

# Learned Compression of High Dimensional MRI Datasets

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# Background

- In MRI large number of images are acquired .
- Coil compression is important for storage and faster computation
- Traditional methods SVD and GCC are computationally expensive and lossy
- We propose a neural network-based coil compression for faster and more accurate compression

# Problem Statement

- Inputs: the original coil images from the physical coil array.
- Outputs: a set of virtual coil images
- We use the square root of sum-of-square (SSOS) to combine individual coil images into one image.

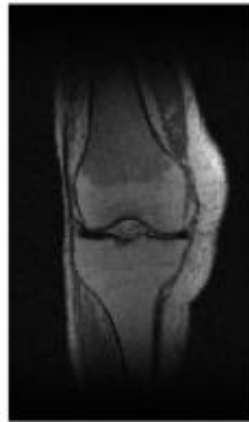
$$SSOS(m) = \sqrt{\sum_{i=1}^n (|m_i|^2)}$$

- Metric: the root mean square (RMS) loss between the SSOS images

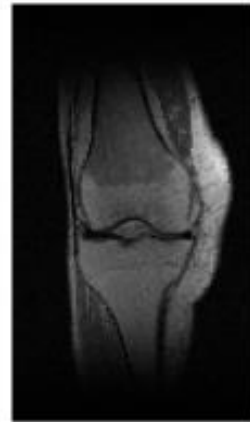
# Datasets

- We use the benchmark multi-coil knee dataset from fastMRI.
- Each subject volume has size 640x368 with 15 coils.
- 973 volumetric subjects for training and 56 volumetric subjects for testing

SSOS Image



Coil 1



Coil 2



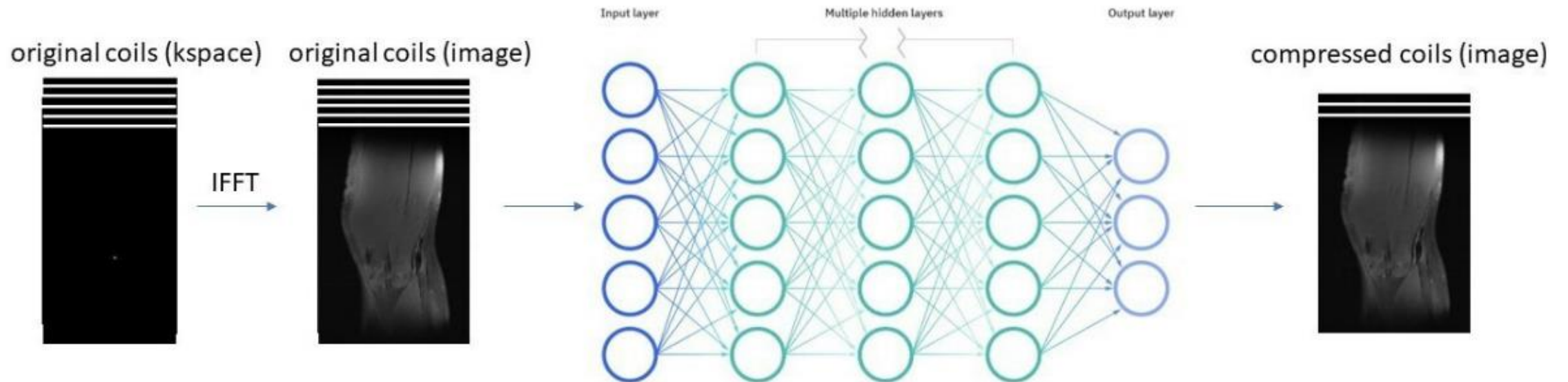
Coil 3



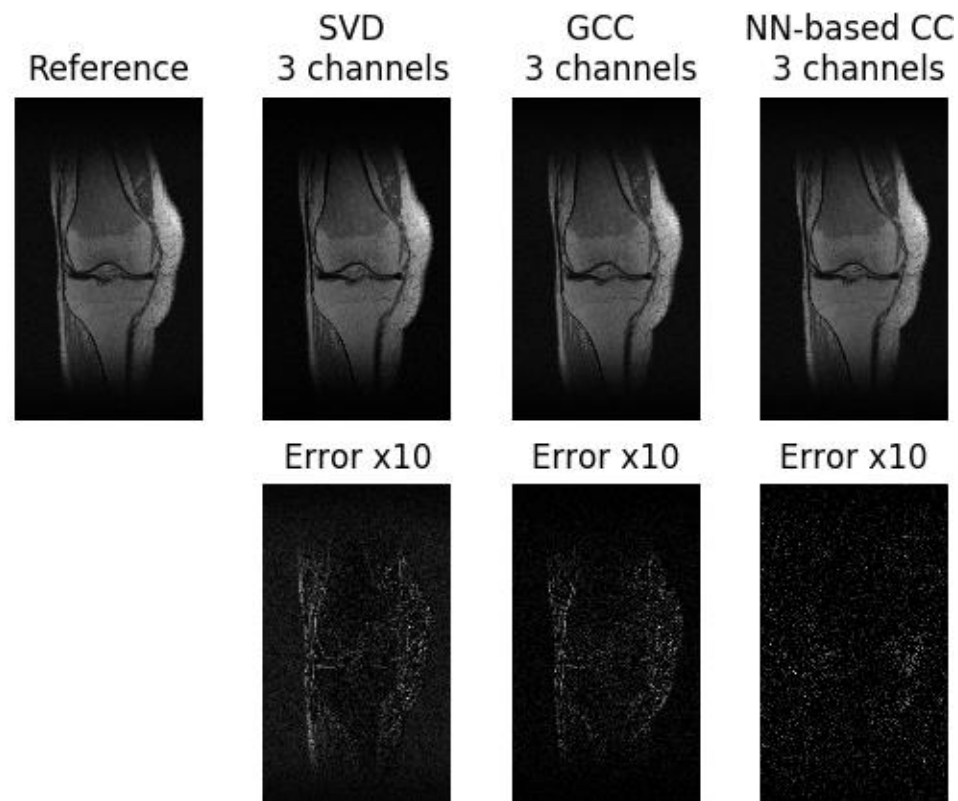
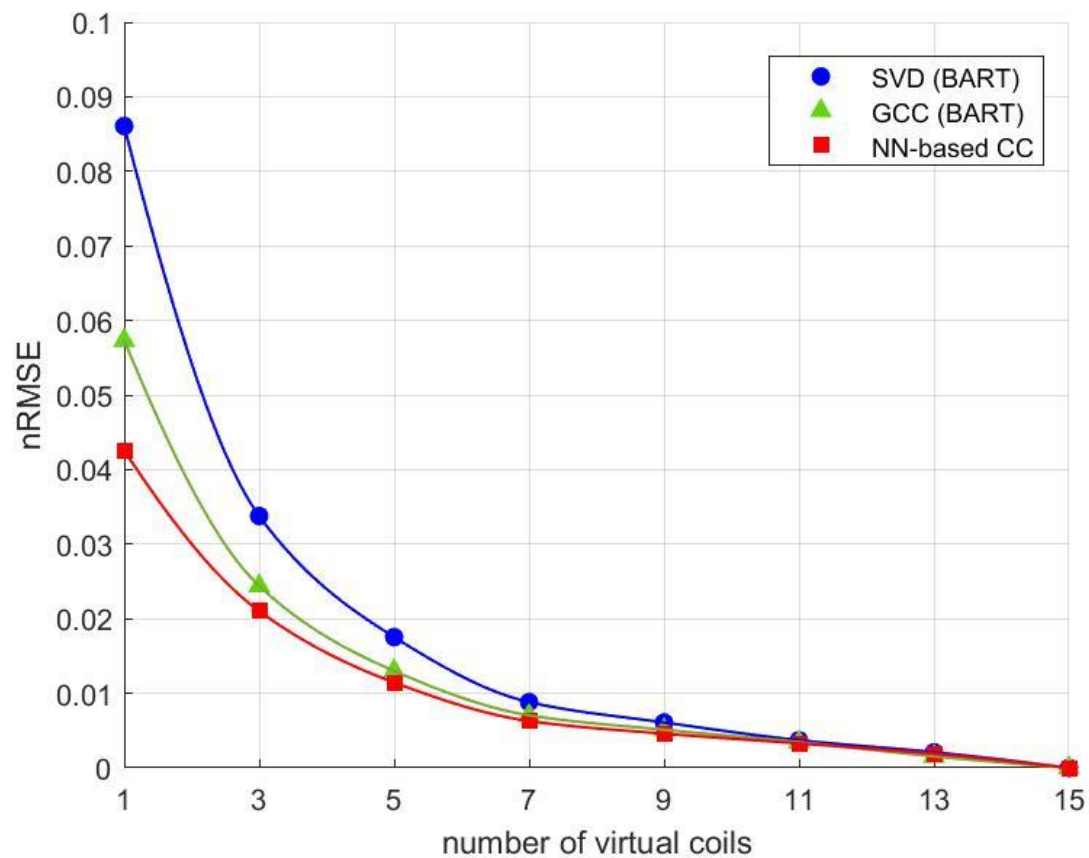
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# Methods

- We tried three different network structure:
  1. Fully-connected Network
  2. 2D Convolutional Encoder
  3. 3D Convolution Encoder



# Experiments & Analysis



# Conclusions & Future Work

- Our methods achieves up to 1.5x lower NRMSE and up to 10 times runtime speed compared to traditional methods.
- One current large limitation is that a different model needs to be trained for every different dimensionality of virtual coils.
- An interesting future work is to train in the frequency domain instead of image domain.