MRI Scan-Time Reduction Using Complex Valued AI In Image Space

by

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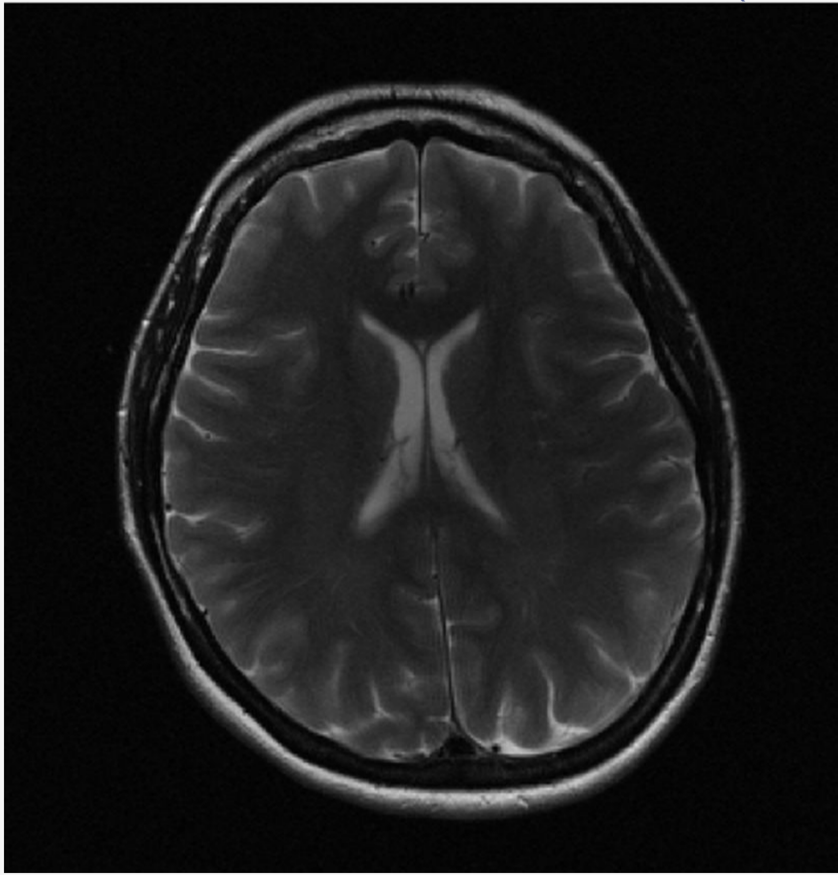
Contents

INTRODUCTION

- Magnetic Resonance Imaging (MRI)
  -medical imaging technique
  -visualizes anatomy and physiological processes
  -without ionizing radiation.
- MRI uses strong magnetic fields, gradients, and radio waves to generate detailed images.
- Unlike CT and PET scans, MRI does not involve harmful radiation, making it safer for repeated diagnostics.
- MRI offers superior soft tissue contrast, useful in
  -brain
  -muscle
  -abdominal imaging.



JUSTIFICATION

- **Long scan times** cause discomfort for injured and paining patients.
- **Motion artifacts** reduce image quality during lengthy scans.
- **Higher operational costs** due to low patient throughput.
- **Limited accessibility** in busy or resource-constrained hospitals.
- **Need for faster MRI** to improve patient care and system efficiency.

OBJECTIVES

- **Reduce MRI scan time** without compromising image quality.
- **Enhance diagnostic throughput** by accelerating MRI imaging.
- **Apply complex-valued AI techniques** for faster k-space data reconstruction.
- **Evaluate performance** using standard image quality metrics (e.g., PSNR, SSIM).
- **Develop a scalable solution** for real-time MRI scan acceleration.

LITERATURE REVIEW

Research Paper	Year	Major Findings
SENSE Pruessmann et al.	1999	Introduced **sensitivity encoding (SENSE)**, enabling faster MRI scans by exploiting multiple receiver coils for parallel imaging, thus reducing scan times.
GRAPPA Griswold et al.	2002	Developed **GRAPPA** (Generalized Autocalibrating Partially Parallel Acquisition), a method that accelerates MRI by using parallel coils and calibration-free reconstruction.
ESPIRiT Uecker et al.	2014	Proposed **ESPIRiT** (Extended Sensitivity Encoding with Iterative Reconstruction), enhancing parallel MRI techniques by improving coil sensitivity maps for more accurate reconstructions.
Compressed Sensing Jaspan et el.	2015	Applied **compressed sensing** to MRI, showing how under-sampled data can still lead to high-quality images, significantly reducing scan time without sacrificing image resolution.
Deep SENSE Xi Peng et al.	2021	Combined **deep learning** with **SENSE** to improve image reconstruction quality and accelerate MRI scans, providing a hybrid approach that outperforms traditional methods.

MRI Fundamentals

MRI Steps

1. Magnetization

- Strong magnetic field aligns body's H protons
- Protons align either parallel or antiparallel to the field, creating a net magnetization.

2.Radiofrequency (RF) Pulses

- RF pulse is applied to disturb proton alignment
- This energy tips protons into a higher energy state.

3.Signal Detection

- Once the RF pulse is switched off, protons 'relax'
- They emit radio signals that are detected by coils around body.

MRI Fundamentals

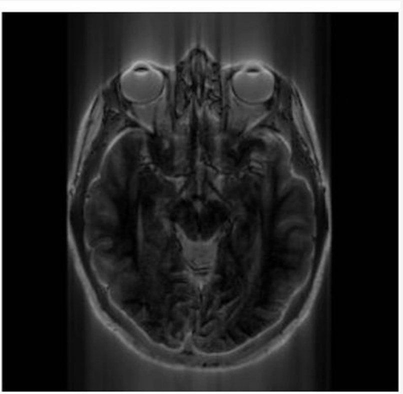
MRI Steps

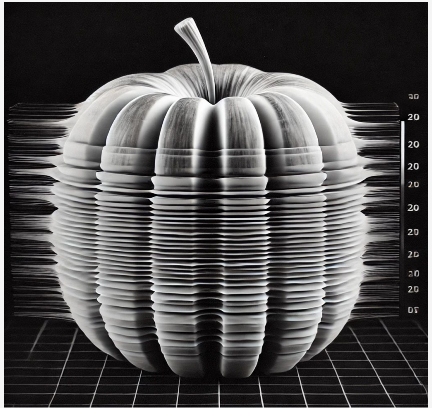
4. K-Space Sampling

- The signals are collected in K-space (a frequency domain).
- Each point in K-space holds phase and frequency information needed to reconstruct the final image.

5. Image Reconstruction

- Using mathematical algorithms (like Fourier Transform), the data from K-space is processed into a detailed 2D or 3D image.



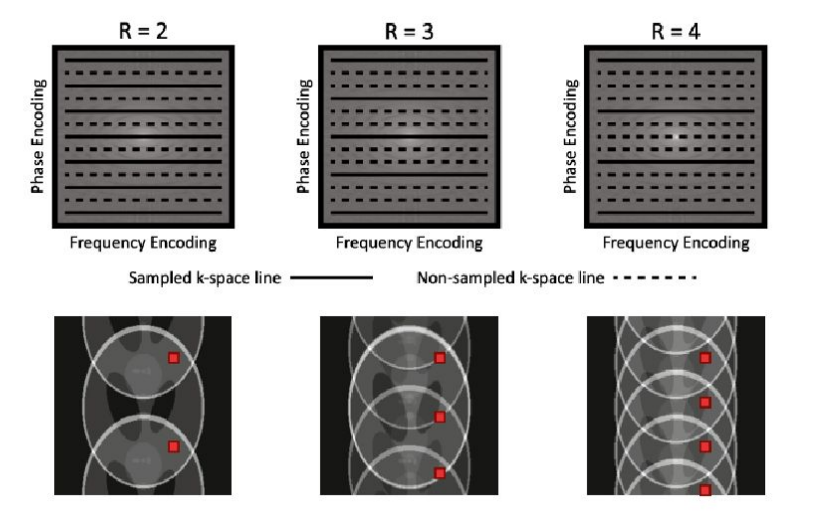


K-Space Visualisations

Aliasing Problem

Aliasing in Accelerated MRI

- Acceleration skips k-space lines → undersampling.
- Causes aliasing: overlapping image structures.
- Multicoil data helps resolve aliasing using the concept of coil sensitivity.
- Reconstruction methods (e.g., SENSE) correct the artifacts.

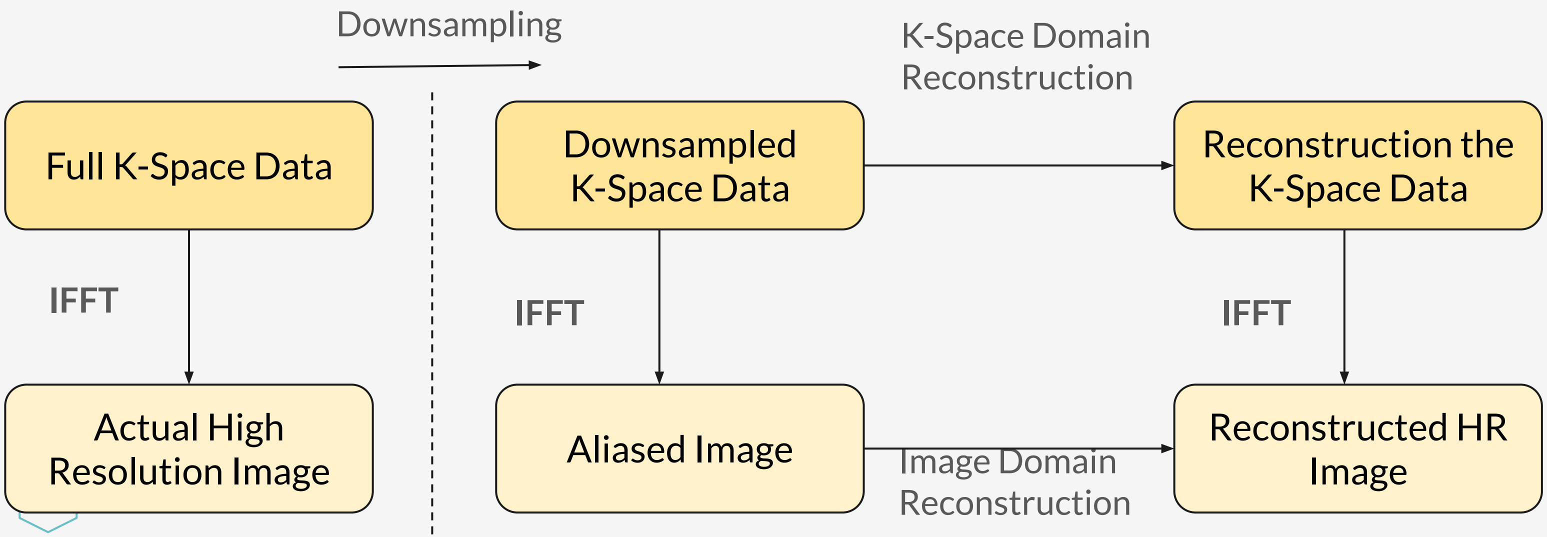


Parallel Imaging - Our best tool

Two kinds of Techniques-

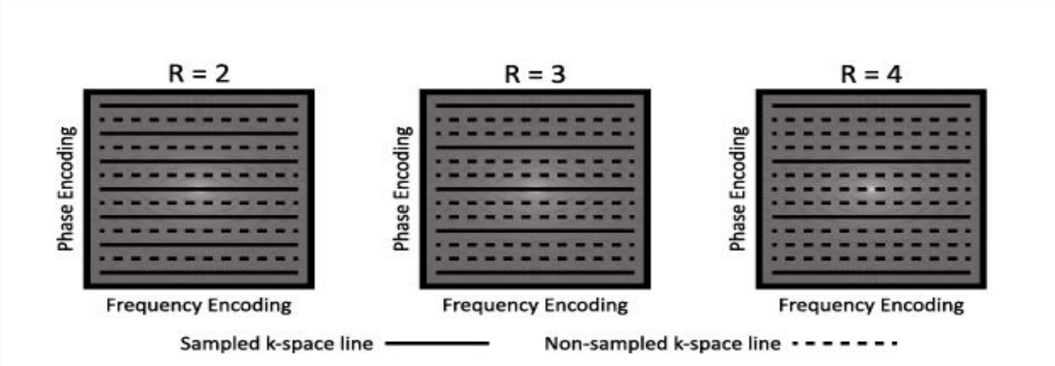
1. **IMAGE- DOMAIN** based technique
   -performed in image space *after* reconstruction of data from the individual coils

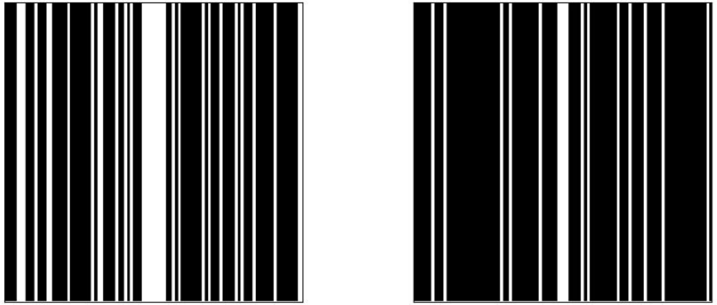
2. **K-SPACE** based technique
   -operate primarily on *k*-space data *before* image reconstruction



SENSE (1999)
Sensitivity Encoding for Fast MRI

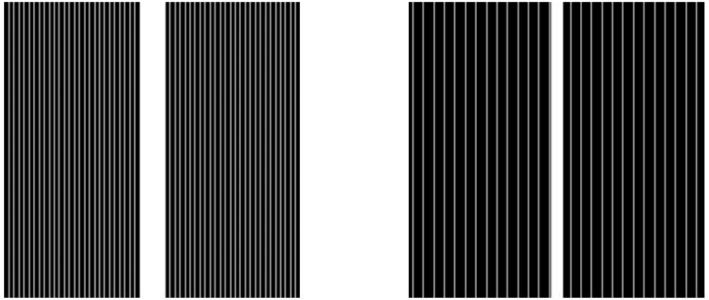
Visual representation of Sampling under Acceleration





(a) Random mask with 4-fold acceleration

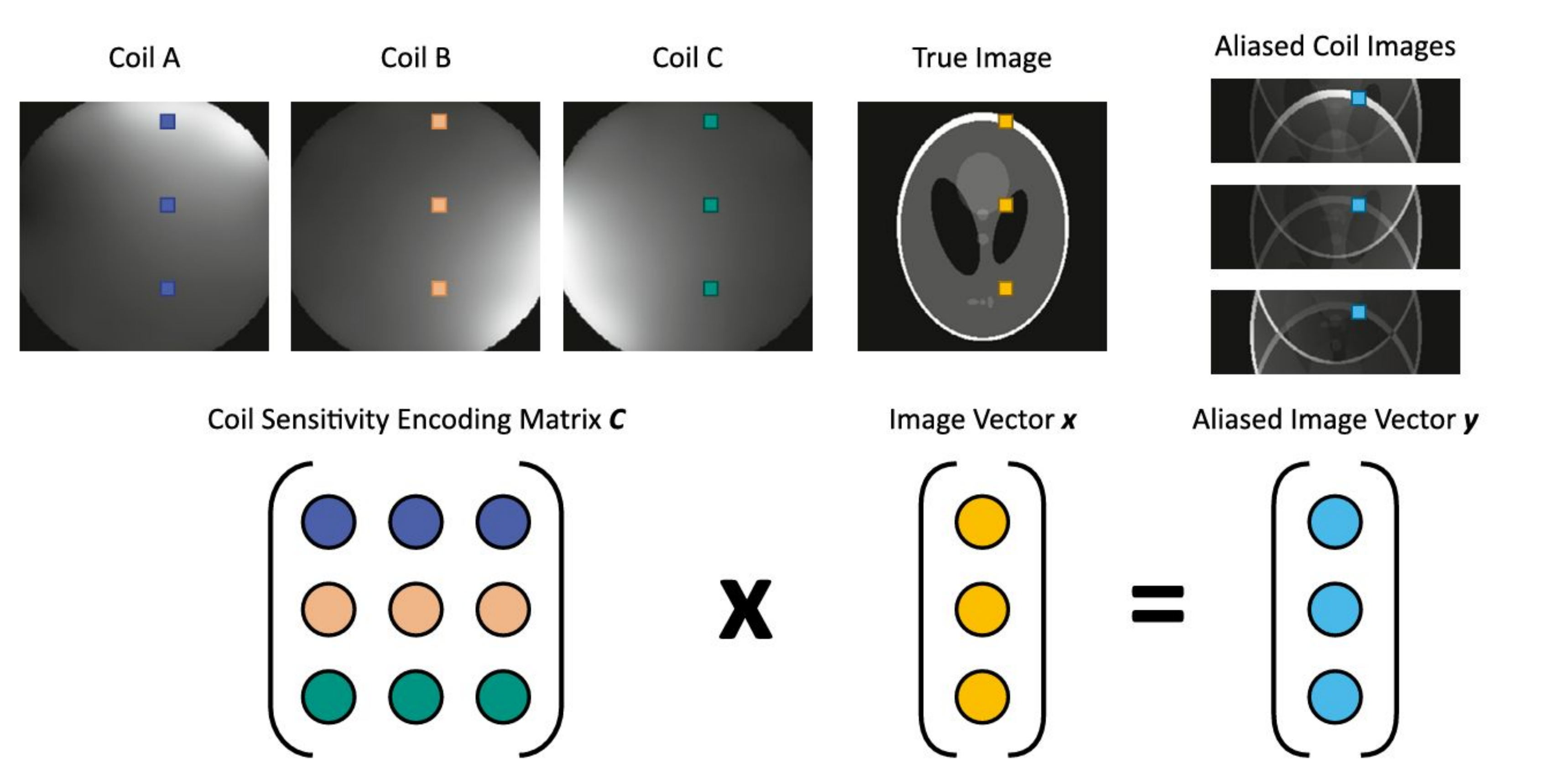
(b) Random mask with 8-fold acceleration

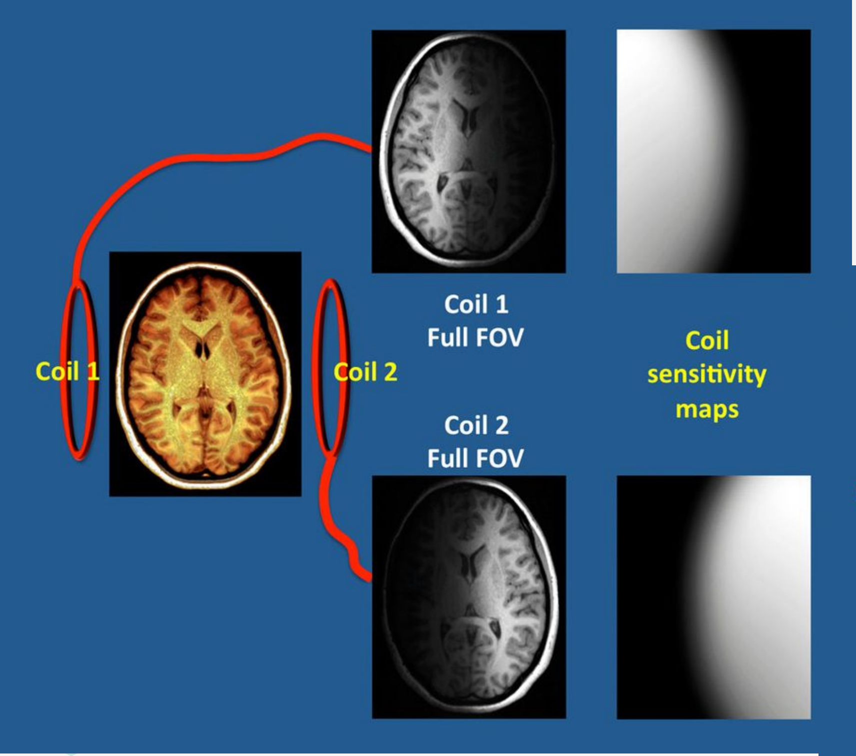


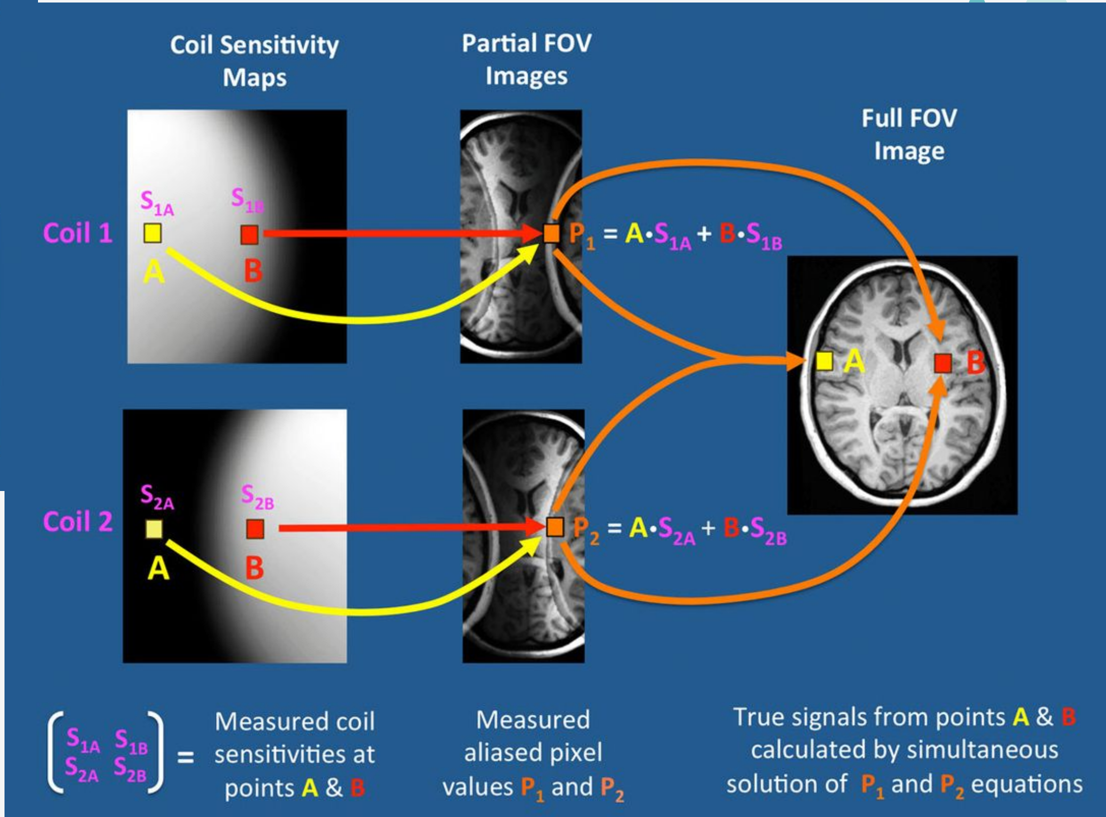
(c) Equispaced mask with 4-fold acceleration

(d) Equispaced mask with 8-fold acceleration

ALIASING- Resolution Approach




Coil 1
Coil 2
Coil 1
Full FOV
Coil 2
Full FOV
Coil
sensitivity
maps


Coil Sensitivity
Maps
Partial FOV
Images
Full FOV
Image
Coil 1
S_{1A}
S_{1B}
A
B
$P_1 = A \cdot S_{1A} + B \cdot S_{1B}$
Coil 2
S_{2A}
S_{2B}
A
B
$P_2 = A \cdot S_{2A} + B \cdot S_{2B}$
A
B
$\begin{bmatrix} S_{1A} & S_{1B} \\ S_{2A} & S_{2B} \end{bmatrix}$ = Measured coil sensitivities at points A & B
Measured aliased pixel values P_1 and P_2
True signals from points A & B calculated by simultaneous solution of P_1 and P_2 equations

Materials and Methods

- ## fastMRI Dataset: An Open Dataset and Benchmarks for Accelerated MRI

Designed to advance MRI reconstruction.
The fastMRI raw k-space data is stored in the HDF5 (.h5) file format, which efficiently organizes large, complex datasets, enabling fast access to MRI raw data and associated metadata for training and evaluation.

Data Types:

Raw multi-coil k-space data (complex-valued measurements)
Emulated single-coil k-space data (simulated from multi-coil)
Ground-truth images (root-sum-of-squares reconstruction)
DICOM images (diverse scanners, post-processed)

Tasks Enabled:

Single-coil reconstruction
Multi-coil reconstruction

Modalities & Organs:

Knee MRI (1,594 multi-coil raw scans; 10,000 DICOM scans)
Brain MRI (6,970 multi-coil raw scans; 10,000 DICOM scans)

BART: Berkeley Advanced Reconstruction Toolbox

-Computational Magnetic Resonance Imaging

- Free and open-source framework for **Computational MRI**.
- Designed **for research use only** (not for diagnostic use).
- Over **100 commands** covering diverse reconstruction tasks.
- Strong support for **FFT** and **Non-Uniform FFT (NUFFT)** operations.
- Facilitates **parallel imaging** (SENSE, POCSENSE) and **compressed sensing**.
- Scriptable via **command-line interface** for easy automation.

Key Features-

- Nonlinear inversion and compressed sensing reconstruction.
- Deep learning integration with TensorFlow and Reconet.
- Synthetic data generation (phantoms, fake k-space).
- Image evaluation tools (NMRSE, ROI stats, MIP views).
- Wavelet transforms, TGV and ICTV regularization.
- Fast, lightweight, suitable for rapid MRI research prototyping.

```
BART. Available commands are:
avg         bench       bin         bitmask     cabs        calc
caldir      calmat      carg        casorati    cc          ccapply
cdf97       circshift   conj        conv        conway      copy
cpyphs      creal       crop        delta       ecalib      ecaltwo
epg         estdelay    estdims     estshift    estvar      extract
fakeksp     fft         fftmod      fftrot      fftshift    filter
flatten     flip        fmac        fovshift    homodyne    ictv
index       invert      itsense     join        looklocker  lrmatrix
mandelbrot  measure     mip         mnist       moba        mobafit
morphop     multicfl    nlinv       nlmeans     nnet        noise
normalize   nrmse       nufft       nufftbase   onehotenc   ones
pattern     phantom     pics        pocsense    poisson     pol2mask
poly        psf         reconet     repmat      reshape     resize
rmfreq      rof         roistat     rss         rtnlinv     sake
saxpy       scale       sdot        show        signal      sim
slice       spow        sqpics      squeeze     ssa         std
svd         tensorflow  tgv         threshold   toimg       traj
transpose   twixread    upat        var         vec         version
walsh       wave        wavelet     wavepsf     whiten      window
wshfl       zeros       zexp
```

Methodology: MRI Reconstruction Pipeline

1. **Input Handling**
   - Supports both .cfl (BART-native) and .h5 (fastMRI) data formats.
   - Data is preprocessed and formatted for compatibility with BART tools.

2. **Preprocessing**
   -.cfl: Loaded directly with readcfl, already compatible with BART.
   -.h5: Slice selected, transposed, reshaped, and written to .cfl using writecfl.

3. **Coil Sensitivity Map Estimation**
   -Used BART's ecalib command for ESPIRiT calibration.
   - -r24 selects central k-space lines; -m1 generates one map per coil for SENSE.

4. **Undersampling via Masking**
   - **fastMRI-style Variable-Density Masks**: Created using RandomMaskFunc, controlled by center_fraction and acceleration.
   - **Custom Centered Masks**: Manually defined masks for clearer control and interpretability

5. **Image Reconstruction**

- **Reference**: Inverse FFT followed by coil combination using fft and fmac.
- **SENSE**: BART's pics with regularized least-squares and single-set sensitivity maps.
- **ESPIRiT**: Robust multi-map method using pics with ESPIRiT sensitivity maps.

6. **Visual Evaluation**

- Side-by-side comparison of reference, SENSE, and ESPIRiT reconstructions.
- Focused on aliasing, blurring, and sharpness.

7. **Quantitative Analysis**

- Generated **difference maps** to measure deviation from the reference.
- Highlighted areas of high error, especially at tissue boundaries or low-SNR regions.

DATALOADER

Dataset Preparation

- Defined `Custom_FastMRIDataset` class based on `torch.utils.data.Dataset`.
- Loaded `.npy` MRI data with `mmap_mode='r'` to save RAM.
- Applied undersampling masks on k-space (`apply_mask`).

DataLoader Setup

- Created `train_loader_check` with batch size 4 and shuffling.
- Checked data shapes and types to verify correct loading.

Transformations

- Converted k-space to image-space (`convert_K_to_I`).
- Created Root-Sum-of-Squares (RSS) combined images

Flexible Data Return

- Return options controlled by flags: k-space (`K`), image-space (`I`), or RSS-combined (`rss_combine`)

Visualization

- Picked first item from batch (`batchidx=0`).
- Displayed the ground truth (`loader_rss`) and masked version (`loader_masked_rss`) using `matplotlib.pyplot.imshow()` with grayscale colormap.

Results and Discussions

BART Implementation

-Implemented BART on CFL files
-Implemented BART on fastMRI data file

1. **Reference Scan Visualization**

Downsampled Scan with AF=2

Calibration: `bart ecalib` estimates coil sensitivity maps from k-space data.

Fourier Transform: `bart fft -i` converts k-space data to coil images.

Combination: `bart fmac -C` performs a **sensitivity-weighted sum** across coils to generate the final image.

Scan Reconstruction Result Comparison

1. Reference Scan

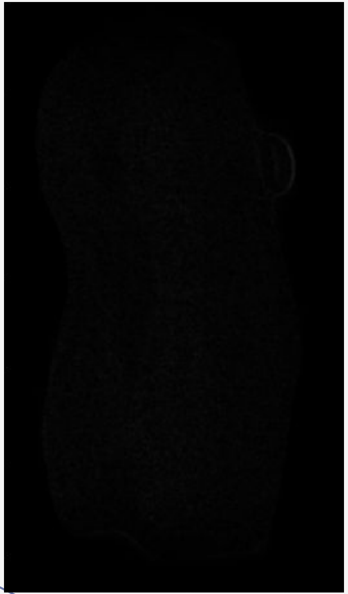
2. ESPIRiT

3. SENSE

4. Downsampled(with AF=2)

Difference Map Comparison

1. Reference Scan



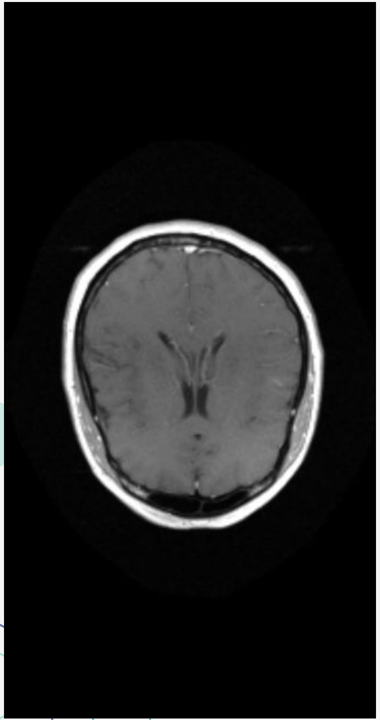
2. ESPIRiT

3. SENSE

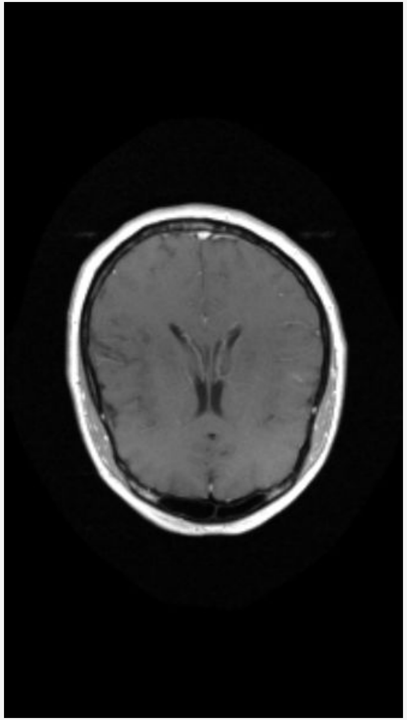
4. Downsampled(with AF=2)

Scan Reconstruction Result Comparison

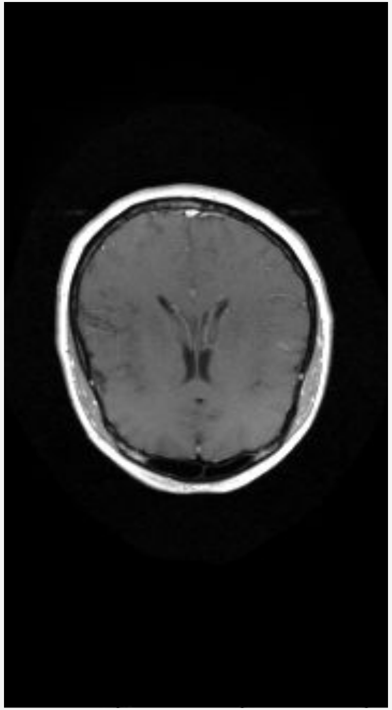
1. Reference Scan



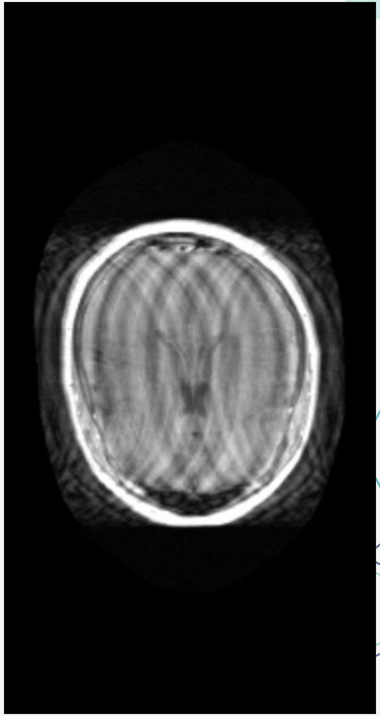
2. ESPIRiT



3. SENSE

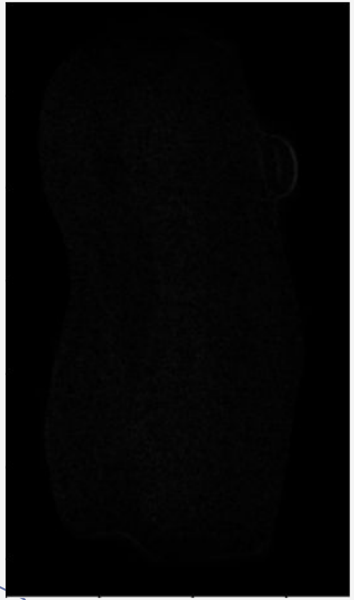


4. Downsampled(with AF=4)



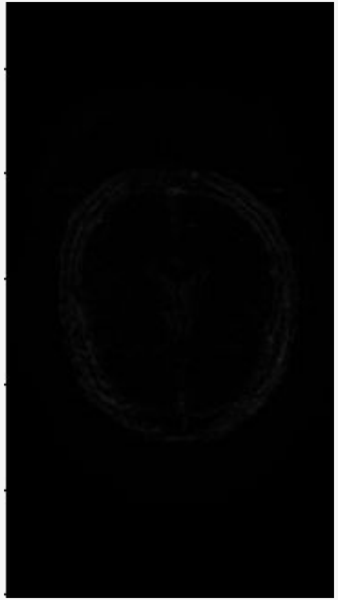
Difference Map Comparison

1. Reference Scan



2. ESPIRiT

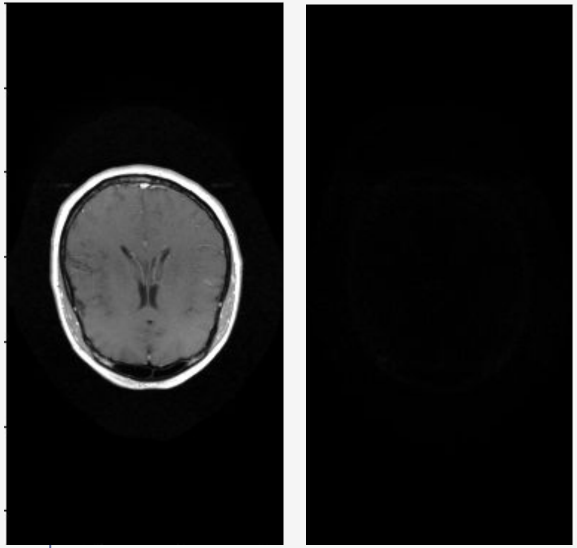
3. SENSE



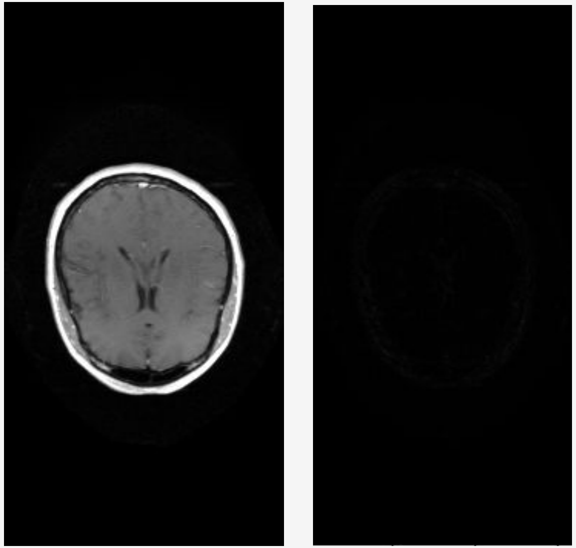
4. Downsampled(with AF=4)

ESPIRiT Results for Various Acceleration Factors

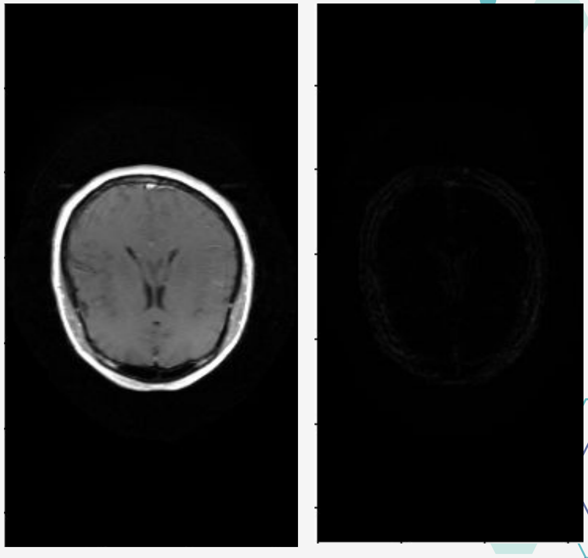
Acceleration Factor=2



Acceleration Factor=3

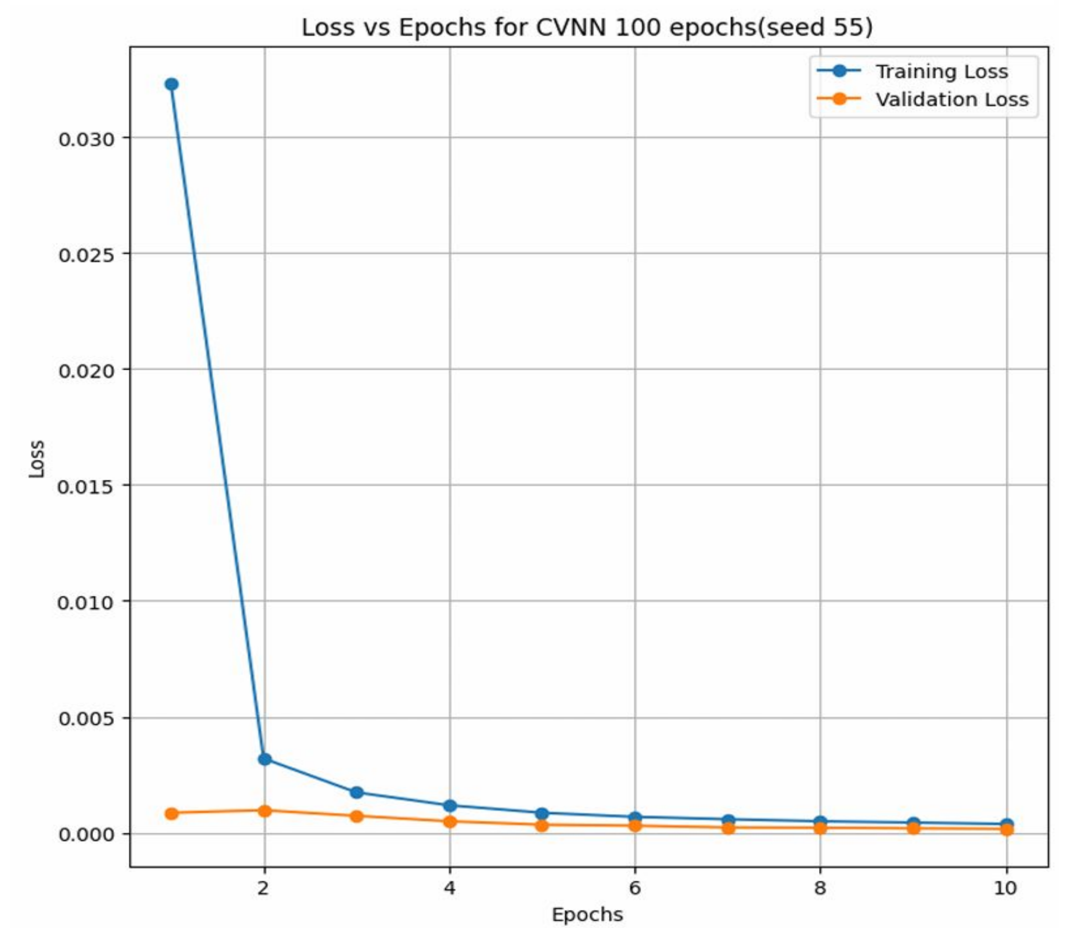


Acceleration Factor=4



Thus, a need for better Deep Learning alternatives arises.

CVNN Training Loss Result Plot



- Sharp drop in **training loss** during early epochs.
- **Validation loss** decreases steadily, indicating good generalization.
- Both losses **stabilize after ~5 epochs**, showing convergence.
- No overfitting observed – validation closely follows training loss.
- Confirms effective training of the complex-valued U-Net for 2x upscaling.

Conclusion

Implemented a complete MRI reconstruction pipeline:

- Used *BART toolbox* to reconstruct MR images with classical methods like **SENSE**, **ESPIRiT**, and **PICS**.
- Understood and applied concepts of fourier transforms, *coil sensitivity estimation*, and *parallel imaging*.

Built robust masking and preprocessing functions:

1. Designed custom **undersampling masks** including acceleration factor and centre fraction as arguments, suitable for accelerated MRI acquisition simulation.
2. Developed *efficient preprocessing steps* like **k-space masking**, **inverse Fourier transforms**, **root sum-of-squares (RSS) image combination**.
3. Carefully structured the pipeline to maintain consistency between masked and unmasked data pairs.

Designed robust masking functions and preprocessing pipelines (k-space masking, Fourier transforms, RSS combination) ensuring clean and standardized inputs.

Trained and **Plotted training and validation loss curves** for complex-valued **U-Net** to verify effective learning and convergence during 2x upscaling training.

Built flexible, memory-efficient DataLoaders supporting multiple data formats (k-space, image-space, RSS) for scalable training.

Future Works

1. **Extend current classical reconstruction methods** by incorporating *Compressed Sensing MRI* techniques for better sparsity-based recovery.

2. **Implement deep learning-driven reconstruction models** like *DeepSense* and *SENSE with GAN* for learned k-space to image-space mappings.

3. **Explore advanced architectures** such as *Self-Attention CNNs* and *High-Frequency Diffusion Models* to enhance structural preservation in reconstructions.

4. **Develop densely connected and transformer-based models** (*DenseNet*, *Swin Transformer*, *ReconFormer*) for faster and more accurate MRI reconstruction.

5. **Benchmark and compare all DL models** against the strong *mathematical baselines* (SENSE, ESPIRiT, PICS) already established.

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Thanks

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Questions are Welcomed!