"Deep Learning for sparse-view Filtered Backprojection Imaging"

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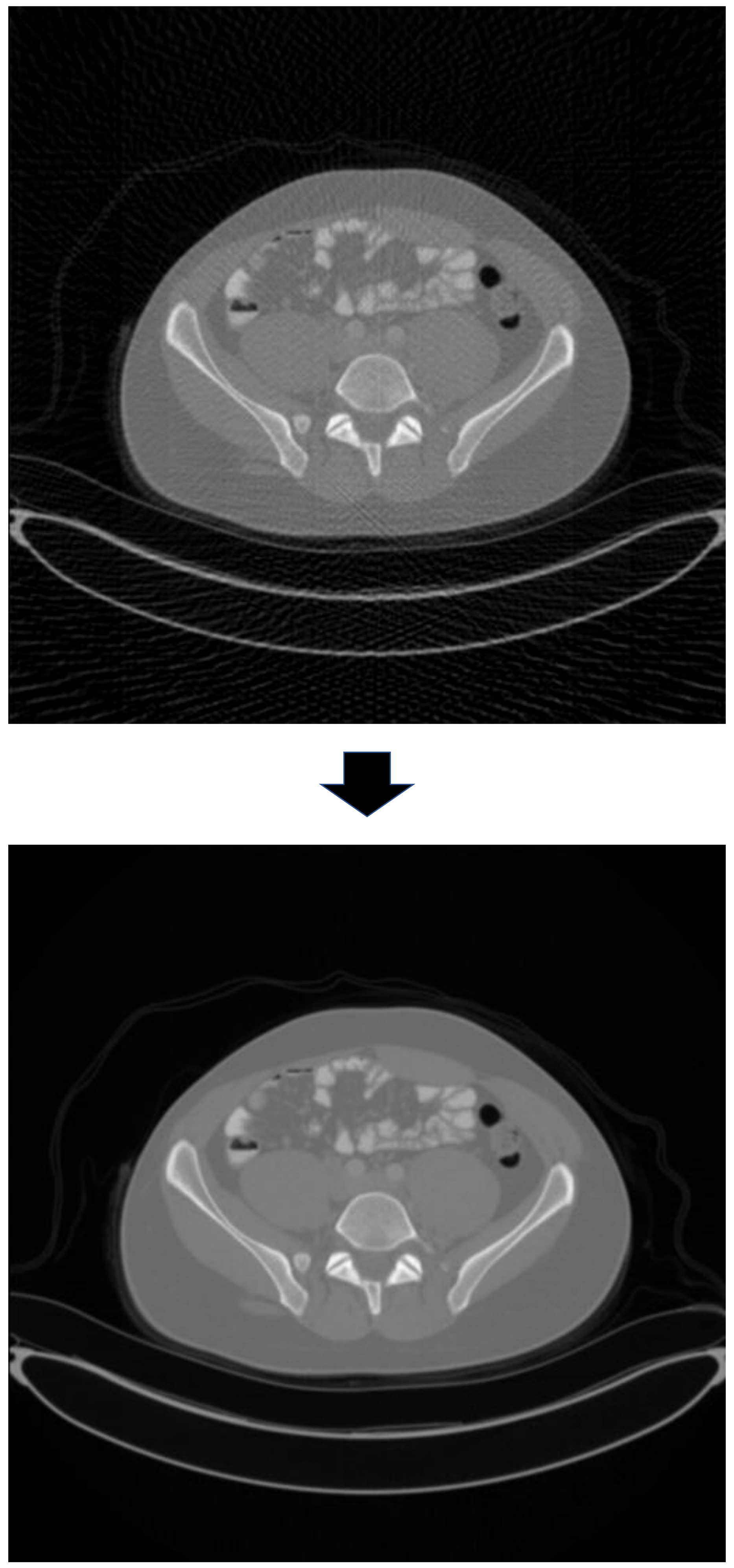
Abstract

Filtered Backprojection (FBP) algorithms are computationally efficient and therefore, widely used. These algorithms however, require a lot of data to correctly compute an image through an inverse function. In the case of Computed Tomography (CT) scans, collecting a lot of data means taking lots of X-ray samples. These X-rays can be both expensive and have health effects on the patient. Sparse-view scans are undersampled, meaning they collect less data. This approach however, has the potential to introduce artifacts into the image. This project focuses on using Deep Learning techniques to remove these artifacts from the sparse-view filtered backprojection CT images.

Artifact Creation

This project focuses on the inverse Radon transform as the FBP algorithm of choice. This algorithm falls short in image reconstruction when the subsampling falls under the Nyquist limit. Under this limit, the reconstruction problem becomes ill-posed due to the artifacts that are introduced. The goal is to use Deep Learning methods to approximate the inverse function to reconstruct the image with artifacts back to the ground truth. The images used are from The Cancer Imaging Archive. The images are 512x512 grayscale images that are converted from a DICOM file format into PNG format. The artifacts were created using Matlab and the image processing toolbox. The pipeline for the functions used to transform the images is shown below:

Mat2gray() -> radon() -> iradon()



Model	MSE	PSNR	SSIM	Epoch
FBPConvNet (CNN)	0.0011	30.03	0.945	10
Pix2pix (GAN)	0.0011	30.12	0.954	60
PAN (GAN)	0.0011	30.15	0.951	280

Deep Learning Methods and Training Configuration

The two Deep Learning approaches used were Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs). All the models were trained on Google Colaboratory. The three architectures used are listed below with their epochs trained for optimal results.

- FBPConvNet (CNN): 10 Epochs
- Pix2pix (GAN): 60 Epochs
- Perceptual Adversarial Network (GAN): 280 Epochs

Future work:

- Tune hyperparameters of the GANs to achieve optimal results.
- Use a smaller learning rate on the PAN network.
- Implement other Deep Learning architectures and compare.
- Apply different loss functions to the networks and compare.

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Results and Conclusion:

Three different quantitative measurements were used: Mean Squared Error (MSE), Peak signal-to-noise ratio (PSNR), and Structure Similarity Index (SSIM). The training epochs that this score was achieved at is also denoted at the right.

The results showed better performance in the SSIM measure for both GAN architectures when compared to the CNN architecture. This is because of the stronger learning GANs can have, utilizing the second network to help the generator learn. Both GANs also have a more complex loss function when compared to the CNN, helping them to learn more features of the input image. Shown below is an example from the best performing network, Pix2pix: