

---

# COSE474-2024F: Final Project Proposal

## ”Modifying UNIFMIR for domain-general isotropic reconstruction of fluorescence microscopy”

---

Jungwoo Park

### 1. Introduction

Fluorescence microscopy faces challenges with anisotropic 3D resolution, but deep learning methods outperform traditional ones by learning complex patterns. Techniques include regression-based reconstruction, adversarial learning, and diffusion models. However, frequent retraining is often required, highlighting the need for foundational models that can generalize across tasks.

### 2. Problem definition & challenges

#### 1) Problem Definition

This project focuses on using the pre-trained, non-generative UNIFMIR model for isotropic reconstruction in fluorescence microscopy, addressing challenges like z-axis continuity and high-frequency detail recovery, while minimizing retraining or fine-tuning.

#### 2) Step-by-step Goals

- (i) Use the pre-trained UNIFMIR for more challenging isotropic reconstruction, focusing on z-axis continuity and generalization beyond pre-training.
- (ii) If fine-tuning isn't enough, modify the model for few-shot inference to adapt with minimal data.
- (iii) Preserve high-frequency details and avoid artifacts, ensuring high-quality reconstruction in demanding isotropic tasks.

#### 3) Problems

- (i) UNIFMIR wasn't trained for z-axis continuity, causing potential 3D reconstruction issues, and requires a new objective function for complex correlations.
- (ii) Few-shot inference is challenging for non-generative models like UNIFMIR, as it focuses on data restoration, not generation, requiring architectural changes.
- (iii) Its non-generative nature limits flexibility, needing more retraining or fine-tuning for new tasks.
- (iv) Fine-tuning without degrading image quality, especially for high-frequency details and z-axis continuity, is difficult in complex tasks.

### 3. Related Works

**Weigert et al.** (2017) tried to solve the reconstruction problem with CNN, using paired setting. **IsoVEM** (2023), based on a video transformer model, improves axial resolution and achieves isotropic reconstruction in volume electron microscopy, enhancing the study of large-scale biological architectures. **Lee et al.** (2024) employs INR with 2D diffusion prior to facilitate 3D volumetric reconstruction, ensuring axial continuity.

**Lumentut et al.** (2021) introduced meta learning based generalizable universal framework for joint image reconstruction, based on meta learning. **Korkmaz et al.** (2021) suggests zero-shot based self-supervised transformer model for MRI reconstruction.

### 4. Datasets

CREMI, FIB, Mouse neuron confocal microscopy image are used for checking generalizing performance. Simulated 3D volume with various tubular object is used for checking if the reconstruction is continuous.

### 5. State-of-the-art methods and baselines

Result from Lee et al.'s work will be set as SOTA. Result from Weigert et al.'s, result from Non-modified UNIFMIR, simply interpolated images will be set as Baseline. Evaluation is done in a quantitative manner with PSNR, SSIM, LPIPS.

### 6. Schedule & Roles

- (i) Week 1,2 : running UNIFMIR baseline for dataset, searching for adaptation method
- (ii) Week 3,4 : implementation, experiment & evaluation
- (iii) week 5,6 : report

### References

He, J. and et al. IsoVem: Isotropic reconstruction for volume electron microscopy based on trans-

former. <https://www.biorxiv.org/content/10.1101/2023.11.22.567807v3>, 2023. bioRxiv Preprint.

Korkmaz, Y., Dar, S., Yurt, M., Özbey, M., and Çukur, T. Unsupervised mri reconstruction via zero-shot learned adversarial transformers. *IEEE Transactions on Medical Imaging*, 41:1747–1763, 2021. doi: 10.1109/TMI.2022.3147426.

Lee, K. and Jeong, W. K. Reference-free Axial Super-resolution of 3D Microscopy Images using Implicit Neural Representation with a 2D Diffusion Prior . In *proceedings of Medical Image Computing and Computer Assisted Intervention – MICCAI 2024*, volume LNCS 15007. Springer Nature Switzerland, October 2024.

Lumentut, J. S., Marchellus, M., Santoso, J., Kim, T. H., Chang, J. Y., and Park, I. K. Universal framework for joint image restoration and 3d body reconstruction. *IEEE Access*, 9:162543–162552, 2021. doi: 10.1109/ACCESS.2021.3132148.

Ma, C., Tan, W., He, R., and Yan, B. Pretraining a foundation model for generalizable fluorescence microscopy-based image restoration. *Nature Methods*, 21:1558–1567, 2024. doi: 10.1038/s41592-024-02244-3.

Weigert, M., Schmidt, U., Boothe, T., Müller, A., Dibrov, A., Jain, A., Wilhelm, B., Schmidt, D., Broaddus, C., Culley, S., Rocha-Martins, M., Segovia-Miranda, F., Norden, C., Henriques, R., Zerial, M., Solimena, M., Rink, J., Tomancak, P., Royer, L., Jug, F., and Myers, E. W. Content-aware image restoration: pushing the limits of fluorescence microscopy. *Nat methods*, 15:1090–1097, 2018.