Dissertation Proposal

Improving Generalisability of Transformer-Based Inverse Models for Diffuse Optical Tomography

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1. Motivation

Diffuse Optical Tomography (DOT) is a non-invasive imaging technique that recovers internal tissue properties such as absorption and scattering by using light measurements captured at the boundary of the tissue. Deep learning models, especially those using transformers, have recently shown promise in learning inverse mappings for DOT reconstruction, producing real-time, high-resolution results from frequency-domain measurements.

However, many current approaches are limited in generalisability. In particular, one recent transformer-based method used fixed probe geometries and did not incorporate any direct information about the tissue lying between the source and detector positions. This setup, while effective in a controlled simulation environment, may not generalise well to varied clinical scenarios where probe positioning and underlying anatomy can differ significantly.

This project proposes to address this limitation by augmenting the model's input with spatial context — i.e., the structure of the tissue around each measurement — and by training on randomised probe layouts. The hypothesis is that by giving the network more physically meaningful priors and by exposing it to greater variation during training, we can improve robustness to domain shift and out-of-distribution performance.

2. Objectives

The primary aim of this project is to explore and evaluate strategies to improve the generalisability of deep learning-based inverse models for DOT. The project is structured around the following core objectives:

- **O1.** Build a transformer-based inverse model that includes not just boundary measurements and probe positions, but also spatial context about the tissue between each source–detector pair.
- **O2.** Train this model on 2D synthetic datasets with randomised probe geometries and varied tissue structures to encourage learning of general physical relationships.
- **O3.** If time permits, extend the model to handle full 3D volumes, moving from simulated 2D slices to volumetric DOT reconstructions.

O4. Investigate transfer learning by adapting the trained "foundation" inverse model to specific imaging domains (e.g., breast or brain DOT) using small amounts of domain-specific data.

These stages are designed to be incremental. The first objective represents the main novel contribution, while the later objectives build upon it if the earlier stages are successful and time allows.

3. High-Level Methodology

This project will begin by reproducing or adapting an existing transformer-based DOT model that accepts source–detector measurements and positions as inputs. The new component introduced in this project is a spatial context encoder that extracts local information from the tissue region between each source and detector. In simulation, this tissue map will be available, allowing us to crop and feed small 2D image patches or 3D blocks into the model alongside the usual measurements.

The key idea is that each input token to the transformer will represent a measurement, its associated geometry, and a patch of the tissue structure it passes through. This additional context will give the network better prior information about how the tissue is affecting the signal.

Synthetic datasets will be generated using simulation tools such as NIRFAST, where tissue properties and probe geometries can be randomly varied. The transformer encoder will process sequences of such enriched tokens, and a CNN-based decoder will reconstruct the corresponding tissue property maps.

Once the 2D setup is working, the model can be extended to operate on 3D volumes by replacing 2D patches with 3D blocks. Transfer learning experiments will then be conducted by fine-tuning the trained inverse model on small datasets from specific anatomical regions, measuring how well it adapts.

This work sits at the intersection of computer vision, inverse problems, and spatial reasoning in machine learning. It aims to contribute a more general, robust neural inverse model for DOT and to explore whether combining spatial context with geometric variation can improve learning and reliability in medical image reconstruction tasks.