

Sim2Real OCT Style Transfer

General Info

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Project Title: Sim2Real OCT Style Transfer

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1. Project Abstract

This project deals with deep learning approaches to facilitate the style transfer between simulated and real OCT images. An existing simulation pipeline provides synthetic OCT images that contain anatomical structures and image intensity values, however, only approximate the appearance of real OCT images and lack characteristics such as speckle noise patterns and scattering behavior. To increase the realism of the synthetic data, a model should be developed to convert the initially simulated image into a realistic looking OCT image in real-time.

2. Background and Motivation

Recent developments in high-speed swept-source Optical Coherence Tomography (OCT) integrated into surgical microscopes have enabled live imaging of complex surgical ophthalmic interventions. Together with these developments, robotic platforms are also integrated into the operating rooms. These developments pave the way for new simulation and training setups in virtual environments for applications such as surgical education, robotic training, and robotic reinforcement learning. One of the challenges in this field is to generate realistic simulation data in real-time, which models the physical behavior of available imaging systems, such as OCT.

3. Technical Prerequisites

- Good background in deep learning
- Good skills in Python
- Familiar with deep learning frameworks, preferably PyTorch
- Familiar with inference acceleration techniques, e.g. TensorRT

4. Benefits:

- Work with a large and pre-annotated OCT dataset
- Learn about the SOTA of OCT imaging
- High chance of writing a scientific paper

5. Students' Tasks Description

Students' tasks would be the following:

- **WP1:** Getting familiar with OCT domain, physics, and image properties
- **WP2:** Literature review on denoising methods, specifically on OCT domain
- **WP3:** Create a paired dataset between real OCT and synthetic OCT images using existing label maps and an existing simulation pipeline
- **WP4:** Implement a method to transfer real OCT images to synthetic OCT images (denoising)
- **WP5:** Learn the inverse function, with intensity of noise as a prior
- **WP6:** Discuss the limitation of methods and prepare final report
- **WP7:** Prepare final presentation

6. Work-packages and Time-plan:

	Description	#Students	Workload
WP1	Getting familiar with OCT domain, physics, and image properties	2	2
WP2	Literature review on denoising methods, specifically on OCT domain.	2	2
WP3	Create a paired dataset between real OCT and synthetic OCT images using existing label maps and an existing simulation pipeline.	2	2
WP4	Implement a method to transfer real OCT images to synthetic OCT images (denoising).	2	3
M1	Intermediate Presentation II	2	
WP5	Learn the inverse function, with intensity of noise as a prior	2	4
WP6	Discuss the limitation of methods and prepare final report	2	1
WP7	Prepare final presentation	2	1
M2	Final Presentation	2	

7. Reference

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