Title. *<u>Motion-compensated Inverse Radon Transformation using Deep Learning: a Medical application</u>*

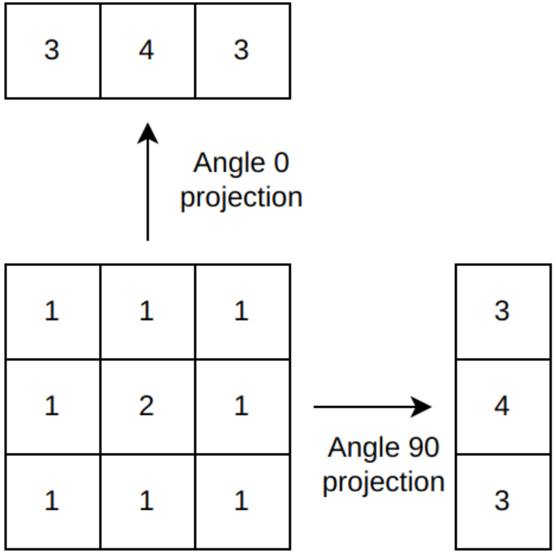
Presenters. Haoran Chang, Ph.D. Candidate, FIT; and Debasis Mitra, Professor, FIT

Abstract. Radon Transform (RT), invented in 1917 by Johann Radon, has its use in medical imaging, astronomy, Seismic imaging, and physics. RT and its inverse, IRT, transform an image between difference spaces, as Fourier Transform (FT) and its inverse, IFT do. RT and FT are quite inter-related mathematically. Many of the imaging applications of RT-IRT are affected by motions of the imaged object during data acquisition. For example, RT allows non-invasive imaging of heart, but a heart beats too fast during some of the imaging modalities with coarse timing-resolutions. While the issues of noise-removed IRT is a subject of research and practice over a half-century, applications of Convolutional Neural Network (CNN) in IRT is only recently being explored. In this work, we show how such a network may correct for cardiac motion using IRT in image reconstruction that is solely based on CNN. We compare our novel network against some existing paradigms of Deep Learning.

Key Words. Medical image Reconstruction; Motion Correction; Inverse Radon Transformation; Deep Learning; Convolutional Encoder Decoder

Radon Transform

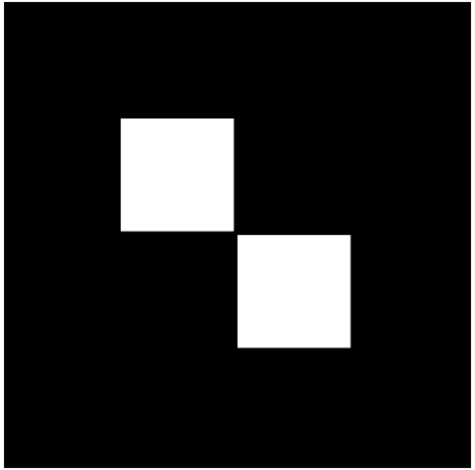
Integral Projection



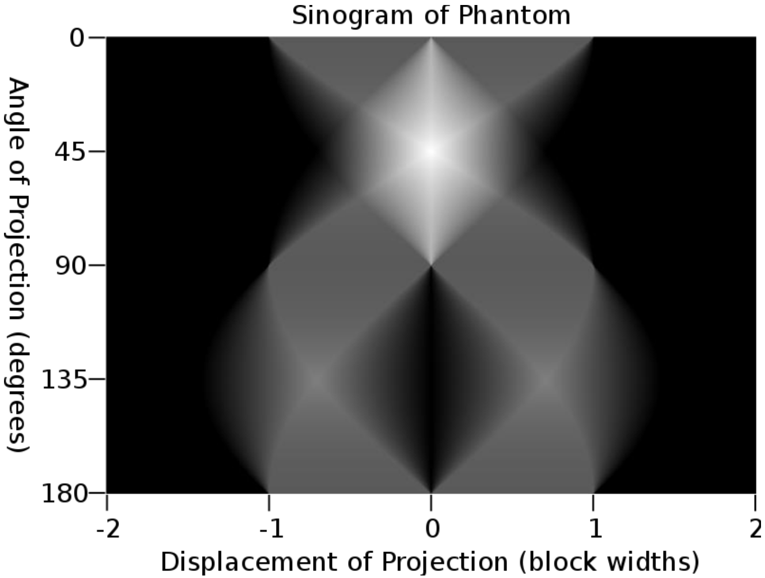
Radon Transform

Sinogram

Phantom



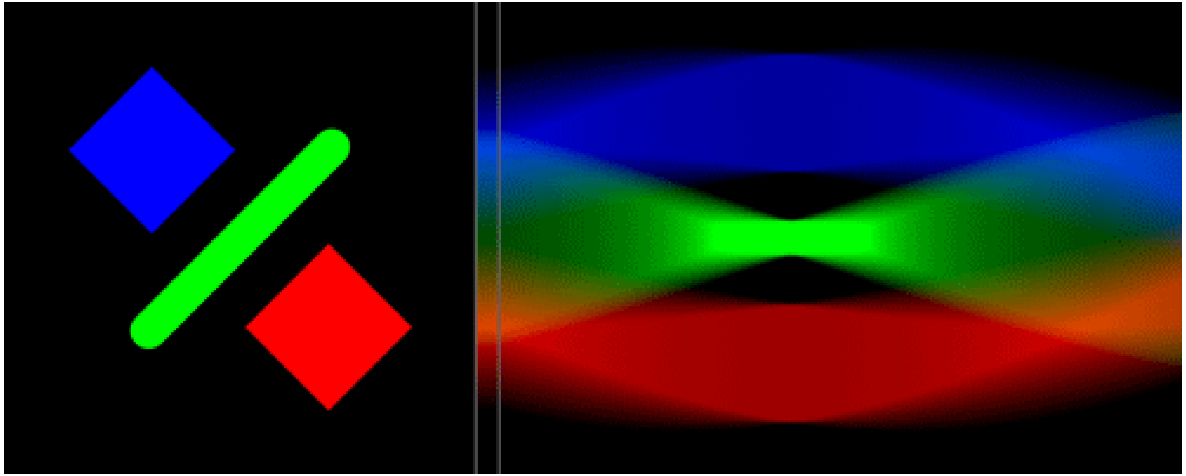
Radon Transform



From wiki page “Radon Transform”: https://en.wikipedia.org/wiki/Radon_transform

Radon Transform

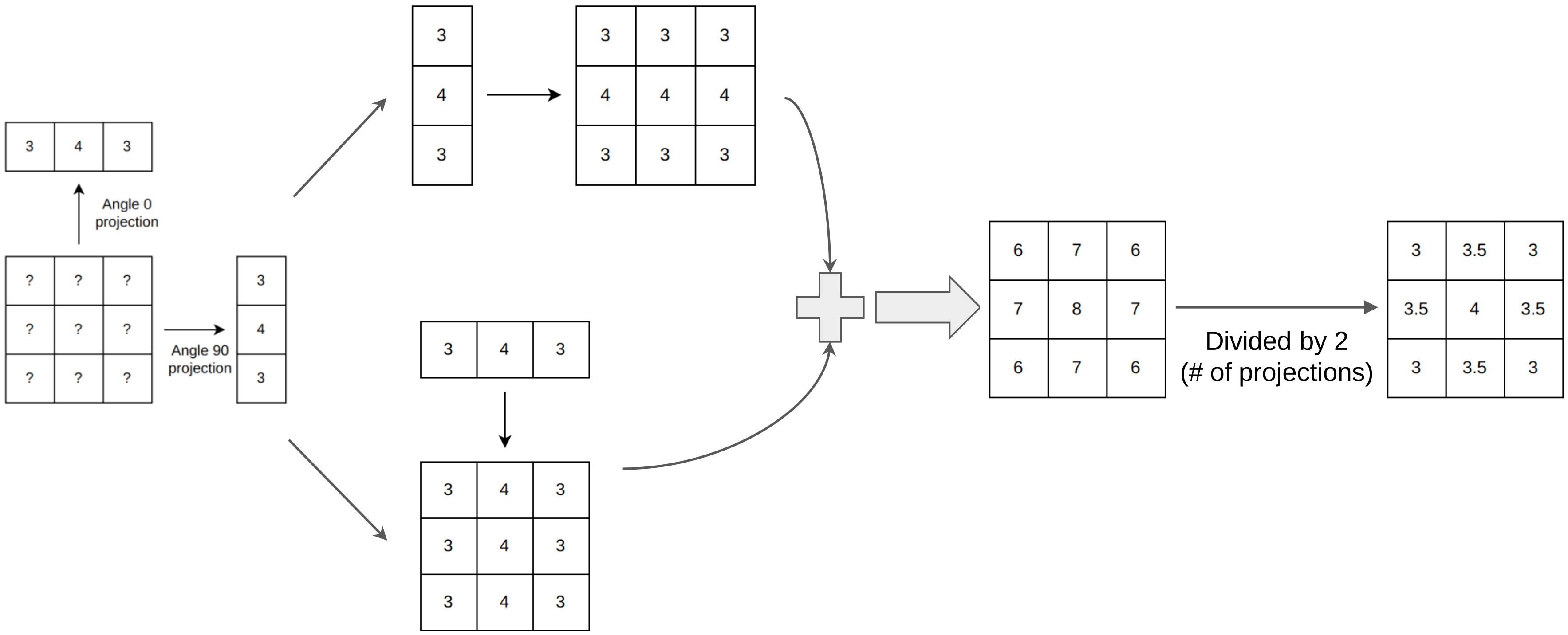
Sinogram (Animation)



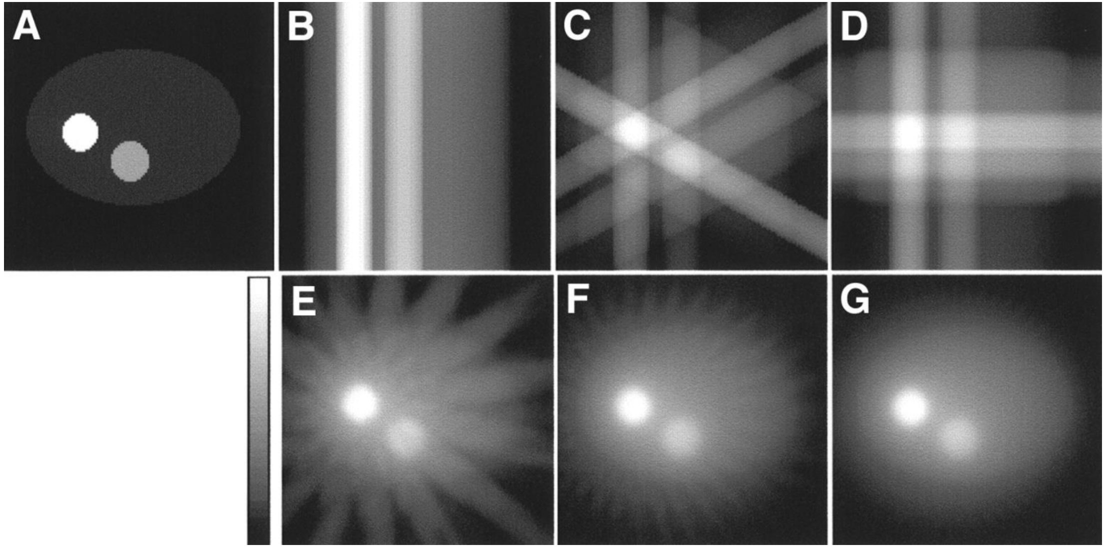
Horizontal projections through the shape result in an accumulated signal (middle bar). The sinogram on the right is generated by collecting many such projections as the shape rotates. Here, color is used to highlight which object is producing which part of the signal. Note how straight features, when aligned with the projection direction, result in stronger signals.

From wiki page “Radon Transform”: https://en.wikipedia.org/wiki/Radon_transform

Inverse Radon Transform (Backprojection)



Inverse Radon Transform (Backprojection)

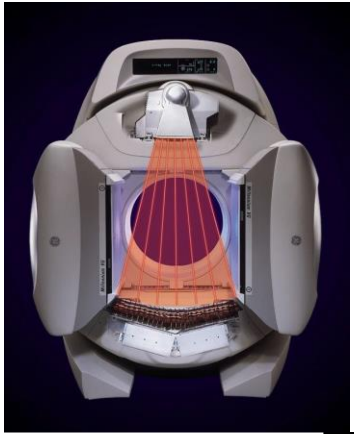


(A) Slice used to create projections. (B–G) 1, 3, 4, 16, 32, and 64 projections equally distributed over 360° are used to reconstruct slice using backprojection algorithm.

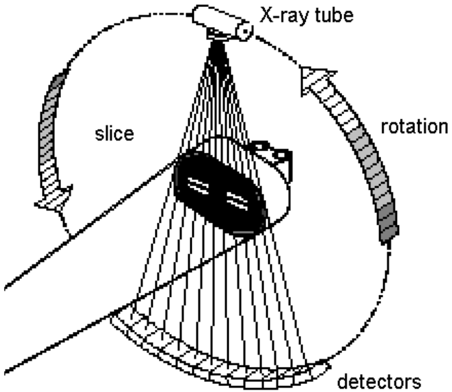
Figure from "Analytic and Iterative Reconstruction Algorithms in SPECT" by Philippe P. Bruyant

Computed Tomography: Absorption of X-ray

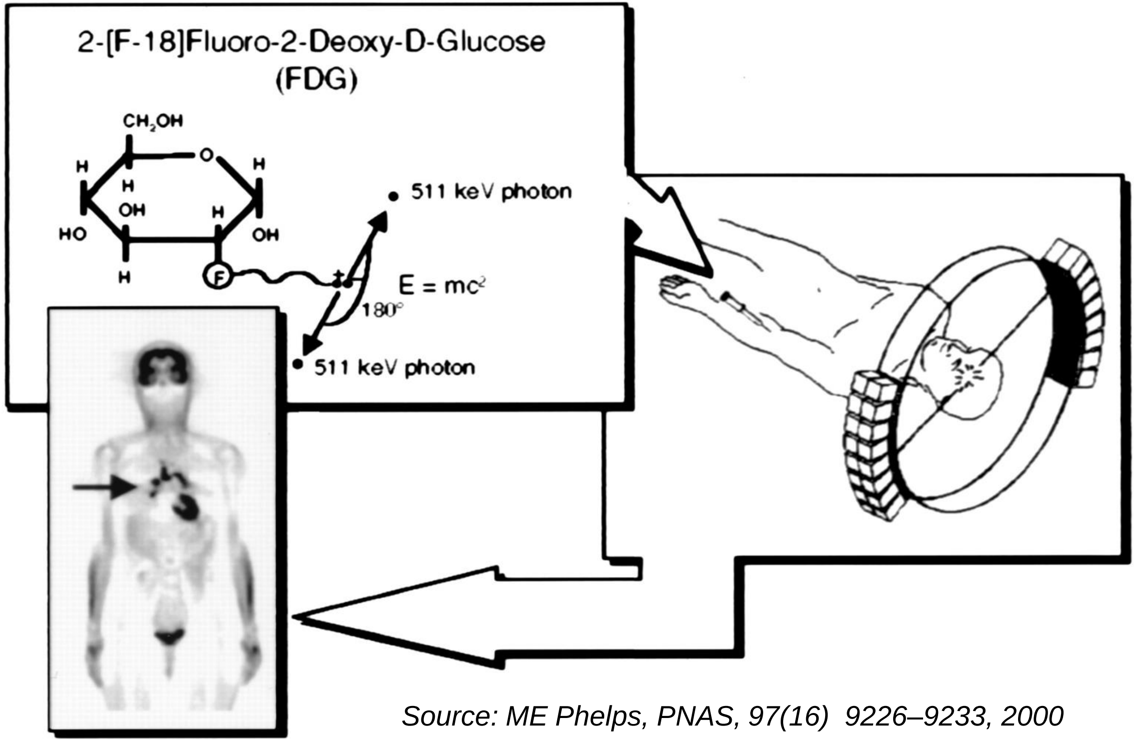
Anatomical Imaging



20-40 keV



Emission Tomography:
Functional Imaging

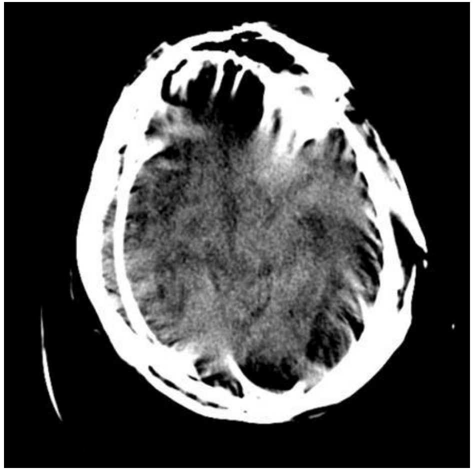


Source: ME Phelps, PNAS, 97(16) 9226–9233, 2000

<u>Problem we are addressing</u>: How to Inverse Motion-added Radon Transform?

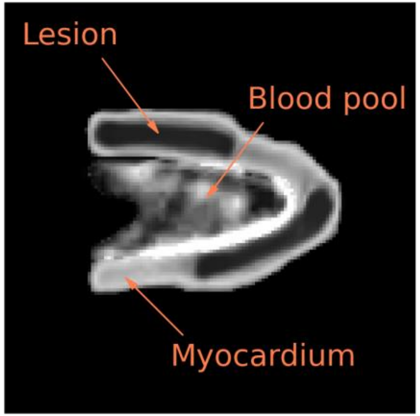
Motion types in medical imaging: Beating heart, Respiration, Patient motion, …

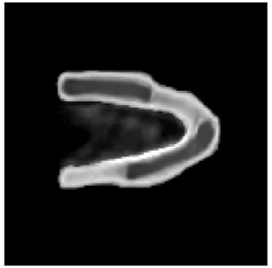
Creates blurriness in sinogram, and results in artifacts Reconstructed images

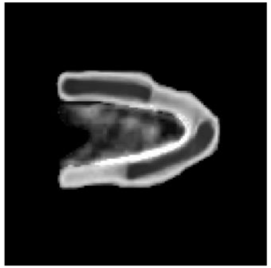


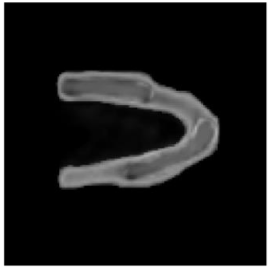
Data Preparation for Training and Validation for Deep Learning

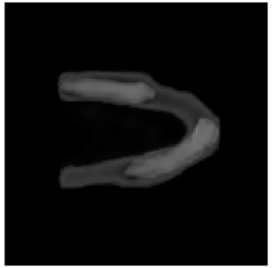
Original Data - Pseudo Heart





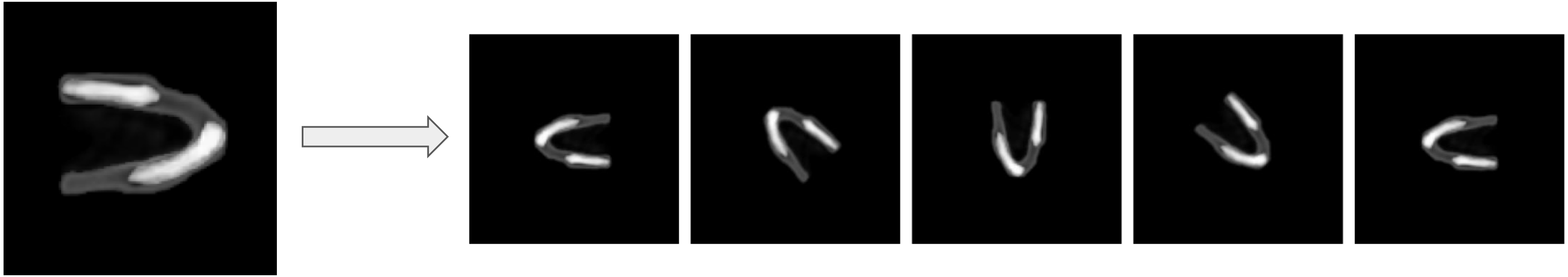






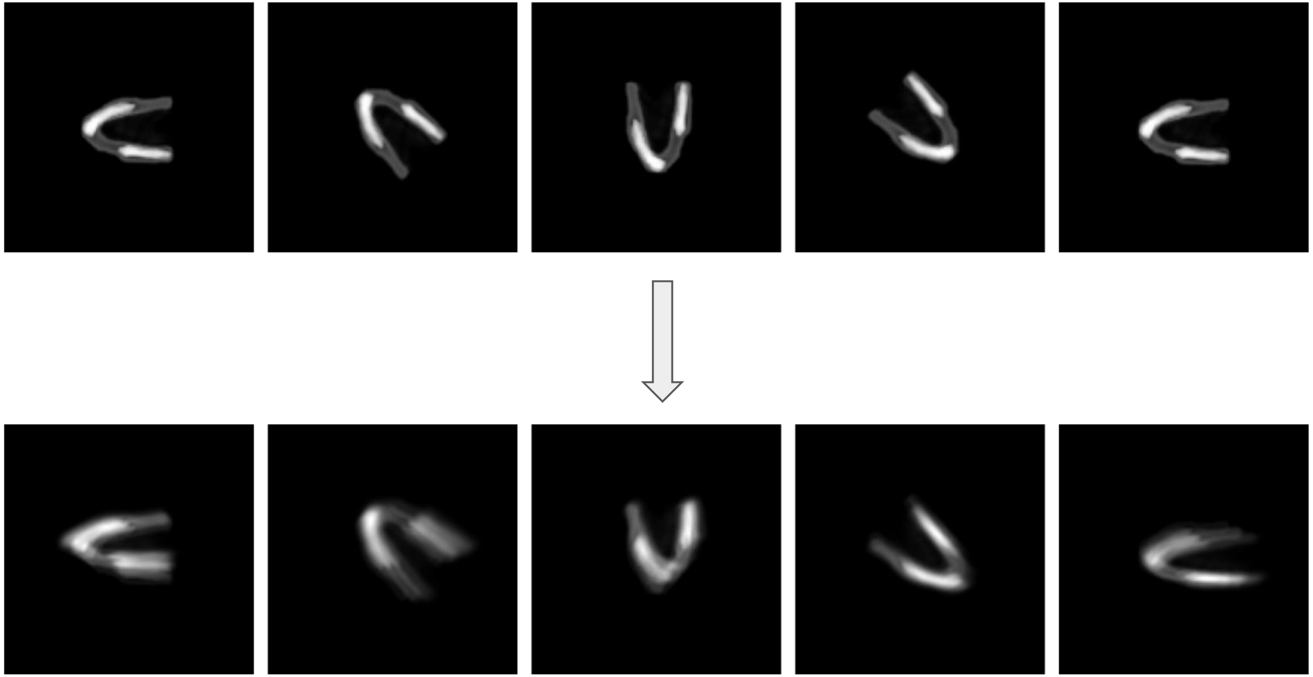
Data Preparation for Training and Validation

Augmentation - Randomly select some frames and perform affine transformations



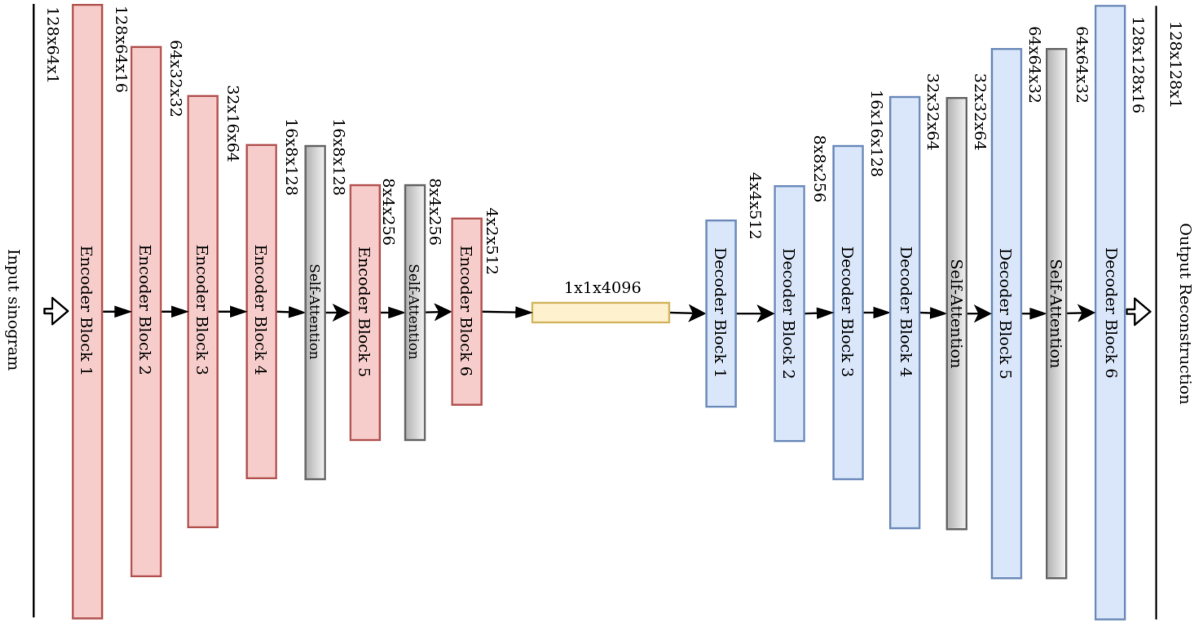
Data Preparation for Training and Validation

Blurring - Affine motion



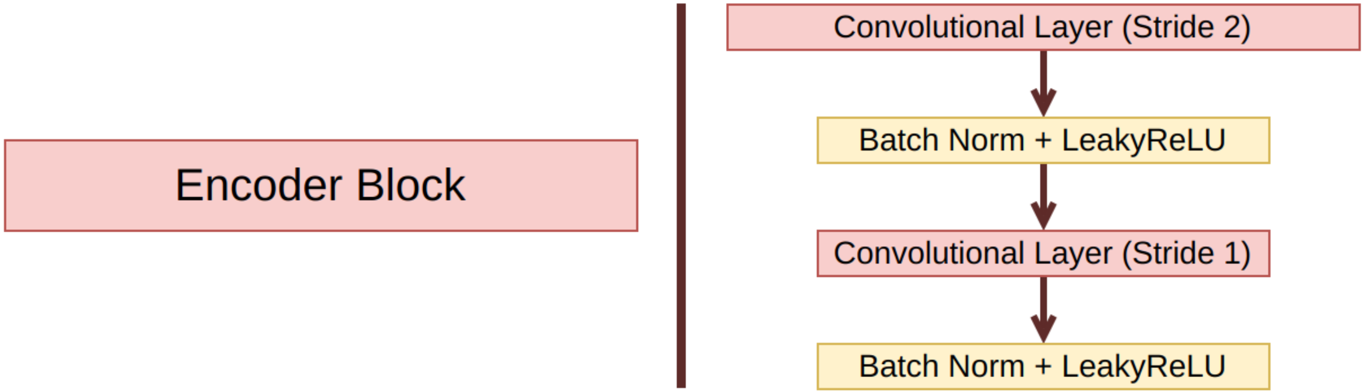
Neural Network Model for Image Reconstruction

Convolutional Encoder-Decoder with Self-Attention



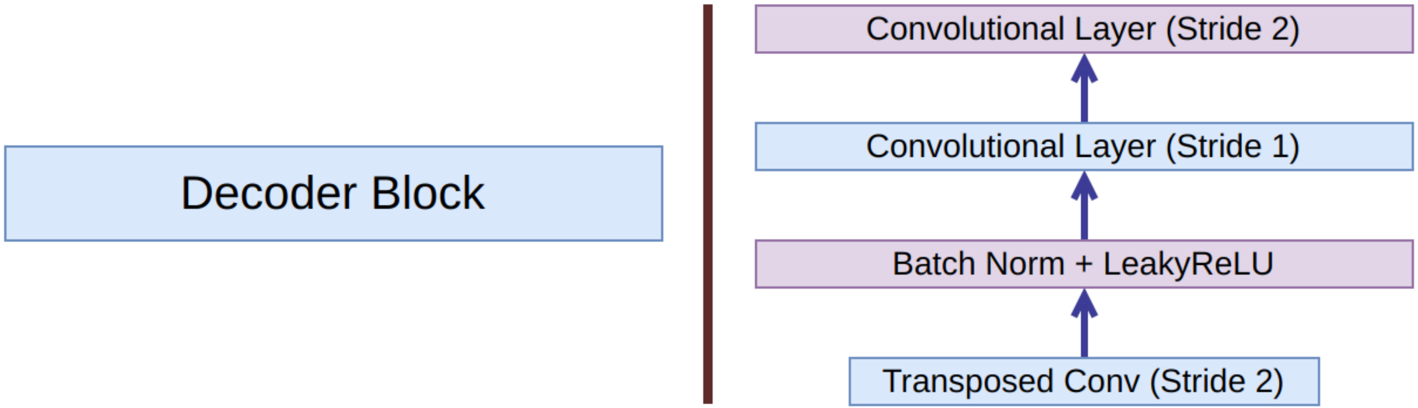
Neural Network Model

CEDA - Encoder Block



Neural Network Model

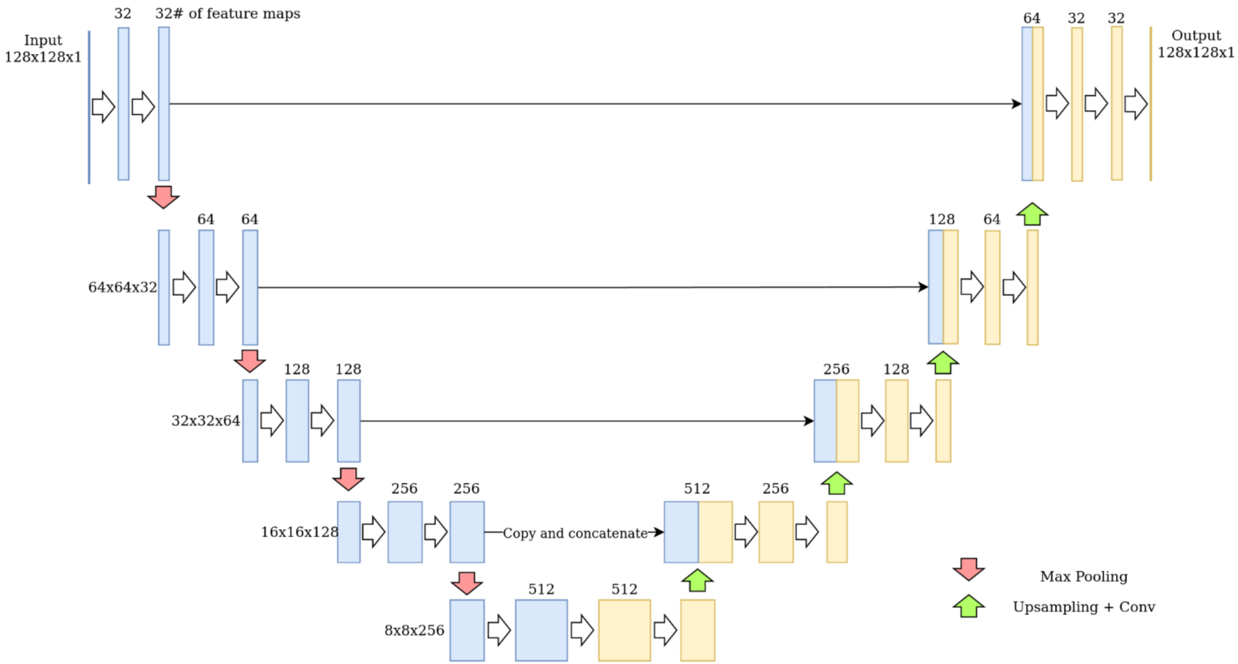
CEDA - Decoder Block



Conventional noise reduction with Deep Learning are performed by U-net

U-net Model for Noise-reduction

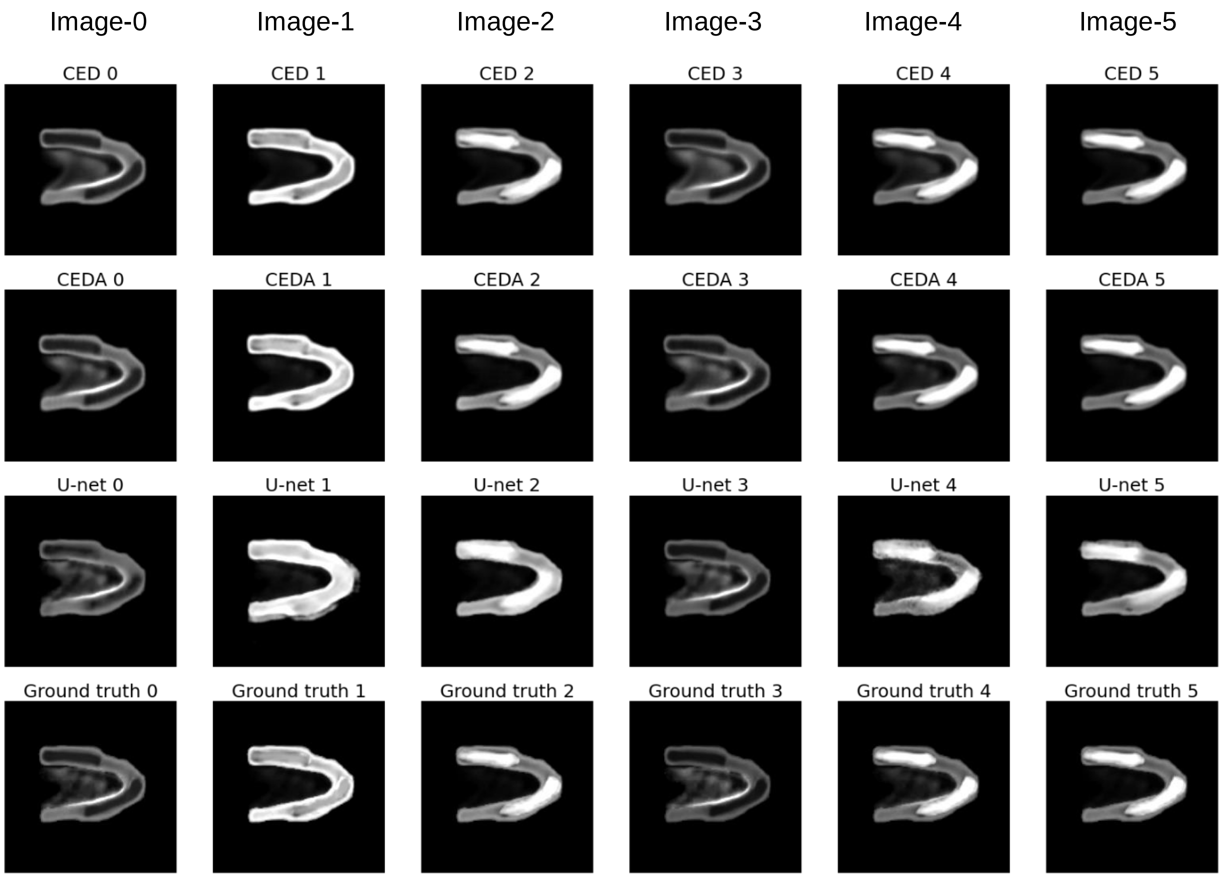
U-net (for comparison against ours)



Conventional noise reduction are performed by U-net

However, U-net maps from image-space to similar image-space

Result: reconstructions



Result: *Comparison Metrics*

1. Visual Information Fidelity (VIF)

$$VIF = \frac{Distorted\ Image\ Information}{Reference\ Image\ Information} = \frac{I(C;F)}{I(C;E)}$$

Where:

I(x;y) - Mutual information between x and y

C - Reference image

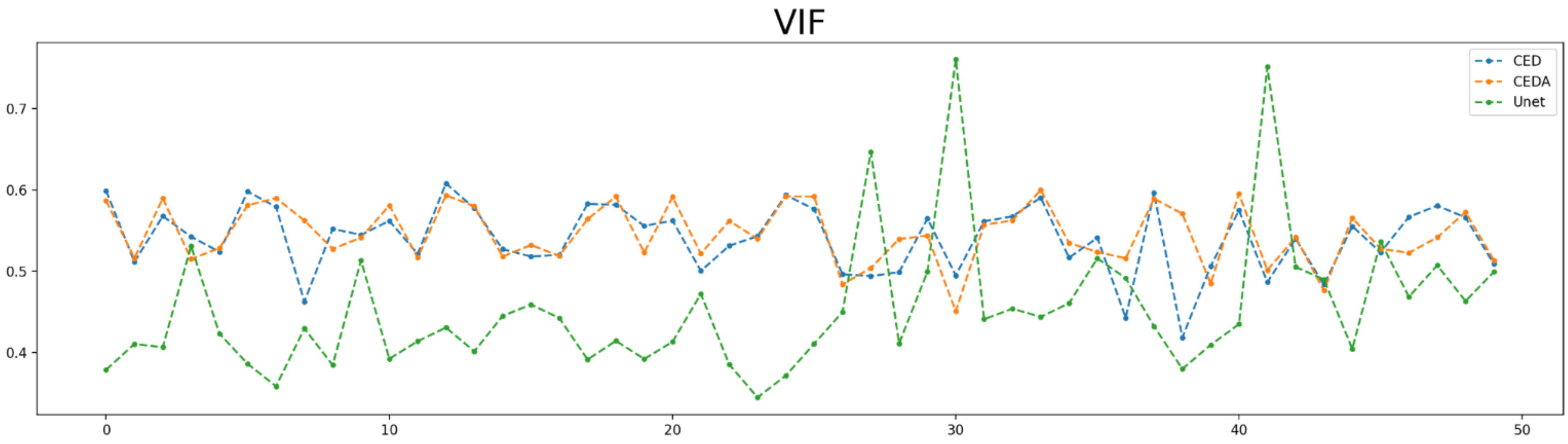
E - Visual signal of C at the output of human visual system (HVS)

F - Visual signal of distorted C at the output of HVS

Result

Comparison

- Visual Information Fidelity (VIF)



Result: *Comparison Metrics*

2. Signal-to-noise Ratio (SNR)

$$SNR = \frac{\mu_{ROI}}{\sigma_{background}}$$

3. Contrast-to-noise Ratio (CNR)

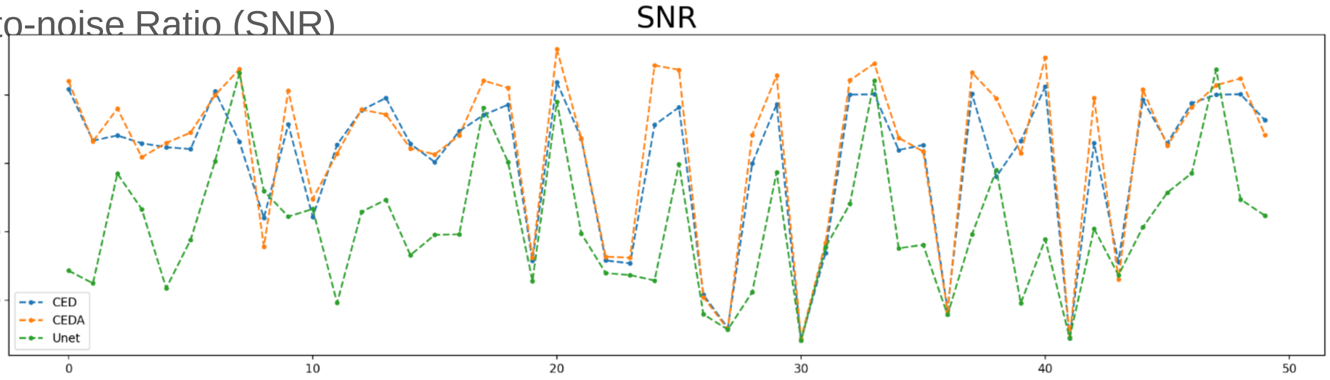
$$CNR = \frac{\mu_{ROI} - \mu_{background}}{\sigma_{background}}$$

μ is mean and
sigma is standard deviation

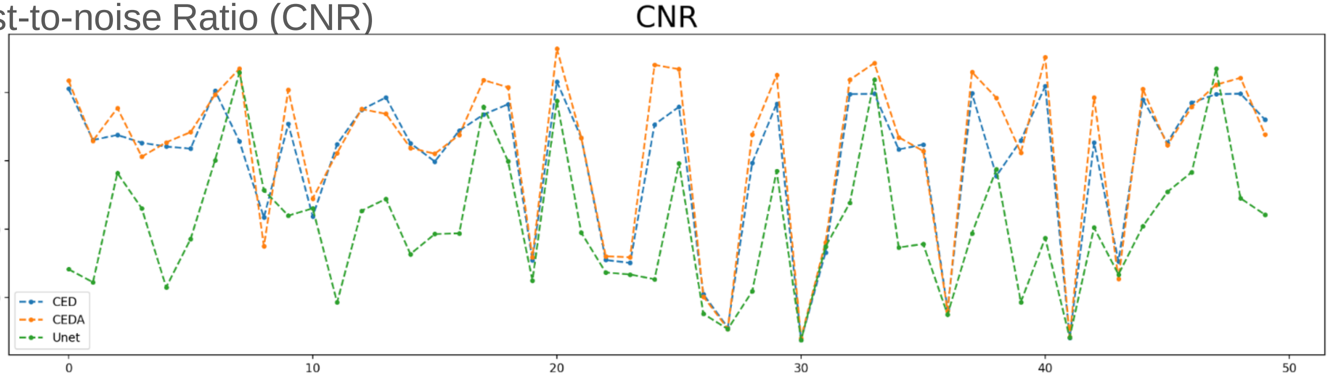
ROI region of interest (heart)

Result

- Signal-to-noise Ratio (SNR)

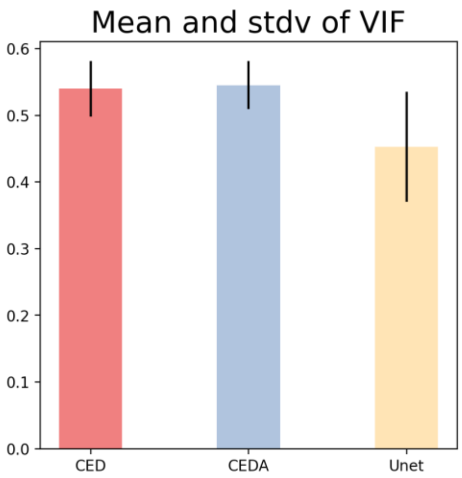


- Contrast-to-noise Ratio (CNR)

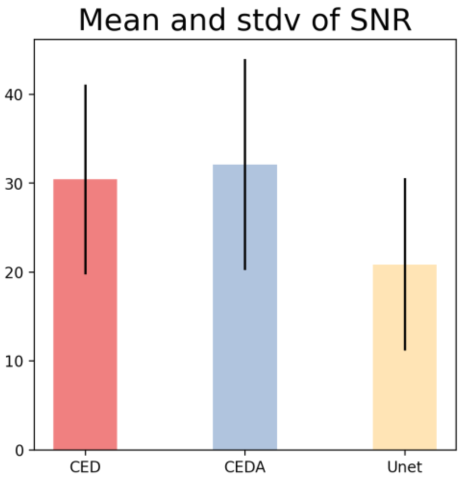


Result

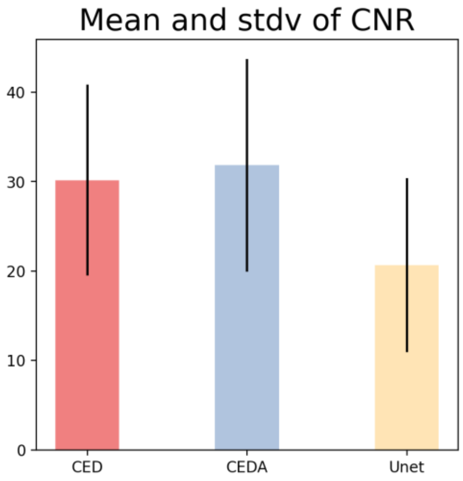
Comparison (mean and stdv)



0.54±0.042 **0.55±0.036** **0.45±0.082**



30.44±10.66 **32.12±11.96** **20.88±9.72**



VIF:
44 out of 50 reconstructed images CEDA reconstruction is better than U-net denoising,

and 26 reconstructed images with CEDA is better than CED.