Hyperspectral CT Reconstruction

1. General Info

Project Title: Hyperspectral CT Reconstruction

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2. Project Abstract

Novel Computed Tomography Devices allows the user to choose a range of energy levels for imaging enabling the acquisition of hyperspectral measurements that can improve reconstruction quality and allow for the identification of different materials leveraging their photon-matter interaction characteristics. The goal of this project is to build a prototyping pipeline for testing different hyperspectral reconstruction approaches leveraging public data and/or simulated data. The overall research goal is to identify a minimal configuration of views and wavelengths for the reconstruction of an object consisting of known materials.

3. Background and Motivation

The reconstruction of objects made up of complex shapes and different materials is challenging as the different materials have varying absorption and transmission properties. Leveraging multiple measurements of different wavelengths can provide additional information about the material parameters and therefore help the reconstruction and identification of materials within an object. Hyperspectral measurements contain a large number of measurements over a wide band of energies. In this project we want to evaluate state-of-the-art methods based on their reconstruction performance under different numbers of views and combinations of energy levels.

4. Technical Prerequisites

- Experience in 3D Computer Vision
- Experience in Machine Learning
- Python/C++/CUDA Programming

5. Benefits:

- Learn about physical material properties and CT simulation
- Learn about traditional CT reconstruction methods
- Learn about ML-based CT reconstruction methods

6. Students' Tasks Description

Students' tasks would be the following:

- Design a prototyping framework for hyperspectral CT reconstruction
- Generate synthetic hyperspectral CT dataset
  - Generate virtual phantoms with different materials
  - Include different sources and levels of noise
  - Simulate full sweep measurements with different energy levels
- Implement at least one traditional baseline method for hyperspectral CT reconstruction
- Implement at least one ML-based method for hyperspectral CT reconstruction

- Evaluate all methods regarding their performance on
  - Different materials
  - Different sources and levels of noise
  - Different views
  - Different energy level combinations

7. Work-packages and Time-plan:

	Description	#Students	From	To
WP1	Literature, code & data review & project planning			
WP2	Create virtual phantoms & generate simulated data			
WP3	Implement traditional CT Reconstruction method(s)			
M1	Intermediate Presentation			
WP4	Implement ML-based CT reconstruction method(s)			
WP5	Compare all methods on selected dataset configurations			
WP6	Evaluation of all methods			
M2	Final Presentation			

References

1. So, A., & Nicolaou, S. (2021). Spectral computed tomography: fundamental principles and recent developments. *Korean Journal of Radiology*, *22*(1), 86.
2. Mory, C., Sixou, B., Si-Mohamed, S., Boussel, L., & Rit, S. (2018). Comparison of five one-step reconstruction algorithms for spectral CT. *Physics in Medicine & Biology*, *63*(23), 235001.
3. Zeegers, M. T., Kadu, A., van Leeuwen, T., & Batenburg, K. J. (2022). ADJUST: a dictionary-based joint reconstruction and unmixing method for spectral tomography. *Inverse problems*, *38*(12), 125002.
4. Shen, L., Pauly, J., & Xing, L. (2022). NeRP: implicit neural representation learning with prior embedding for sparsely sampled image reconstruction. *IEEE Transactions on Neural Networks and Learning Systems*.
5. Rückert, D., Wang, Y., Li, R., Idoughi, R., & Heidrich, W. (2022). Neat: Neural adaptive tomography. *ACM Transactions on Graphics (TOG)*, *41*(4), 1-13.
6. Wu, Q., Feng, R., Wei, H., Yu, J., & Zhang, Y. (2023). Self-supervised coordinate projection network for sparse-view computed tomography. *IEEE Transactions on Computational Imaging*.
7. Saragadam, V., LeJeune, D., Tan, J., Balakrishnan, G., Veeraraghavan, A., & Baraniuk, R. G. (2023). Wire: Wavelet implicit neural representations. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 18507-18516).
8. Liu, J., Anirudh, R., Thiagarajan, J. J., He, S., Mohan, K. A., Kamilov, U. S., & Kim, H. (2023). DOLCE: A model-based probabilistic diffusion framework for limited-angle ct reconstruction. In *Proceedings of the IEEE/CVF International Conference on Computer Vision* (pp. 10498-10508).
9. Wu, Q., Chen, L., Wang, C., Wei, H., Zhou, S. K., Yu, J., & Zhang, Y. (2023). Unsupervised Polychromatic Neural Representation for CT Metal Artifact Reduction. *arXiv preprint arXiv:2306.15203*.

10. Song, B., Shen, L., & Xing, L. (2023). PINER: Prior-informed Implicit Neural Representation Learning for Test-time Adaptation in Sparse-view CT Reconstruction. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision* (pp. 1928-1938).
11. CT simulators
    a. https://github.com/jerichooconnell/fastcat/
    b. https://github.com/xcist
    c. https://github.com/koichi-murakami/g4python
    d. https://github.com/HaarigerHarald/geant4_pybind/
    e. https://github.com/GGEMS/ggems/
12. Loop-X CT Scanner