Conditional Generative Adversarial Network Based Metal Artifact Reduction in X-Ray Computed Tomography Images

CS4090 PROJECT

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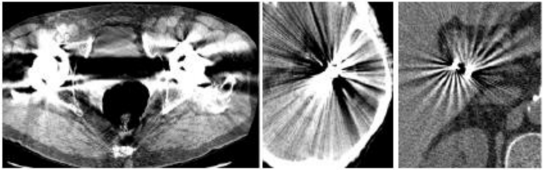
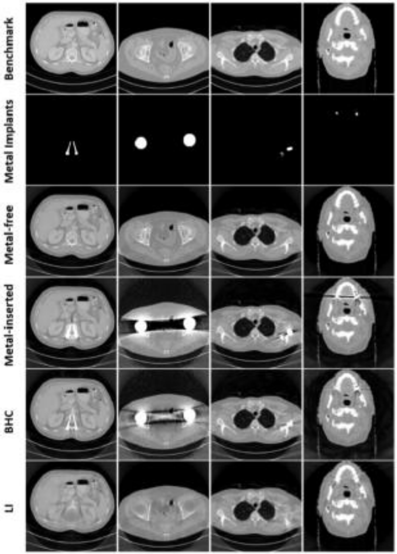
Outline

- CT is a diagnostic imaging test used in neurology and neurosurgery to create detailed images of internal organs, bones, soft tissue and blood vessels.
- Works on the principle wherein X-rays are applied in a circular motion with detectors placed on the other side of the body.
- Body tissue slices are reconstructed and displayed on a gray scale matrix.
- Presence of highly attenuated metal implants in patients like dental fillings, prosthetic hip, etc. cause beam hardening, scatter, photon starvation.
- Leads to strong streak or star-shaped artifacts to the reconstructed CT images.
- Difficulties when planning for treatment due to misinterpretation of data.



- MAR-Process of removing or reducing the size and intensity of the streak effects
- Traditional methods like sinogram in-painting,linear interpolation and beam hardening correction were used as stop-gap measures without satisfactory results
- Since deep learning has attained great success in the field of image processing and pattern recognition, it is used as a method for the reduction of metal artifacts.

Introduction III



Outline

- Metal artifact reduction is carried out generally with the help of three main algorithms which are namely:
  1. Correcting physical effects like beam hardening.
  2. Linear Interpolation in projection domain.
  3. Iterative reconstruction from the unaffected projections.
- A hybrid of techniques is used here. Steps involved include:
  1. metal trace segmentation.
  2. artifact reduction with the LI and BHC.
  3. artifact reduction with the trained CNN. Although the metal artifacts are significantly reduced after the CNN processing, the remaining artifacts are still considerable.
  4. generation of a CNN prior image using tissue processing.
  5. replacement of metal-affected projections with the forward projection of CNN prior, followed by the FBP reconstruction.

Convolutional Neural Network based MAR II

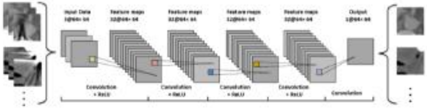


Fig. 3. Architecture of the convolutional neural network for metal artifact reduction.

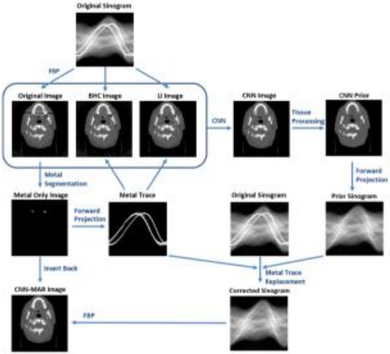


Fig. 4. Flowchart of the proposed CNN-MAR method.

Outline

- In this paper the work is done completely in the sinogram domain and a network is trained over the entire sinogram.
- The steps involved:
  1. Metal segmentation from the FBP reconstructed image.
  2. Then the metal-corrupted sinogram is fed to the trained FCN to obtain the corrected sinogram.
  3. Finally, the FCN corrected sinogram is reconstructed using FBP along with the insertion of the metal image obtained earlier.

Deep Learning based Sinogram Correction for MAR II

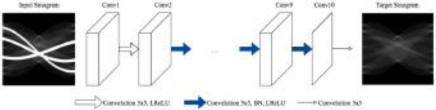
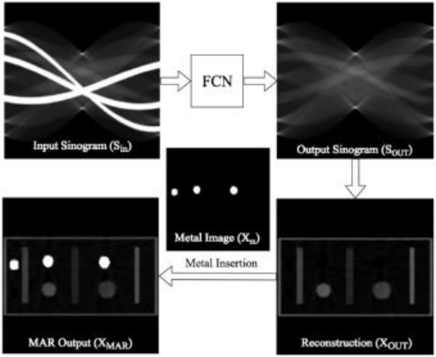


Figure 2. FCN architecture used in this paper to learn sinogram correction.

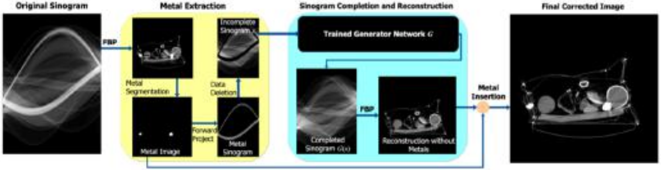


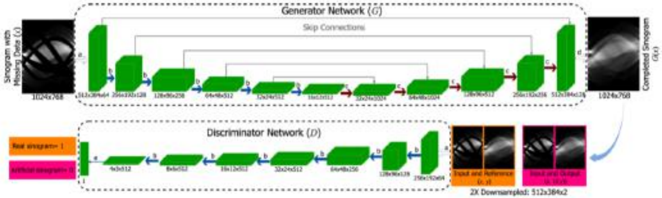
Outline

Fast Enhanced CT MAR using Data Domain Deep Learning I

- The work is done completely in the sinogram domain.
- A conditional generative adversarial network(CGAN) is trained to carry out projection data completion.
- The steps involved include:
  1. We start with a metal-corrupted sinogram which is used to create an FBP reconstruction to identify the metal objects in the image.
  2. delete the corresponding metal-contaminated data in the sinogram.
  3. Incomplete sinogram is input to the generator network to complete the sinogram which is later used for FBP reconstruction. The discriminator network learns to classify the real sinogram and the sinogram completed by the generator, and is used as an penalising factor to train the generator network so as to produce realistic output.

Fast Enhanced CT MAR using Data Domain Deep Learning II



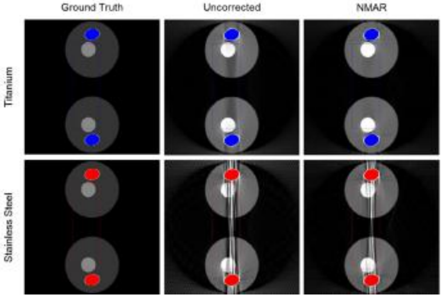


Outline

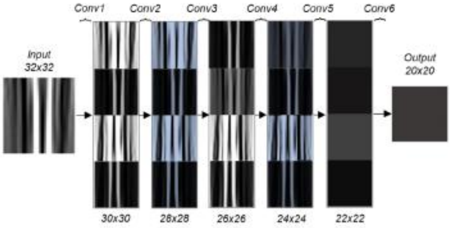
Reducing Metal Streak Artifacts in CT Images via Deep Learning I

- CNN combined with a Normalized Metal Artifact Reduction(NMAR) method is used here.
- NMAR employs interpolation and normalization to correct data in the metal trace.
- Steps involved:
  1. The CT images are initially corrected using NMAR.
  2. This is then fed to CNN consisting of 6 layers.

Reducing Metal Streak Artifacts in CT Images via Deep Learning II



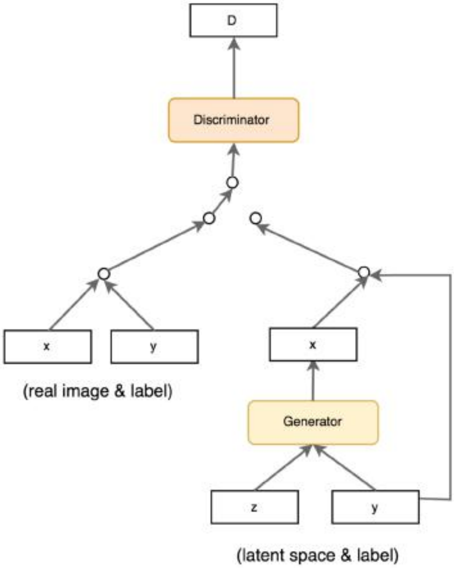
Reducing Metal Streak Artifacts in CT Images via Deep Learning III



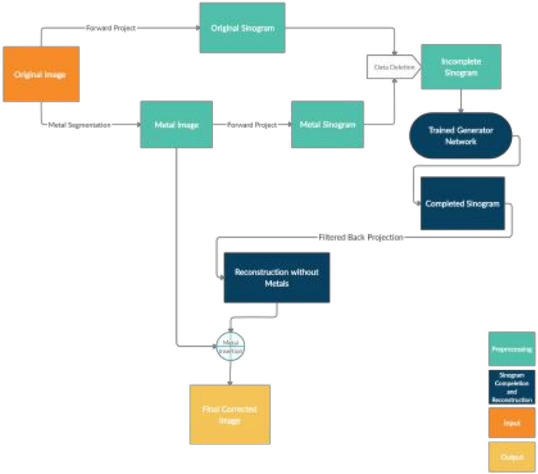
Proposed Method I

- The design we have decided to move forward with is the Conditional Generative Adversarial Network (CGAN).
- CGAN makes use of labels to help the model perform better by generating and discriminating images better.
- In this, we feed incomplete image to be generated (to fill in missing information).
- The discriminator then distinguishes between the real and the generated image and adds in a penalising factor to help train the generator network
- We also build a standard CNN model to compare the results of the CGAN model.

Proposed Method II



Outline

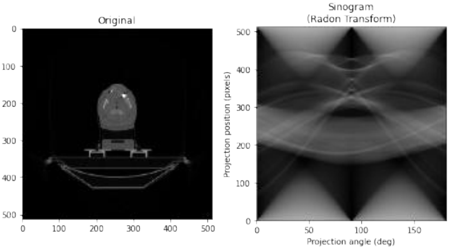

Original Image
Forward Project
Original Sinogram
Data Deletion
Incomplete Sinogram
Metal Segmentation
Metal Image
Forward Project
Metal Sinogram
Trained Generator Network
Completed Sinogram
Filtered Back Projection
Reconstruction without Metals
Metal Insertion
Final Corrected Image
Preprocessing
Sinogram Completion and Reconstruction
Input
Output

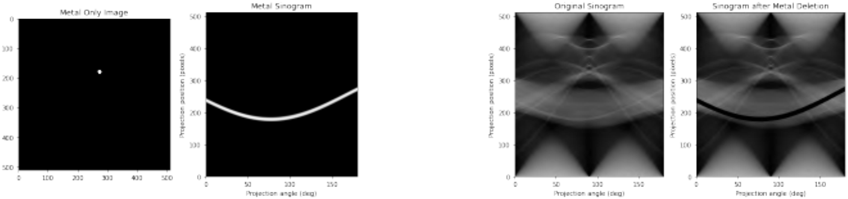
Outline

Preprocessing I

- Importing the CT dataset and making each slice into numpy pixel arrays whose values are converted into Hounsfield Units.
- Images are transformed into their corresponding sinograms in the projection domain by applying the radon transform.
- From the original image, we obtain the metal-only image by applying a threshold function which is followed by erosion and dilation (for finer quality)
- This image is then transformed into the corresponding metal-only sinogram
- The sinograms obtained above are subject to normalization to scale the values in the range 0-255.
- Finally the metal-only sinogram is deleted from the original sinogram which then becomes the input to the two models

Preprocessing II



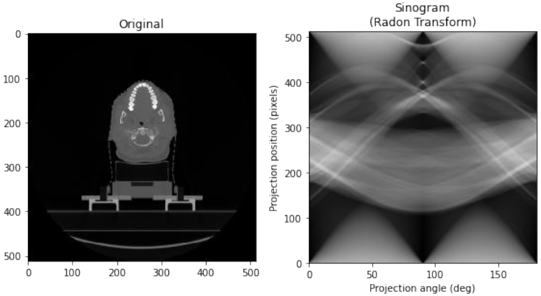


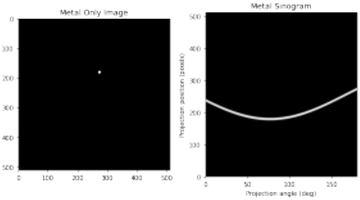
Outline

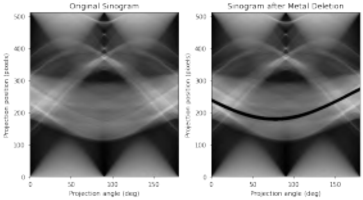
Simulated Dataset I

- From the dataset obtained from MVR, only 72 slices obtained to be used for training.
- The Simulated Dataset was generated for the sole purpose of training the generator for sinogram completion.
- To facilitate the simulation, CT slices were taken from patients that presented with no metal artifacts and after initial preprocessing were converted to their equivalent sinogram
- An arbitrary metal-only sinogram was chosen from the set of metal only sinograms and are deleted from the original sinogram
- This has enabled us to extend our dataset from the initial 72 samples to 1134 samples.

Simulated Dataset II





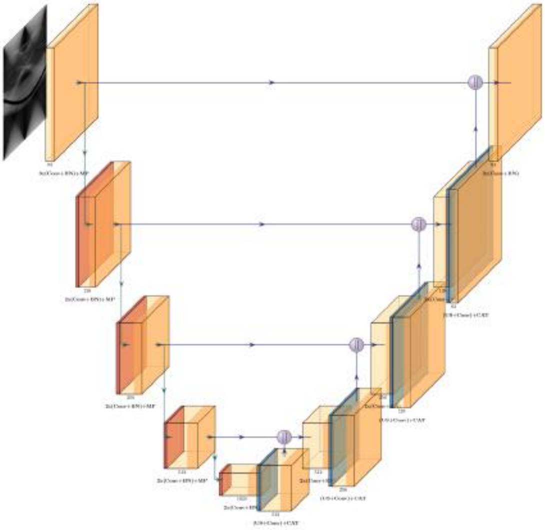


Outline

CNN MODEL I

- Our CNN Model makes use of a U-Net architecture, consisting of four down-sampling layers which is followed by four up-sampling layers.
- Each down-sampling layer consists of applying multiple 2D convolution and batch normalization layers followed by a 2D max pooling function.
- Each up-sampling consists of applying a concatenation function followed by multiple 2D convolution and batch normalization layers.
- Skip connections were included to prevent loss of information due to the application of max pooling and convolution in each layer
- The loss function used is mean squared error.

CNN MODEL II

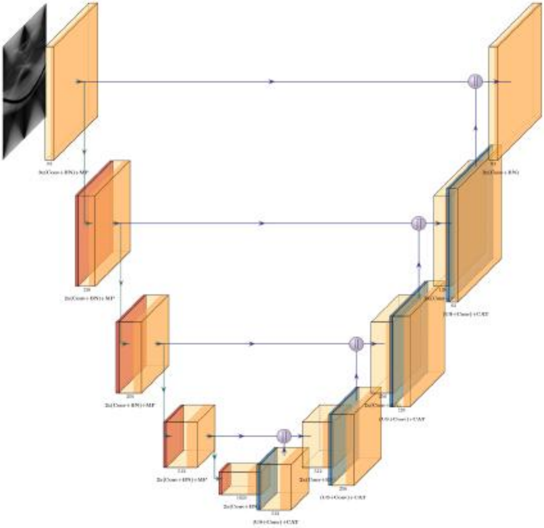


Outline

- Conditional Generative Adversarial Network is a deep learning method which is used as a framework to train generative models
- It comprises of two neural networks, namely, a generator network and a discriminator network
- **Generator**
  The generator fills in the missing data in the metal-deleted sinograms obtained after the preprocessing stage.
  The total generator loss is given by:

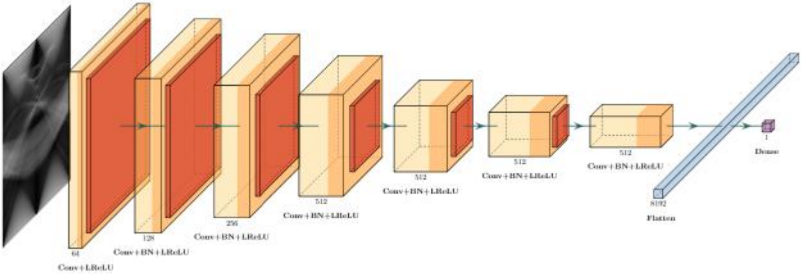
$$GAN_{loss} + (\lambda * L1_{loss})$$

CGAN MODEL II



- **Discriminator**
  It is classifier that tries to distinguish between the true sinogram and the sinogram that has been generated and adds in a penalising factor to help train the generator network.
  The total discriminator loss is given by:

$$Real_{loss} + Generated_{loss}$$



Evaluation Metrics

- Mean Squared Error:

$$MSE = \frac{1}{mn} \sum_{0}^{m-1} \sum_{0}^{n-1} \|f(i,j) - g(i,j)\|^2$$

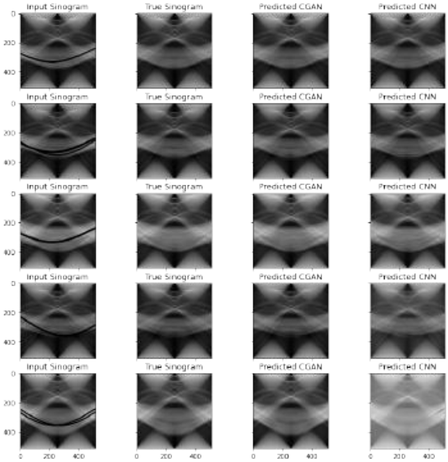
- Peak Signal to Noise Ratio:

$$PSNR = 20 * log_{10} \left(\frac{MAX_f}{\sqrt{MSE}} \right)$$

- Structural Similarity Index:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

- Completion of Sinogram:

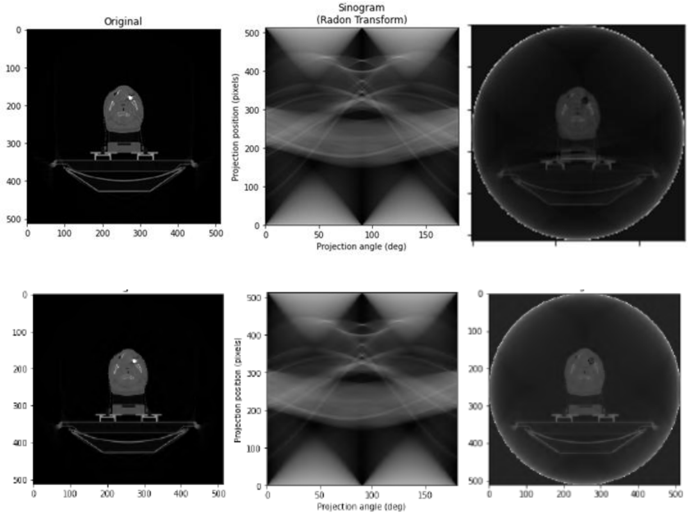


Results II

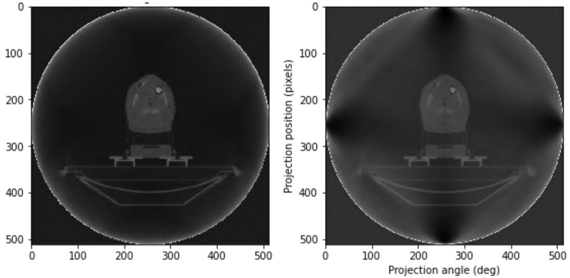
	Uncorrected	CNN	CGAN
psnr	22.70	29.67	32.42
ssim	0.86	0.93	0.95
mse	387.10	148.6	59.28

Table: Average scores of completed sinogram using CNN and CGAN

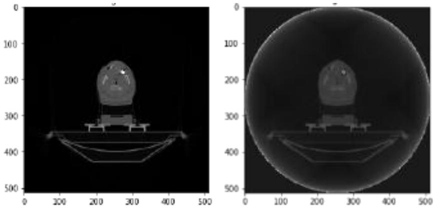
- Reconstruction of Completed Sinograms:



- Addition of Metal:



- Comparing the Input and Output



Results V

- From the results its clear that CGAN model outperforms the CNN model
- In CNN model, the loss function is explicitly fixed due to which no changes can be reflected back to it during the training phase.
- In CGAN model, the generator uses the discriminator as the loss function, meaning that the loss function for the generator is implicit and learned during training phase.

Future Work

- We would like to collaborate with other hospitals in order to accumulate a larger medical CT dataset to overcome the difficulties faced during our training stage to achieve an improved version of our current model.
- We would also like to implement a DCGAN (Deep Convolutional Generative Adversarial Network) model which is a popular and successful network design for GAN that composes of convolution layers without max pooling or fully-connected layers.

Conclusion

- Existence of effects such as metal artifacts which pose serious issues in data interpretation.
- From the papers we have found that simple image processing techniques such as linear interpolation yield unsatisfactory results.
- Greater accuracy and image quality is achieved by the application of deep learning along with the standard techniques.

Thank You.