

# **EC-386**

## Mini Project in Image Processing

***Submitted by :***

Aditya Miskin (191EC202)

K. Sriram (191EC122)

## **Project Mentors**

AV Narasimhadhan



Department of Electronics and Communication Engineering  
National Institute of Technology Karnataka, Surathkal

# MRI Reconstruction using Deep Learning

## Aim

To evaluate approaches to Convolutional Neural Network (CNN) reconstruction for accelerated cardiac Magnetic Resonance Imaging (MRI).

## Theory

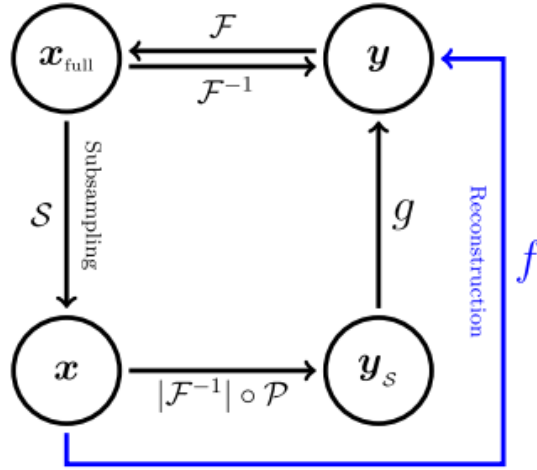
Magnetic resonance imaging (MRI) produces cross-sectional images with high spatial resolution using strong nuclear magnetic resonances, gradient fields, and hydrogen atoms inside the human body. MRI does not use damaging ionizing radiation like X-rays, but the scan takes a long time and involves confining the subject in an uncomfortable narrow bow. Shortening the MRI scan time might help increase patient satisfaction, reduce motion artifacts from patient movement, and reduce the medical cost.

The MRI scan time is roughly proportional to the number of time-consuming phase-encoding steps in k-space. Many efforts have been made to expedite MRI scans by skipping the phase encoding lines in k-space while eliminating aliasing, a serious consequence of the Nyquist criterion violation (Nyquist 1928) that is caused by skipping.

Compressed sensing MRI and Parallel MRI are some of the techniques used to deal with these aliasing artifacts. The CS method takes advantage of the intrinsic sparsity of the data in a specific transform domain and random k-space sampling (incoherent point spread function) to remove noise-like image artifacts in the image.

Compressed sensing MRI uses prior information on MR images of the unmeasured k-space data to eliminate or reduce aliasing artifacts. Parallel MRI installs multiple receiver coils and uses space-dependent properties of receiver coils to reduce aliasing artifacts. In undersampled MRI, we attempt to find an optimal reconstruction function  $f: x \rightarrow y$ , which maps highly undersampled k-space data ( $x$ ) to an image ( $y$ ) close to the MR image corresponding to fully sampled data.

In undersampled MRI, we attempt to find an optimal reconstruction function  $f: x \rightarrow y$ , which maps highly undersampled k-space data ( $x$ ) to an image ( $y$ ) close to the MR image corresponding to fully sampled data. Undersampled MRI consists of two parts, subsampling and reconstruction, as shown in figure 1.



**Figure 1.** General strategy for undersampled MRI reconstruction problem. The inverse Fourier transform of a fully sampled  $k$ -space data  $\mathbf{x}_{\text{full}}$  produces a reconstructed MRI image  $\mathbf{y}$ . The goal is to find a subsampling function  $\mathcal{S}$  and learn an undersampled MRI reconstruction  $f$  from the training dataset. Here,  $\mathbf{y}_s = |\mathcal{F}^{-1}| \circ \mathcal{P}(\mathbf{x})$  is an aliased image caused by the violation of the Nyquist criterion. We use the U-net to find the function  $g$  that provides the mapping from the aliased image  $\mathbf{y}_s$  to an anti-aliased image  $\mathbf{y}$ .

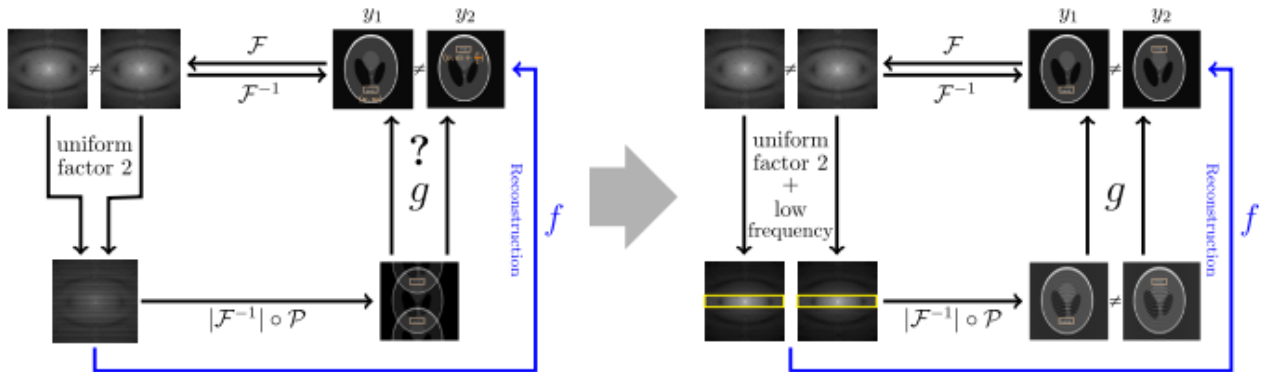
Undersampled MRI consists of two parts, subsampling and reconstruction, as shown in figure 1.

## Methods

### Subsampling strategy

Let  $\{(\mathbf{x}(j), \mathbf{y}(j))\}_{j=1}^M$  be a training set of undersampled and ground-truth MR images. The vectors  $\mathbf{x}(j)$  and  $\mathbf{y}(j)$  are in the space  $\mathbb{C}^{N \times N}$ . Figure 1 shows a schematic diagram of our undersampled reconstruction method, where the corresponding inverse problem is to solve the underdetermined linear system  $\mathcal{S} \circ \mathcal{F}(\mathbf{y}) = \mathbf{x}$ . Given undersampled data  $\mathbf{x}$ , there are infinitely many solutions  $\mathbf{y}$  of (1) in  $\mathbb{C}^{N \times N}$ . It is impossible to invert the ill-conditioned system  $\mathcal{S} \circ \mathcal{F} : \mathbb{C}^{N \times N} \rightarrow \mathcal{R}_{\mathcal{S} \circ \mathcal{F}}$ , where  $\mathcal{R}_{\mathcal{S} \circ \mathcal{F}}$  is the range space of operator  $\mathcal{S} \circ \mathcal{F}$  and its dimension is much lower than  $N^2$ . We use the fact that the MR images of humans exist in a much lower dimensional manifold  $\mathcal{M}$  embedded in the space  $\mathbb{C}^{N \times N}$ . With this constraint  $\mathcal{M}$  which is unknown, there is the possibility that there exists a practically meaningful inverse  $f$  in the sense that

$$f(\mathcal{S} \circ \mathcal{F}(\mathbf{y})) = \mathbf{y} \text{ for } \mathbf{y} \in \mathcal{M}. \quad (1)$$

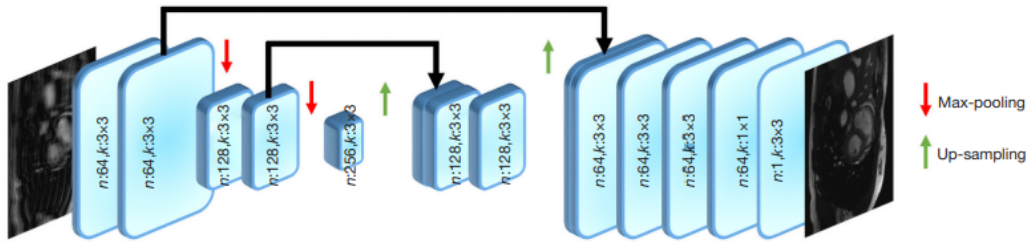


In the left of figure 2, we consider the case that  $S$  is the uniform subsampling of factor 2. With this choice of  $S$ , two different images  $y_1 \neq y_2$  produce identical  $|F-1| \circ P \circ S \circ F(y_1) = |F-1| \circ P \circ S \circ F(y_2)$ . This means the uniform subsampling of factor 2 is inappropriate for learning  $f$  satisfying. Here,  $y_1$  is the standard Logan phantom image and  $y_2$  is a modified image of  $y_1$  obtained by moving three small anomalies to their symmetric positions with respect to the middle horizontal line. In contrast, if we add a few low frequencies to the uniform subsampling of factor 2, as shown in the image on the right of figure 2, the situation is dramatically changed and separability may be achieved.

$$y_1 \neq y_2 \text{ implies } |F-1| \circ P \circ S \circ F(y_1) \neq |F-1| \circ P \circ S \circ F(y_2).$$

## UNet

The convolutional UNet has been used previously to solve inverse problems in computed tomography and MRI reconstruction. In general, it consists of two paths: (i) the contracting path, which contains a number of down-sampling stages; (ii) the expanding path, which includes a number of up-sampling stages. In order to preserve high-level features, it consists of dense connections from the early stages to the later stages of the network.



The figure above shows a Simplified version of UNet with two Max-Pooling stages. The number of convolution filters and the kernel size are specified in each layer. To preserve information, some features from the contracting path is concatenated onto features in the expanding path.

## Code to generate T number of training images

```
clc
clear all
close all
% Input MRI image
I = imread('slp.gif');
Inp = im2double(I); % Ground truth (original image)
[R C] = size(Inp);
% 2DFT of MRI image
F = fft2(Inp);
% Total number of measurements
N = R*C;
% Consider less measurements than original (M<N)
M = round( N*0.7);
% Number of aliased images we want i.e., T
T = 100;
% Creating aliased images i.e A_im ( each cell in A_im is one
aliased image)
for it = 1 :1:T;
% Create a random vector
x = zeros(N,1);
x_ind = randi(N,M,1); % non-zero entries
% Ensure M-sparseness by cancelling repetitions of the same index
done = 0;

while done == 0
    done = 1;
    x_ind = sort(x_ind);
    for i = 1:M-1
        if x_ind(i) == x_ind(i+1)
            x_ind(i+1) = randi(N,1,1);
            done = 0;
        end;
    end;
end;
x(x_ind) = F(x_ind);
F_modi = reshape(x,[R,C]);

% Inverse 2DFT of MRI image

A_im{it} = abs(ifft2(F_modi));
imshow(F_modi)
imshow(A_im)

end
```


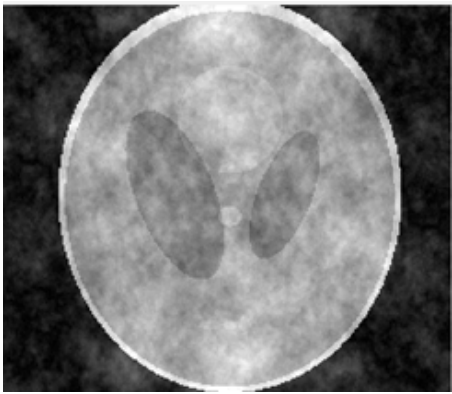

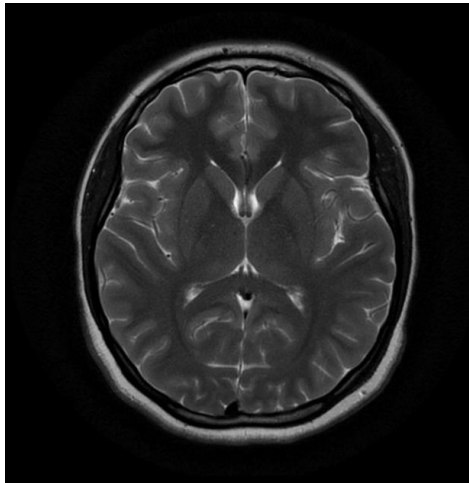
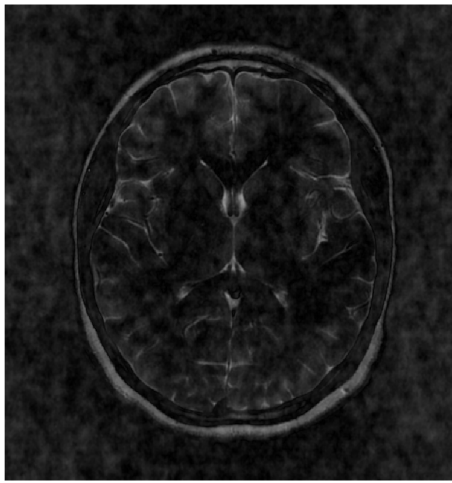
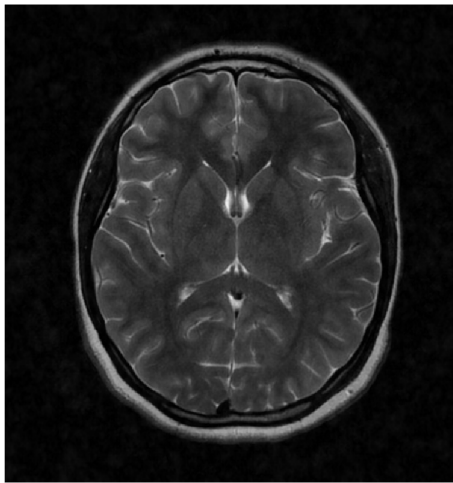
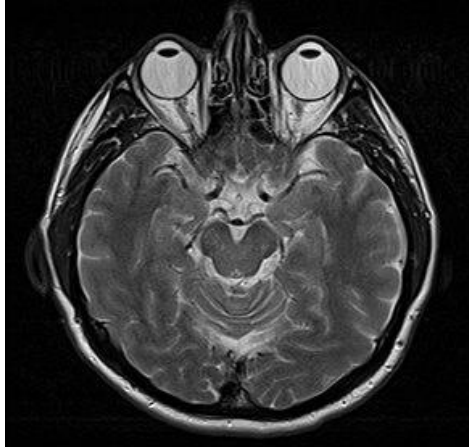

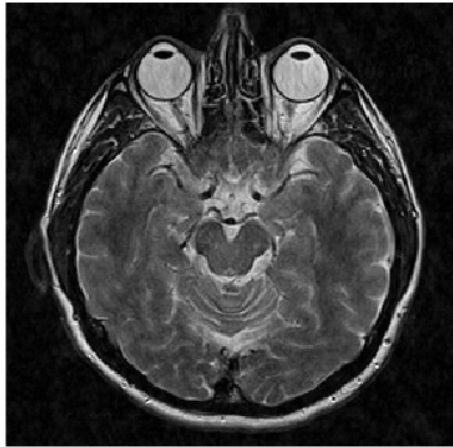
## Results

The following images show the proposed method for a brain image in the test set.

The first column shows the ground truth image.

Second, the aliased image, generated by subsampling with a factor of 0.7.

Third, the aliased image generated after reconstruction of the K space DFT sample.

Ground truth image	Aliased Image	Corrected Image
		
		
		

## References

- Ghodrati, Vahid, Jiaxin Shao, Mark Bydder, Ziwu Zhou, Wotao Yin, Kim-Lien Nguyen, Yingli Yang, & Peng Hu. "MR image reconstruction using deep learning: evaluation of network structure and loss functions." *Quantitative Imaging in Medicine and Surgery* [Online], 9.9 (2019): 1516-1527.
- Chang Min Hyun et al 2018 *Phys. Med. Biol.* 63 135007