Deep Learning and its Applications Project Presentation on MRI-Image Reconstruction Group-01

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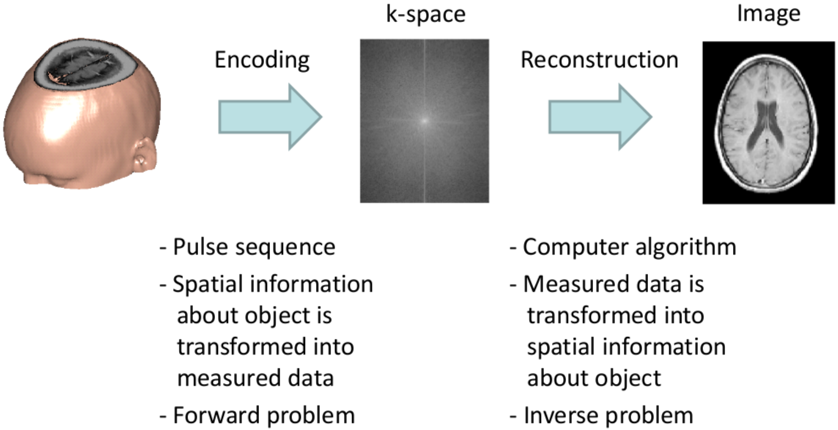
Problem Statement

A standard mri reconstruction problem can be understood with the following figure



Problem Statement

1. k-space is fourier space and samples are collected in this space from mri machine.
2. If we had infinite points in k-space then image can be reconstructed perfectly.
3. But we only have a specific sampled portions of this k-space and so the problem is to reconstruct from these sample an image which is as close as true image.

Some Related Work

The most important theorem in all of signal reconstuction field is shannon theorem which is a follows

Nyquist/Shannon theorem

– A bandlimited signal with bandwidth B can be reconstructed perfectly from its samples if they are taken at a rate no larger than 1/2B

$$\text{Nyquist rate}: \Delta r \leq \frac{1}{2W}$$

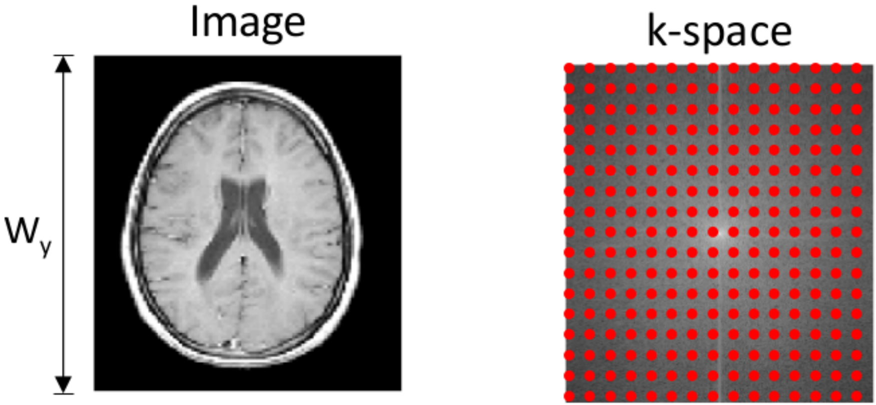
1. This reconstruction is perfect only if we have infinte number of k-space sample points.
2. In real life scenario we only have a finite portion of these k-space samples.

Some Related Work

We would follow in our project sampling as follows

Equidistant rectilinear sampling

Bandwidth is defined in the image domain



Motivation and Challenges

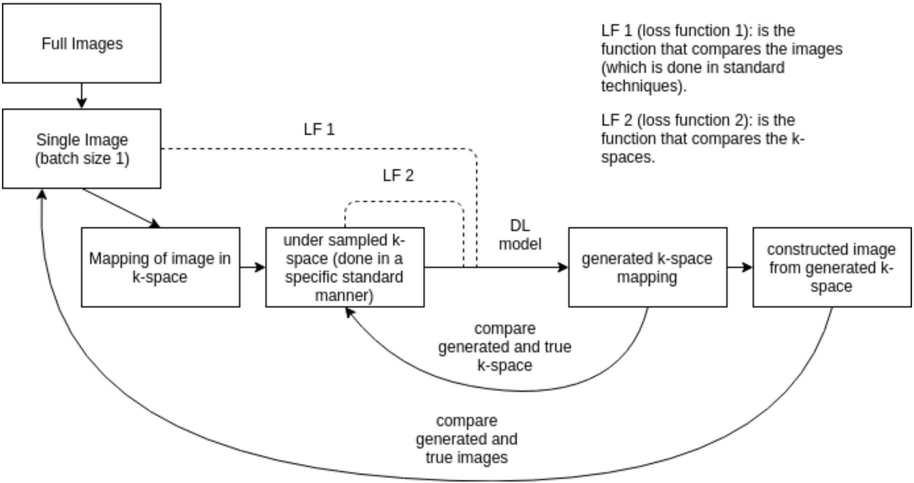
1. New methods of Deep Learning can acheive state of the art performance.
2. The challenges faced while is that any architecture would involve computing fourier transforms apart from training computations and this drastically increases the training and overall model processing time.
3. This makes DL models to be very inefficient in these kinds of reconstruction problems.

Dataset

The anonymized imaging dataset provided by NYU Langone comprises raw k-space data from more than 1,500 fully sampled knee MRIs obtained on 3 and 1.5 Tesla magnets from 10,000 clinical knee MRIs also obtained at 3 or 1.5 Tesla. Curation of these datasets are part of an IRB approved study. The raw dataset includes coronal proton density-weighted images with and without fat suppression

Proposed Methodology

The proposed flow architecture is as follows



Loss functions

LF 1 (loss function 1): is the function that compares the images (which is done in standard techniques).

LF 2 (loss function 2): is the function that compares the k-spaces.

Proposed Methodology

The detailed architecture at NN level is yet to be formulated. Some additional inputs to the above workflow can be done which are as follows

1. To avoid computing fourier transforms which are computationally very heavy we can instead use another network to generate these fourier transforms (as it is just a mapping).
2. To acheive a more robust model we can use a representation layer after under sampled k-space block which would learn the representation of these k-space points.
3. The representation would be such that its counter part in image space would be convolution operation.

Progress

1. Currently the code for converting images to fourier transforms is in working state.
2. Neural Network for generating the fourier transforms is in tranining phase.

Conclusion and Future work

According to the above discussion the tasks for future is

1. Find good loss functions both for k-space and image space and appropiate tuning of coupling constant of the two.
2. A representation operator analogous to kernel in image space and assosiated operation analogous to convolution that can be used to represent the samples of fourier space which itself can be learnt just like kernels are learnt in CNN.