Physics-Informed Neural Networks for Photoelectric-Compton Decomposition in Duel-Energy CT Tissue Classification

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ABSTRACT

This project is for CT scanning.

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1 INTRODUCTION

Spectral Computed Tomography (CT) extends traditional CT by making use of the energy-dependence of X-ray attenuation. The conventional CT process produces a single "grayscale" attenuation map which can result in indistinguishable results when comparing similar bulk density materials. Spectral CT records two separate x-ray photon energy spectra which allows for recording different attenuation properties at different energies. Typically x-ray photons interact with materials through the photoelectric effect, which typically occur at low photon energies, and Compton scattering, which typically occur at higher photon energies. The dataset provided by the American Association of Physicists in Medicine (AAPM) contains the "low-kVp" and "high-kVP" dual energy CT measurements collected at two different tube voltages. The low-kVp transmission with the x-ray tube operating at 50 kVp and the high-kVp transmission operating at 80 kVp.

Extracting reliable photoelectric and Compton maps from noisy or limited-view data is challenging. Classic algebraic or statistical decomposition methods require careful regularization and often struggle with low photon counts or beam-hardening artifacts. Deep learning approaches, by contrast, can learn complex nonlinear mappings but may overfit to the training distribution and produce physically inconsistent outputs (e.g., negative attenuation, or tissue maps that fail to reproduce the measured projection data).

This work proposes a physics-informed neural network (PINN) framework for multi-energy CT tissue classification by first converting paired low- and high-kVp sinograms into per-pixel attenuation coefficients via the Beer–Lambert law, then applying a closed-form basis decomposition to recover photoelectric and Compton component images. The core model is a lightweight multilayer perceptron that directly classifies each pixel into adipose, fibroglandular, or calcification classes. The training loss is augmented with the standard cross-entropy loss with a physics consistency term that enforces agreement between the network's class-probability–weighted reconstruction and the measured attenuation data. This hybrid loss encourages the network to respect fundamental attenuation physics while retaining the flexibility of data-driven learning.

This approach is applied on the publicly available AAPM DL-Spectral CT Challenge dataset, performing comprehensive EDA, sinogram-domain preprocessing, and network training entirely in PyTorch, with future future work that could integrate ASTRA-based differentiable forward projections. Results show improved material separation and robustness compared to purely data-driven classifiers, highlighting the potential of PINNs for reliable, quantitative spectral CT tissue mapping.

2 RELATED WORK

3 PROPOSED WORK

3.1 Problem Statement

Accurate discrimination of soft-tissue types in X-ray computed tomography (CT) remains a fundamental challenge in medical imaging. Conventional single-energy CT produces grayscale images in which different materials with similar attenuation coefficients (e.g. muscle vs. iodine-enhanced blood or bone) can appear indistinguishable, leading to diagnostic ambiguity. Dual-energy and photon-counting CT systems acquire multiple energy-resolved measurements, but extracting robust tissue-specific maps from these spectral data is nontrivial: standard material-decomposition methods are sensitive to noise, beam-hardening, and detector imperfections, and purely data-driven deep-learning approaches often fail to generalize beyond their training domain.

This project proposes to address these limitations by developing a *physics-informed neural network* (PINN) that directly incorporates the known Beer–Lambert attenuation law and the two dominant interaction mechanisms—photoelectric absorption and Compton scattering—into its architecture and training loss. By decomposing each pixel's dual-energy attenuation pair $[\mu_{\text{low}}, \mu_{\text{high}}]$ into physically meaningful photoelectric and Compton components and enforcing consistency with both the measured attenuation maps and sinogram data, our approach aims to (1) improve classification accuracy of key tissue types (adipose, fibroglandular, bone) and (2) enhance robustness to noise and out-of-distribution scenarios. This integration of first-principles physics with modern deep learning promises more reliable, interpretable, and generalizable spectral CT tissue characterization.

3.2 Data Preparation

3.3 Methodology

4 EVALUATION

5 DISCUSSION

6 CONCLUSION