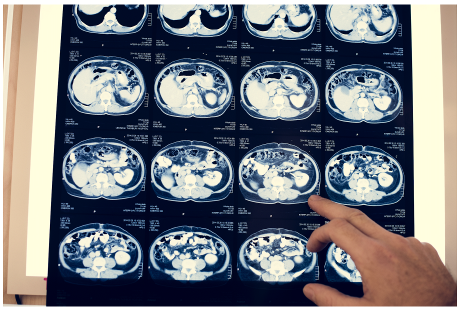
Memory-efficient deep learning algorithms for computed tomography image reconstruction

Unmet Need

Using high resolution images such as computed tomography (CT) has become a popular tool to guide medical interventions from radiotherapy to dental implantation. The market for CT services is expected to grow from $91B in 2017 to $121B in 2024, with an estimated CAGR of 4.6%. However, as imaging technologies improve, the size and complexity of the data collected in scans also grows, making reconstruction of images with software an increasingly computationally intensive task. Theoretically powerful artificial intelligence approaches like deep learning suffer from increased graphics processing memory requirements, slowing their adoption. There is a need for more efficient deep learning systems for reconstructing CT images.

Technology

Duke inventors have developed an efficient deep learning system for reconstructing CT images. To overcome the memory bottleneck of deep learning approaches, the technique greatly reduces the number of parameters necessary in the neural network layers. Specifically, geometrically restricting the reconstructed voxels associated with each pixel on the projection to only those which the original beamlet passed through allows one large fully connected neural net layer to be broken up into smaller fully connected layers. This allows the algorithm to focus on the most relevant connections between projection pixels and reconstruction voxels, greatly reducing the memory requirements. This technique has been validated against state-of-the-art reconstruction algorithms with ground truth cone-beam CT (CBCT) data.



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Meet the Inventors

Yin, Fang-Fang
Lu, Ke
Ren, Lei

Department

Radiation Oncology

Publication(s)

External Link(s)

- Links From the lab of Dr. Fang-Fang Yin, Ph.D.

Advantages

- Estimated 1/1000th the memory requirement as compared to other deep learning CBCT reconstruction approaches
- Works on 2D and 3D CT images
- Reconstruction time, quality, and accuracy comparable to other reconstruction approaches
- System can be trained with a smaller training dataset than other deep learning reconstruction approaches
- System does not need to be retrained for different numbers of projections or initial angles
- Postprocessing component effectively reduces image artifacts due to undersampling