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

Karl Schmidt
karl.schmidt@colorado.edu
University of Colorado Boulder
Boulder, CO, USA

ABSTRACT

This project is for CT scanning.

Keywords: Physics-Informed, Duel-Energy CT, Clasification, Machine Learning

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 basic Convolutional Neural Network (CNN) framework for multi-energy CT tissue classification where the output of the CNN will contain percentages of each tissue type - adipose, fibroglandular, and calcification. By using the Beer-Lambert law, low- and high-kVp transmission data are converted into per-pixel attenuation coefficients before applying a closed-form basis decomposition to recover photoelectric and Compton component images. Effectively, the low-energy region, 50 kVp, are considered the photoelectric effect interactions while the high-energy region, 80 kVp, are considered Compton scattering.

These images are stacked and used with two core models with specific hyperparameter tuning to determine the model and parameters which demonstrate the lowest Binary Cross Entropy (BCE) loss. The first model contains 11 convolutional layers structured in an encoder-decoder architecture. It downsamples the input images from 512×512 to a bottleneck of 128×128 pixels, capturing mid-level semantic features before reconstructing the output at the original resolution. It's designed for moderately complex tasks with a balance between model depth and computational cost. The second model includes 15 convolutional layers, adding an extra downsampling stage that allows the network to capture more abstract and global features. It also downsamples to a 128×128 latent space, despite having more layers, making it suitable for learning finer distinctions in more complex images or tasks.

The model is trained using the binary cross-entropy loss between the predicted tissue probability maps and the ground-truth i phantom tissue labels. This loss directly penalizes voxel-wise deviations from the true tissue distribution.

During evaluation, the model's output is also used to compute the mean tissue composition percentages across the image volume. These predicted percentages are compared to the true phantom percentages using an average absolute error metric, which provides an interpretable assessment of how well the model recovers the tissue mix — but this is not used for training.

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 an explaination of future work that could integrate ASTRA-based differentiable forward projections.

2 METHODOLOGY

2.1 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, $I = I_0 e^{-\mu x}$, 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, this approach aims to (1)

improve classification accuracy of key tissue types (adipose, fibroglandular, calcification) and (2) enhance robustness to noise and out-of-distribution scenarios. This integration of first-principles physics with modern deep learning may achieve more reliable, interpretable, and generalizable spectral CT tissue characterization.

2.2 Exploratory Data Analysis

Show data stuff here...

2.3 Data Preparation

The dataset from AAPM [1] contains data in compressed numpy array format. Both 'lowkVpTransmission' and 'highkVpTransmission' datasets contain the two energy beams, 50 kVp and 80 kVp, respectively. The transmission data contains the normalized spectrum of the number of photons detected after passing through tissue. Ground trut tissue maps are also provided for the simulated Adipose, Fibrogandular, and Calcification tissues.

To prepare the dataset, an *MLPTestTraindataset* class is used to:

- load the raw data,
- compute the attenuation coefficients,
- vectorize the attenuation coefficients,
- create labels from adipose, fibroglandular, and calcification ground truth data,
- flatten to (num_pixels,)
- apply scaling to the attenuation coefficients
- compute the prototypes
- split the data into train (80%) and test (80%) sets.

The intent of this project is to calculate the attenuation using the from the transmission data and stack the results into 2-component feature vectors $[\mu_{\text{low}}, \mu_{\text{high}}]$. translate the data into a vectorized low and high energy spectrum sets

3 EVALUATION & ANALYSIS

4 DISCUSSION

5 CONCLUSION

REFERENCES

[1] Emil Y. Sidky, Xiaochuan Pan, and Working Group on Grand Challenges. 2024. Data repository for the 2022 AAPM Deep-Learning Spectral CT Grand Challenge. https://github.com/aapm/spectral-ct-challenge. Hosted by the AAPM HQ Community Collection.