EE367 Project Proposal: Synthesis of Spectral CT Tissue Maps from Single-Energy CT Using Conditional Diffusion Models

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Winter 2025

1 Motivation

Spectral CT, including forms like Dual-energy CT (DECT), enables material decomposition by capturing transmission data across two distinct X-ray spectra. This enables clinicians to isolate specific tissue types that would otherwise overlap, allowing for clearer distinction of tissue boundaries - especially for tissues that share similar X-ray attenuation profiles at a given energy level that cannot be determined from a conventional single-energy CT (SECT) scan.

Major barriers to broad clinical adoption of spectral CT is hardware availability, workflow complexity, and especially costs. This makes a learning based approach attractive because it can ideally approximate some spectral benefits from standard single-energy acquisitions and preserve the existing scanning workflows.

This project aims to develop a conditional DDPM to generate material decomposition tissue maps (adipose, fibroglandular, calcification) directly from single-energy CT, using the AAPM DL-Spectral CT Grand Challenge dataset, which contains ground truth tissue maps and high/low kVp CT images of breast tissue phantoms (1).

2 Related Work

Generation of High Energy CT image: Lyu et al. (2) proposed a material decomposition CNN that estimates high-energy CT images from corresponding low-energy CT input images and a single high-energy image, demonstrating that learned mappings can be derived from standard CT acquisitions.

Conditional DDPMs for CT synthesis: Gao et al. (3) proposed a C-DDPM for generating contrast-enhanced DECT from non-contrast SECT by concatenating the conditioning image channel-wise with the noisy target at each reverse step. Their approach, which focused on head and neck data, outperformed Pix2PixGAN and CNN baselines. A prior paper from the same group demonstrated that the same framework can be utilized for iodine map synthesis (4).

Diffusion Posterior Sampling (DPS): Jiang et al. (5) introduced using DPS as a framework for solving material decomposition. This approach performed on par with, if not better than, conditional DDPMs, had faster compute times, and as the authors noted, does not need to be retrained like DDPM approaches, which are much more narrow in training vs application. Depending on timing this implementation could potentially serve as a stretch goal.

3 Approach

A conditional DDPM taking the 50 kVp FBP image $y \in \mathbb{R}^{1\times512\times512}$ as input and generating three tissue maps $x_0 \in \mathbb{R}^{3\times512\times512}$ will be trained. The SECT image y is concatenated with the noisy sample x_t along the channel dimension at each denoising step. A U-Net predicts the added noise and is trained using the following objective:

$$\mathcal{L} = \mathbb{E}_{x_0,y,t,\epsilon}\left[\|\epsilon - \epsilon_\theta(x_t,t,y)\|_2^2\right]$$
$$\text{where } x_t = \sqrt{\bar{\alpha}_t}\, x_0 + \sqrt{1-\bar{\alpha}_t}\, \epsilon$$

A U-Net trained with MSE loss on the same pairs will serve as a baseline comparison.

4 Evaluation

The AAPM DL-spectral-CT training cases will be used to create a local train/validation/test split. The dataset provides paired FBP images and ground-truth tissue maps. The primary evaluation metric that will be used is average RMSE across the three tissue maps and will additionally report per-tissue SSIM and PSNR. The performance of the conditional DDPM will be compared against a U-Net baseline.

5 Timeline

- **Week 1:** Download and preprocess the AAPM dataset, train U-Net baseline, and begin C-DDPM implementation
- **Week 2:** Troubleshoot any issues, complete C-DDPM training, and run inference on the test set
- **Week 3:** Summarize results, finalize the report and poster

References

[1] E. Y. Sidky, D. P. Clark, Y. Guo, C. T. Badea, and X. Pan, "Report on the aapm deep-learning spectral ct grand challenge," *Medical Physics*, vol. 51, no. 2, pp. 772–785, 2024.

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[3] Y. Gao, R. L. J. Qiu, H. Xie, C.-W. Chang, T. Wang, B. Ghavidel, J. Roper, J. Zhou, and X. Yang, "Ct-based synthetic contrast-enhanced dual-energy ct generation using conditional denoising diffusion probabilistic model," *Physics in Medicine & Biology*, vol. 69, no. 16, p. 165015, 2024.

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[5] X. Jiang, G. J. Gang, and J. W. Stayman, "Multi-material decomposition using spectral diffusion posterior sampling," *IEEE Transactions on Biomedical Engineering*, 2025.