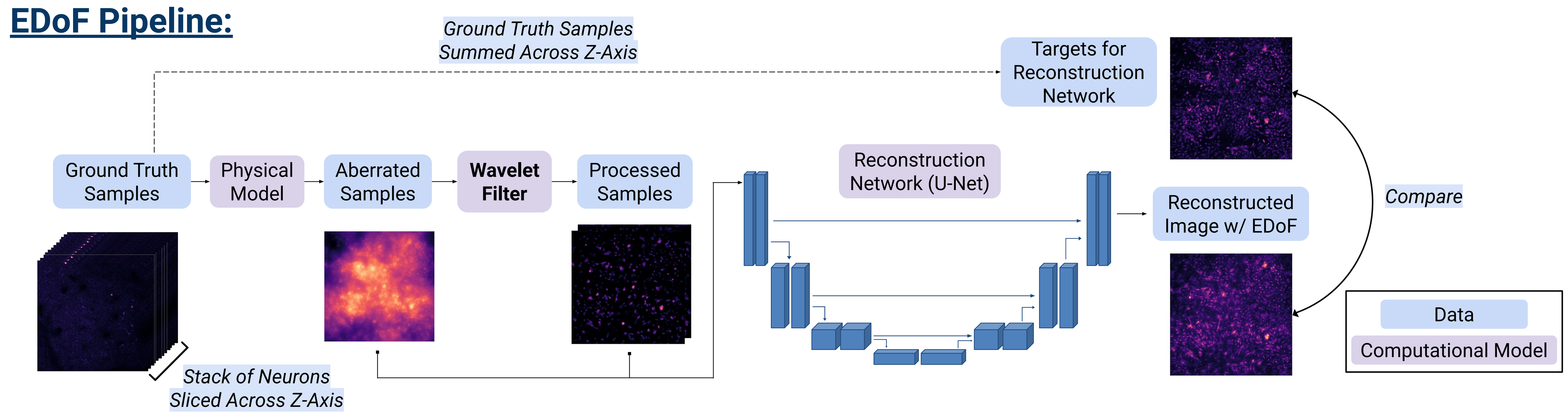
INTRODUCTION

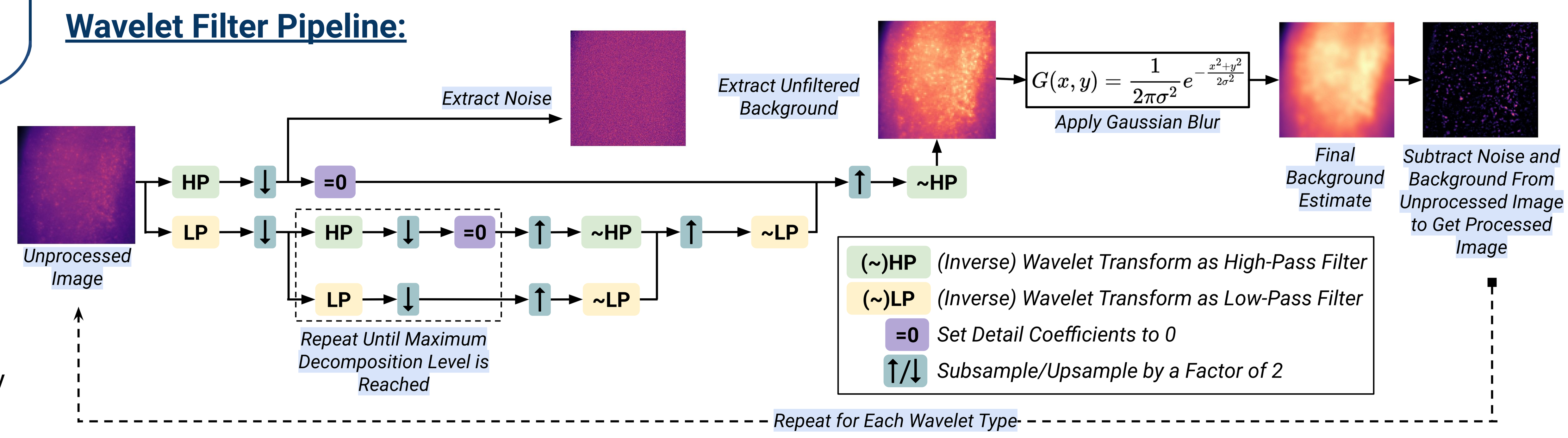
- Miniaturized microscopes (**miniscopes**) have a **limited depth of field** → the Tian Lab is developing an **extended depth-of-field (EDoF)** miniscope using deep learning and optics to view deeper into the brain[1]
- **Issue:** Images taken with miniscopes contain slow-varying background, due to fluorescence from out-of-focus planes and scattered light. High frequency noise is also introduced by the detection system.
- **Wavelet Filter:** Applies wavelets (small wave-like oscillations localized in time) as a high- and low-pass filters to **separate and extract the low-frequency and high-frequency components** of an image[2]
- **Objective:** Implement a wavelet filter in our end-to-end EDoF pipeline's preprocessing steps to remove out-of-focus noise and background from our data

METHODOLOGY

EDoF Pipeline:



Wavelet Filter Pipeline:



- **Physical model's weights were frozen** → pre-trained weights were imported and **model trained on weights in the reconstruction network**
- Trained for 60,000 epochs and utilized three loss metrics:
  1) 1) **Mean-squared error (MSE)**: ensure similarity between target and output
  2) **Gradient-based loss (GradLoss)**: ensure similar edges to retain neuron shapes
  3) **Fourier mean average error (fMAE)**: ensure similarity between Fourier domain of target and output

RESULTS

Model Metrics

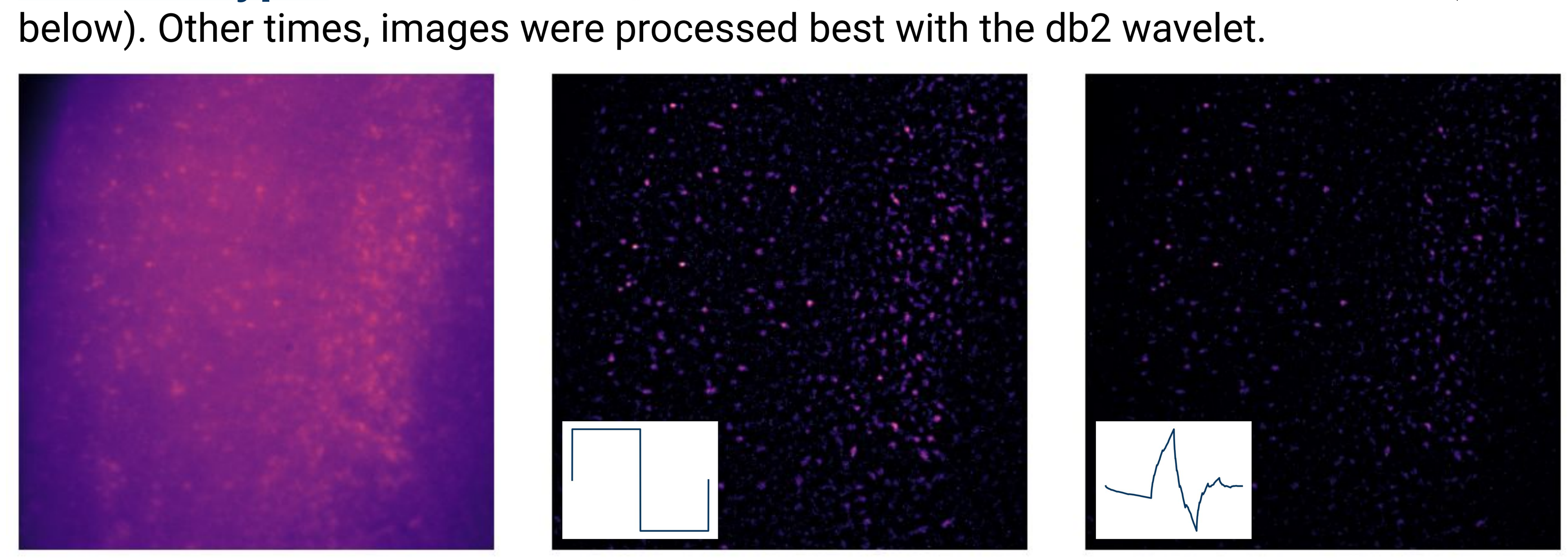
- **Code Environment**: Visual Studio Code
- **Implementation**: Python – Pytorch – Pytorch-Wavelets[3]
- **GPU**: NVIDIA A100/A4/L40S (depending on run)
- **Loss**: MSE + GradLoss + fMAE
- **Wavelet Basis**: db1 and db2
- **Full-Width of Half-Maximum (FWHM) of PSF**: 8.0
- **Noise Level**: 2.0

- **Runtime With No Preprocessing Layer**: 5hr 40min
- **Runtime With Wavelet Filter***: 5hr 52min

*Calculated by averaging 6 runs with different hyperparameters (learning rate, scheduler, wavelet type, etc.)

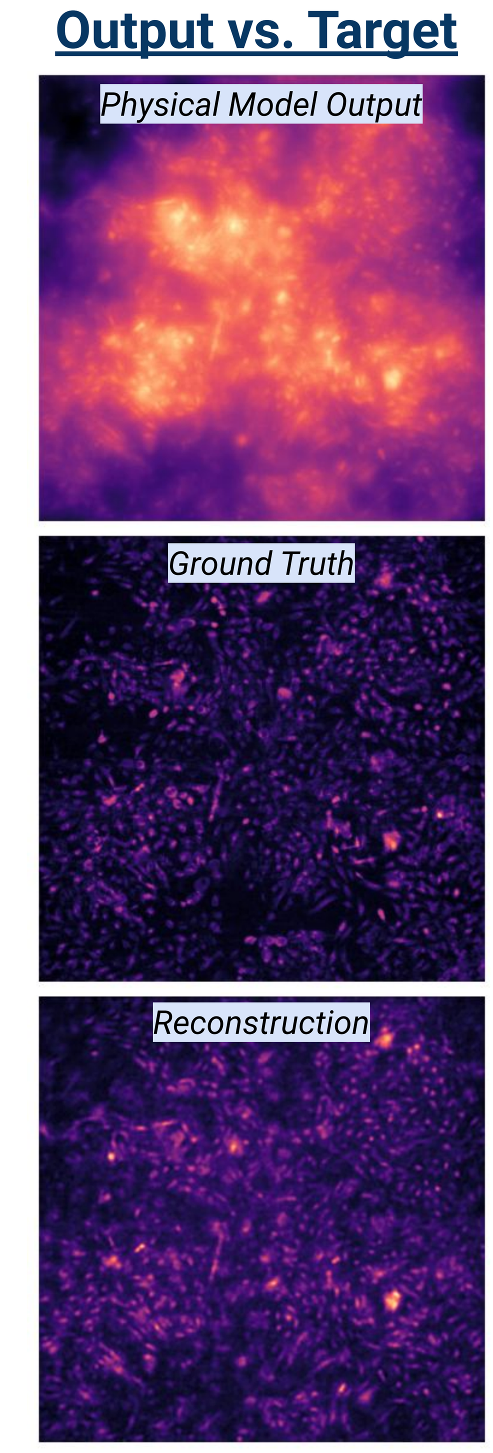
Wavelet Type:

Sometimes, images were processed best with the db1 wavelet (shown below). Other times, images were processed best with the db2 wavelet.



Unprocessed — *Processed w/ db1 (Wavelet Shown in Corner)* — *Processed w/ db2 (Wavelet Shown in Corner)*

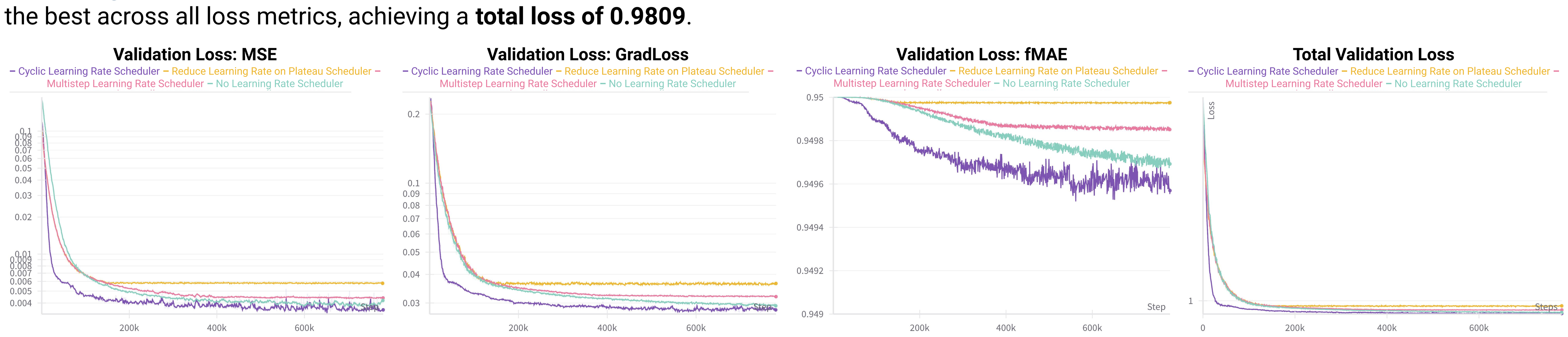
Output vs. Target



PSNR: 20.96
SSIM: 74.15
MSE: 0.080

Learning Rate Scheduler:

The Cyclic Learning Rate Scheduler (causing the learning rate to cycle between 5e-9 and 5e-7 every 2000 epochs) performed the best across all loss metrics, achieving a **total loss of 0.9809**.



Losses:

Cyclic Learning Rate: 0.9809

Reduce Learning Rate on Plateau: 0.9916

Multistep Learning Rate: 0.9861

No Scheduler: 0.9827

CONCLUSIONS

- Hyperparameter tuning shows that **setting the FWHM of the PSF and the noise level as fixed values based on the optical system** yields best results following the preprocessing layer
- The wavelet filter ensured that the model could **converge fast and accurately** by getting rid of the out-of-focus fluorescence background and noise, thereby encouraging it to focus training on the most important parts of the data with **little significant increase in computational time**
- Model performed best when wavelet filter outputted a stack of the **unprocessed image**, the image processed with the **db1** wavelet, and the image processed with the **db2** wavelet
- **Future Directions:**
  - Test Wavelet Filter with **different combinations of wavelets** to find the most optimal one: run more tests with the Symlet family because of its small support and use in denoising images
  - Improve loss metrics: focus on **decreasing loss within the Fourier domain**

REFERENCES

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(2) Hüpfel, M.; Yu. Kobitski, A.; Zhang, W.; Nienhaus, G. U. Wavelet-Based Background and Noise Subtraction for Fluorescence Microscopy Images. *Biomed Opt Express* **2021**, *12* (2), 969–980. https://doi.org/10.1364/BOE.41318.

(3) Moritz, W.; Blanke, F.; Garcke, J.; Tapley Hoyt, C. Ptwt - The PyTorch Wavelet Toolbox. *Journal of Machine Learning Research* **2024**, *25* (80), 1–7.

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