DEEP LEARNING APPLICATIONS IN MRI ACQUISITION & RECONSTRUCTION

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Abstract

Under sampled magnetic resonance image (MRI) reconstruction research might improve MRI imaging speed while also reducing patient discomfort. This review paper reviews certain deep-learning based MRI techniques for MRI acquisition and reconstruction. The paper starts off with LOUPE which is a Learning based Optimization of the Under-sampling PattErn which is a technique to get optimized under-sampling patterns of the k-space for MRI acquisition and reconstruction later using U-Nets. On a series of full-resolution MRI scans, LOUPE trains a neural network model, which is then retroactively under-sampled on a 2D Cartesian grid and transmitted to an anti-aliasing (a.k.a. reconstruction) model, which computes a reconstruction, which is then compared to the input. The paper then moves onto Deep Cascaded CNNs which is a staged CNN based technique for MRI reconstruction. It entails employing a deep cascade of convolutional neural networks (CNNs) to recreate dynamic sequences of 2D cardiac magnetic resonance (MR) images from under-sampled data in order to speed up the data collecting process. Generative Adversarial Network based approaches like DAGAN which uses a refinement learning approach to stabilize a U-Net-based generator, resulting in an end-to-end network that reduces aliasing artefacts and SARA-GAN which to circumvent the difficulty of restricted convolution kernel size, a self-attention mechanism is introduced into the generator's high-layer to construct long-range dependency of the picture.

Introduction

Compressed Sensing Magnetic Resonance Imaging is a very well-known technique in the MRI industry where under-sampling of the k-space is done to get faster MRI reconstruction times and faster scans. However, CS-MRI has 2 problems mainly, one being where to sample in the k-space and the second being how to reconstruct a full image scan from the under sampled k-space. These problems mainly form the whole idea of speeding up MRI scans and what we can do.

Deep Learning which is a subset of Machine Learning is an Artificial Intelligence method which has widespread applications nowadays. From image processing to object detection in self driving cars, to video surveillance, deep learning has immense potential. Even in the medical imaging domain, deep learning is being used widely with many algorithms receiving FDA approvals and being used in the hospitals nowadays to perform basic classification, object detection or segmentation tasks for detecting tumors, lesions and organs in the body directly from the X-Ray scans, MRI or CT. Although lots of applications are seen in the diagnosis stage of medical imaging, new applications of deep learning have also popped up like MRI reconstruction, acquisition, super-resolution,[6] etc.

LOUPE (Learning-based Optimization of the Under-sampling PattErn) [1] is a new technique using deep learning in CS-MRI for optimizing the under-sampling pattern to get the best masks for optimal under-sampling and optimal weights of the U-Net model for reconstruction. LOUPE is reviewed in detail in this term paper.

Many other techniques based on Neural networks are also researched with one very interesting architecture being that of the Deep Cascaded CNNs [2] where numerous CNNs are used in a multi-stage structure giving us great reconstruction results.

Finally, techniques based on Generative Adversarial Networks are explored in which mainly 2 models are seen the DAGAN (Deep De-Aliasing Generative Adversarial Networks) [3] and the SARA-GAN (Self-Attention and Relative Average Discriminator Based GANs) [4] provide state-of-the-art results for MRI reconstruction.

Methods:

Searching for different papers in the domain of MRI and deep learning was not difficult. I started off with searching for papers off Google directly which got me to different journals and conferences which had some very good review papers as well as conference and journal papers in this domain. For MRI acquisition using deep learning, Professor Wang suggested me to look at one of Professor Sabuncu's papers on the same which I found readily on ArXiv. For deep learning used in MRI reconstruction, I searched on Google with exact keywords "deep learning for MRI" and got various review papers and articles like Alexander Selvikvåg Lundervold et al. “An overview of deep learning in medical imaging focusing on MRI” published in the Zeitschrift für Medizinische Physik which was cited by more than 700 people since 2019. This paper had all around applications of deep learning in MRI right from data acquisition and image reconstruction to image restoration, super-resolution, registration and image segmentation for diagnosis and prediction. Another notable paper that I found was by Arghya Pal et al. A review of deep learning methods for MRI reconstruction from Harvard University preprint from September 2021 on ArXiv which conducted a very detailed review of MRI reconstruction techniques using Deep Learning.

I also searched for “Deep learning for MRI reconstruction” and came across papers for Deep Cascaded CNNs, DAGAN and SARA-GAN which are all different methods for MRI reconstruction. All of these papers were somewhat a part of the review papers above and were different deep learning architectures to reconstruct MRI images from under sampled k-space data.

Finally, I went through the references of the above papers and selected more papers to read.

Deep Learning Techniques in MRI Acquisition and Reconstruction

1) LOUPE[1]

Conventional MRI acquisition is generally very slow and one of the biggest drawbacks of MRI is the long scan times. Many techniques like Compressed sensing MRI significantly reduce the scan time required to acquire an image. CS-MRI is a technique which uses the concept of k-space under sampling (below the Nyquist rate) to achieve very fast scan times. As the paper [1] rightly points out, CS-MRI is plagued with two main problems: 1) Where to sample in the k-space (MRI selective acquisition) 2) reconstruction of under-sampled scans. The authors introduce LOUPE (Learning-based Optimization of the Under-sampling PattErn). LOUPE’s main objective is to reconstruct a full-resolution MRI scan from a set of under-sampled values using neural networks. LOUPE has an end-to-end deep learning pipeline which solves 2 problems at once that are the optimization of the sampling mask and the best reconstruction. This is done by using a combination of deep learning and selecting different probabilistic masks for the optimal under-sampling of the k-space for CS-MRI.

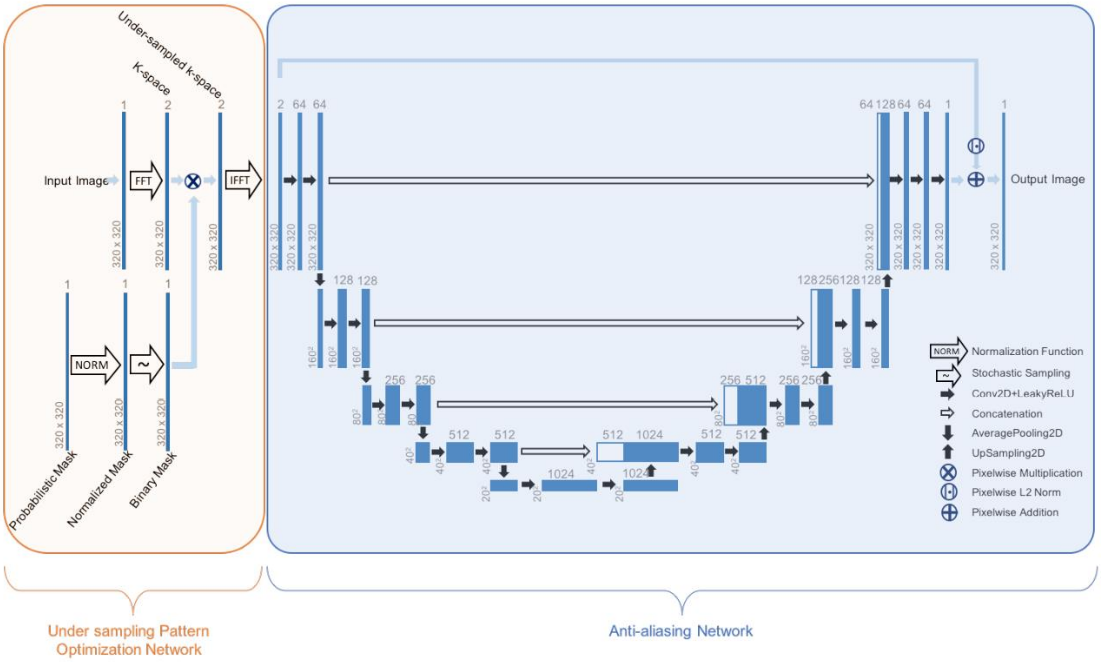

Figure 1 LOUPE architecture[1]. It consists of a 2-stage approach with the first stage being the k-space mask optimization network and the 2nd stage being a traditional 2D U-Net.

As depicted in Figure 1, the model takes in an MRI scan image which is converted to frequency domain by FFT and multiplied with a probabilistic k-space mask to gain a k-space which has only some frequencies. This under sampled image is then converted back into an image and passed through a U-net which is a very common architecture in the field of deep learning for medical image segmentation, which gives the reconstructed full image as an output. The loss function tries to minimize the output of the U-net with the original image and the weights of the U-Net and the under-sampling network are learned accordingly. The U-net uses convolutional 2D layers with Leaky ReLU activation function and an L2 norm and batch normalization. The U-net also has skip connection which mean the data flows better through the network.

The dataset that was used was the NYU fastMRI dataset which is an open-source public large-scale free dataset consisting of knee MRI scans. Proton Density (PD) and PD Fat Suppressed (PDFS) weighted images are the 2 pulse sequences through which the 2D coronal knee scans were acquired. The Emulated Single-Coil k-space data from the 3T scanner is used and 100 volumes of such data are used as the training set with the validation and the test set both being 10 volumes (split from the original validation set). The actual test data of fastMRI was not used because the test data consisted of under-sampled k-space images which were not enough to compare with the ground truth and for masks in the given case. The sequence parameters of the dataset were a matrix of 320x320, an echo train length of 4, in-plane resolution of 0.5 mm X 0.5 m, 3mm slice thickness. TR values were varied between 2200 and 3000ms and TE values ranged from 27 to 34ms. Each training volume had 34-42 slices and the validation volumes had 34-40 slices and the test volumes had 38-42 slices.

The evaluation metrics that were used are the 3 most common ones in MRI reconstruction namely the Peak Signal to Noise Ratio (PSNR), Structural Similarity Index (SSIM) and the High Frequency Error Norm (HFEN)

PSNR is widely used in CS-MRI evaluation and can be defined as:

$$\text{PSNR}(x, \hat{x}) = 10 \log_{10} (\max(x)^2 d) / \|x - \hat{x}\|_2^2 \qquad (1)$$

Where d is the full-resolution grid pixels and x^ is the reconstructed image with x being the ground truth.

SSIM is a measure to quantify the image quality perceived:

$$\text{SSIM}(x, \hat{x}) = (2\mu_x \mu_{x^\wedge} + c_1) + (2\sigma_{xx^\wedge} + c_2) / (\mu^2_x + \mu^2_{x^\wedge} + c_1)(\sigma^2_x + \sigma^2_{x^\wedge} + c_2) \qquad (2)$$

Where μ_x and $\mu_{x^\wedge}$ are the local average values of the reconstructed and ground truth images. σ^2_x and $\sigma^2_{x^\wedge}$ are the local variances and the $\sigma_{xx^\wedge}$ is the covariance. C_1 and C_2 are the constants for making the division stable.

High frequency error norm (HFEN) is used to quantify the quality of fine feature and edge reconstruction. A Laplacian of Gaussian (LoG) filter is used to compute the HFEN between the true images and the reconstructed images.

Various sampling masks were used as initializations for the LOUPE network. Starting off with 2D cartesian masks to under sample, these are typically used for 2D imaging technologies with 2 phase encoding dimensions without a frequency encoding gradient and 3D acquisition with one frequency encoding dimension and 2 phase encoding dimensions. Some of the common functions are depicted in Figure 2. The black dots represent the frequencies in the k-space which are sampled and the white spaces are the ones which are not sampled.

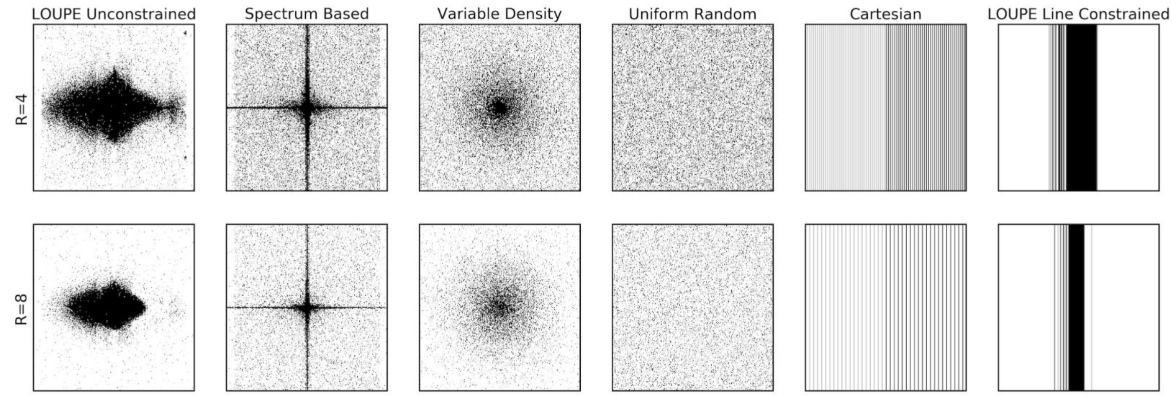

Figure 2 Various under-sampling masks used in [1]. R=4 is for a 4-fold acceleration and R=8 is 8-fold acceleration. The last 2 far right masks are 1D constrained while the others are 2D constrained.

The results are shown in Figure 3 where it was found that the LOUPE unconstrained mask performs the best amongst all the other masks that were chosen as starting points to the masks. Even without the U-net reconstruction, LOUPE performs the best overall and can be used with different anti-aliasing networks.

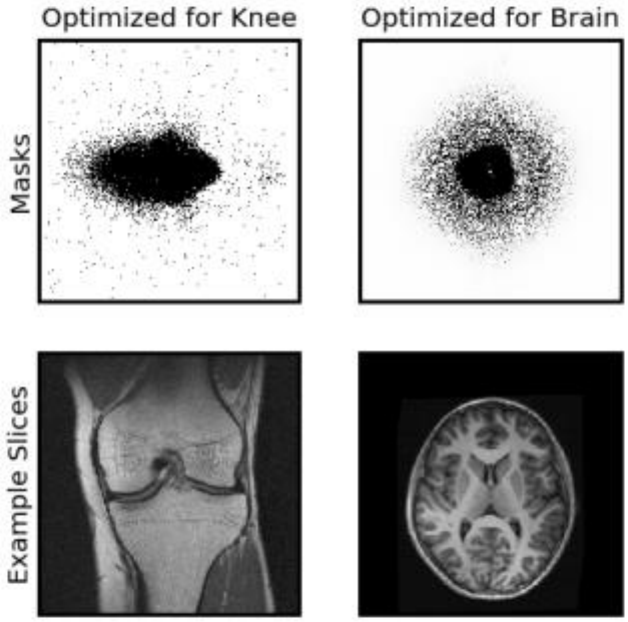

Figure 3 The optimal masks obtained [1] for the Knee and brain applications for 8-fold acceleration. As we can see the masks are a bit different according to the application.

Figure 3 depicts the masks that are different for different applications (different organ scans). It remains to be found out a general optimized mask for all different MRI applications. Interestingly, we can see in Figure 3 that the mask for knee MRI emphasizes more on lateral frequencies for under-sampling rather than vertical frequencies which can be credited to the anisotropy of the FOV of the sagittal knee scans. This is a very different result as compared to Brain MRI scans, where the k-space mask resembles a radially symmetric nature similar to the variable density mask. This again tells us that adapting the under-sampling pattern to a given application can give us better results rather than a generalized sampling pattern.

LOUPE largely outperforms different masks as shown in Figure 4. As we can see in the Figure 4, LOUPE constrained and unconstrained achieves a higher PSNR as well as a SSIM value which means that it performs better. For HFEN, where lower values are better, we can see the same trend of LOUPE optimized masks outperforming the other 2D cartesian and 1D cartesian masks. This shows us that LOUPE or actually learning the mask is very beneficial for the proper reconstruction of a CS-MRI image and we can consistently get better results than under-sampling at random.

A very big drawback of the LOUPE framework is that the authors have ignored the actual implementation costs of the under-sampling pattern in an actual MRI scanner pulse sequence. This can also be a significant cost or hindrance to the actual implementation of these under-sampled masks in the scanners and industry.

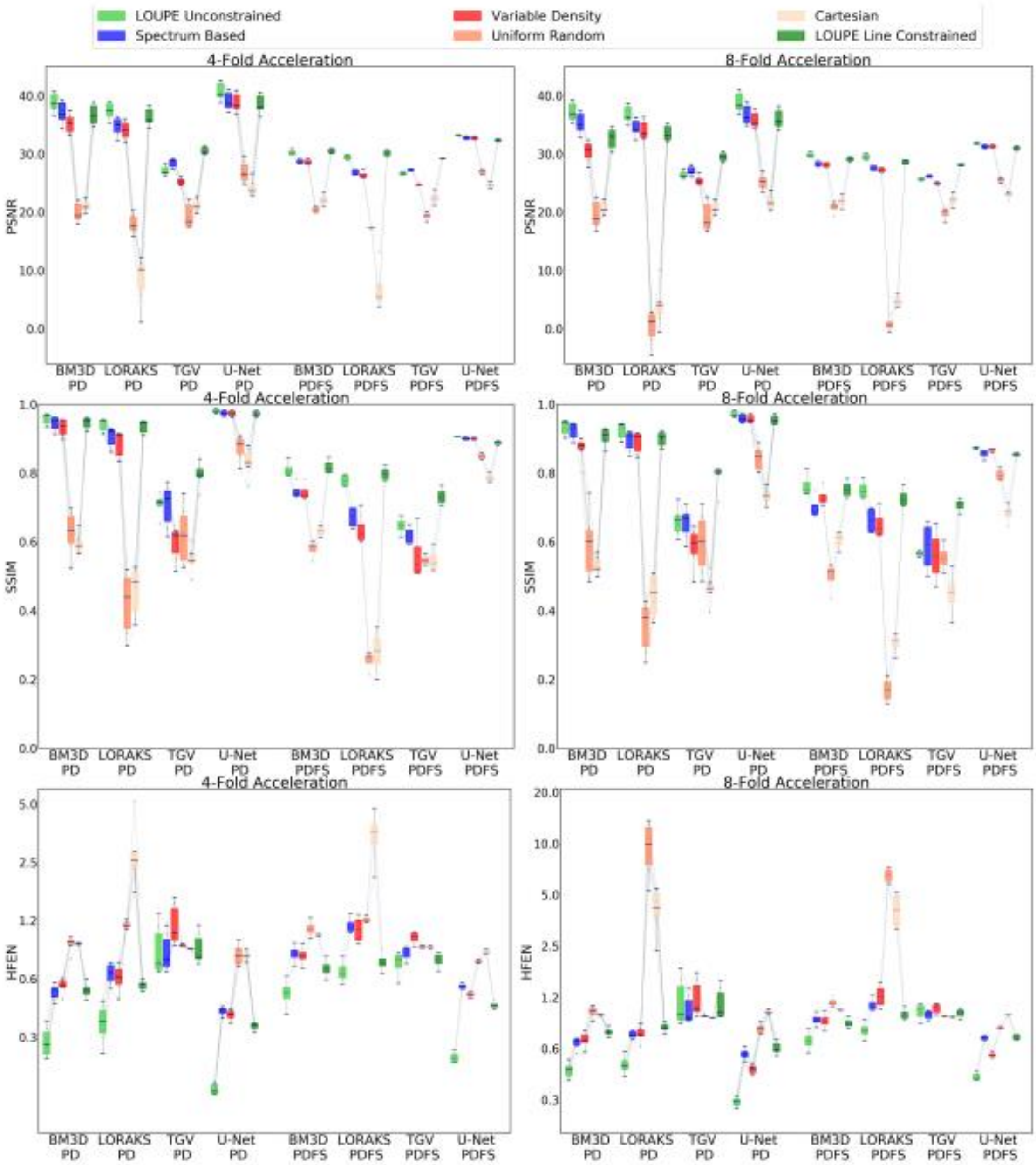

Figure 4 Different metrics for 4-fold and 8-fold acceleration for different masks[1].

2) Cascaded CNNs for Dynamic MRI reconstruction [2]

Like the previous discussed approach of using a U-Net for the anti-aliasing network for CS-MRI, some researchers have also implemented CNN based architectures. The main challenge they have tackled in [2] is to find an algorithm that can recover a fully sampled image from an under-sampled image by using the a-priori knowledge of the properties of the image to be reconstructed. In this paper, the researchers aim to reconstruct dynamic sequences of 2D cardiac MRI from sub-Nyquist data using a deep cascade of CNNs to speed up the data acquisition.

They try 2 different approaches, one being the reconstruction of dynamic MRI sequences and one being reconstruction of each frame independently using CNNs. Reconstruction is thought of as challenging since the images have a low SNR and a high SNR is needed for clinical applications. A deep cascade of CNNs is proposed which allows for an end-to-end reconstruction optimization.

CS- based methods used a coordinate-descent type algorithm which alternates between the anti-aliasing network and the data consistency step until it is optimized. With CNNs, this is not possible since although they are very powerful, CNNs have a nature of overfitting when the same network is used over different iterations. Also, CNNs have a long training time and unless there is a huge training dataset, the fine-tuning also takes a lot of time. So, it is best to use a cascade of CNNs rather than having only 1 CNN.

A very obvious solution can be to train a 2nd CNN to which the output of the 1st CNN is given as an input that is to concatenate another CNN after the first CNN which makes very deep networks which have both de-aliasing CNNs and the data consistency layers. This is essentially what a cascading network is. This cascaded network can be trained in an end-to-end manner thus giving us one large network instead of subnetworks.

Data Sharing Layer: For the reconstruction of dynamic sequences, the temporal correlation between frames, that is the information assumed to be constant over different time samples can be taken together to further de-alias the images. 3D convolutions are used to learn the spatio-temporal features of the input sequences and if the change in image content is very small for surrounding frames, the combination of the frames can be taken together to give more information as it is assumed to be similar. Figure 5 depicts the data sharing approach and the sharing of data acquired over different time frames.

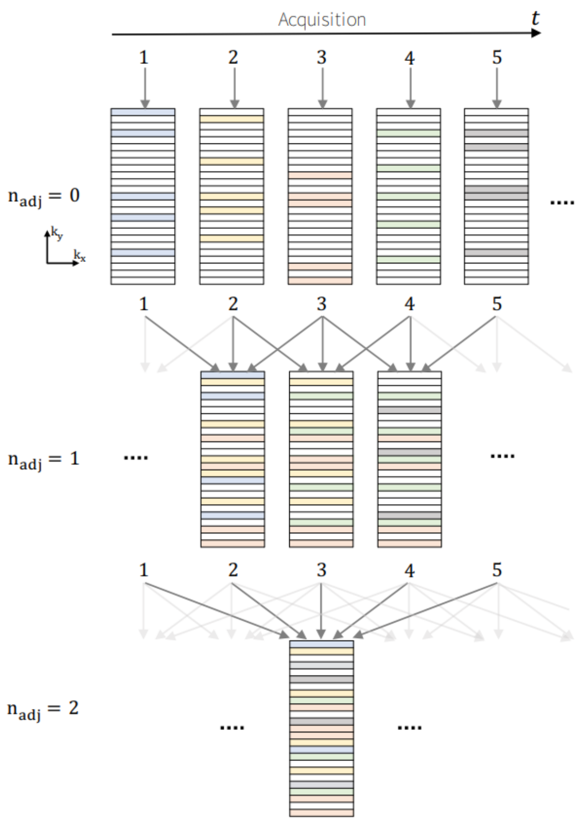

Figure 5 Data Sharing Illustration. Acquired lines are color coded for each time frame and the mean is taken for overlapping lines.[2]

In practice, combining different time frames may be a wrong step as cardiac sequences contain dynamic content around the heart and the combination of frames results in a very bad data inconsistency around the dynamic region, hence giving us bad results. So instead of using them as final reconstructions, we can use these extra images as an extra input to train the network. For the DC-CNN, Data sharing layers are implemented which take an input image and generate multiple data-shared images. This essentially transforms the problem into joint estimation of aliasing and dynamic motion.

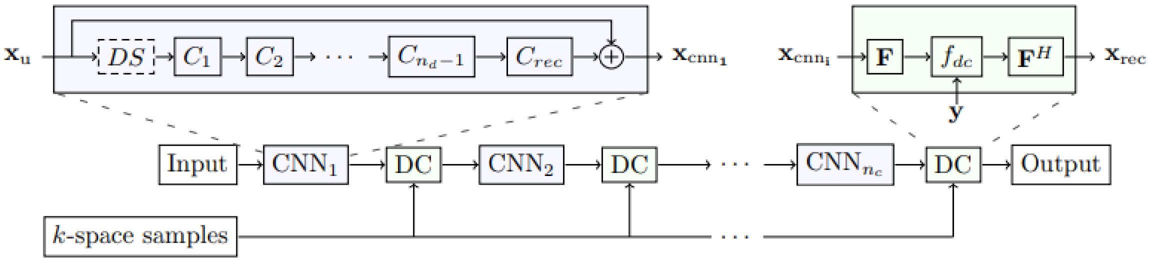

Figure 6 Architecture of a DC-CNN. DS stands for the data sharing layer and DC stands for the Data consistency layer where the k-space samples are fed again to the various stages of the CNN to ensure data continuity.[2]

Figure 6 depicts the architecture of a DC-CNN. The dataset that was used in this technique comprised of 10 completely sampled short-axis cardiac cine scans. Each MRI scan consisted of a single slice SSFP acquisition with 30 temporal frames, each having a 320x320mm FOV and 10 mm thick slices.

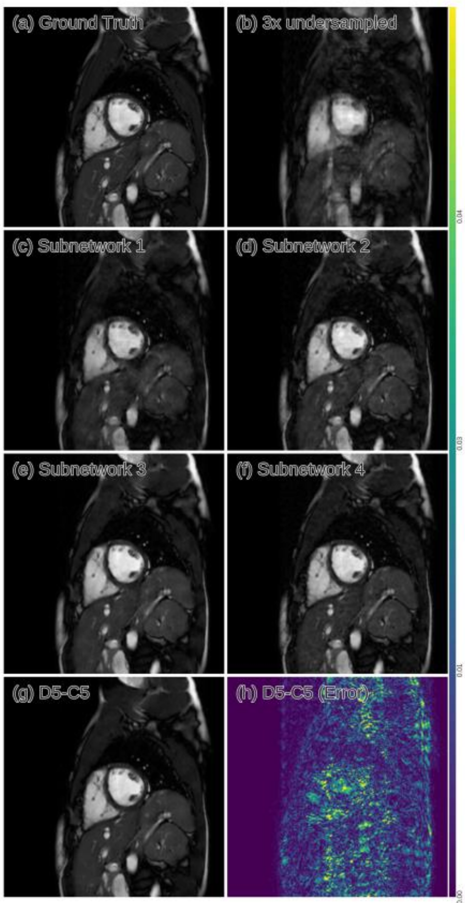

Figure 7 Outputs of the CNN subnetworks. As we take the output of the later stages, the reconstructed image looks clearer.[2]

3) GAN based approach towards MRI reconstruction

Generative Adversarial Networks are very powerful networks which consist of a generator network G and a discriminator network D where both the networks compete to fool each other. The D tries to distinguish the true images and the synthetic data generated by G and thus after the feedback from the D, the G tries to make more realistic synthetic images.

3.1 DAGAN (Deep De-Aliasing Generative Adversarial Networks):

GANs can be used for fast CS-MRI reconstruction like we saw with CNNs and U-Net in the above sections. DAGAN developed in [3] standing for Deep De-Aliasing Generative Adversarial Networks is a GAN based model that aims to reconstruct under-sampled MRI images. For the generator, a U-Net architecture with skip connections is proposed. A new learning approach for GANs is also designed to stabilize GAN learning for fast convergence. A combined loss consisting of adversarial loss and MSE and perceptual loss is used.

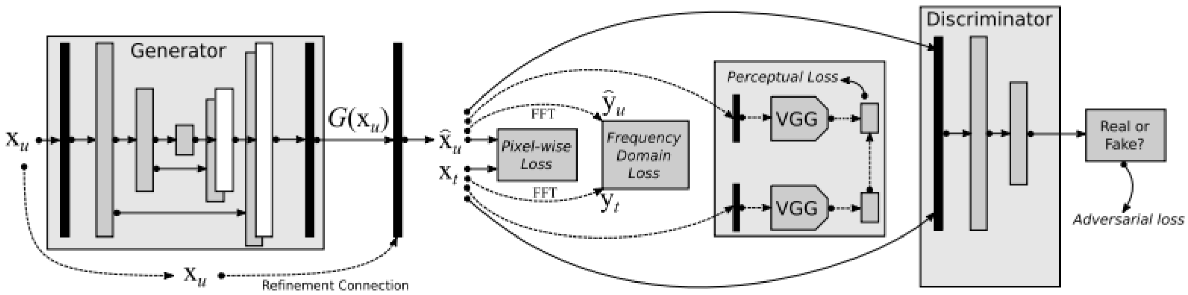

Figure 8 Architecture of the proposed DAGAN [3].

Figure 8 depicts the architecture of the proposed model of DAGAN. The input to the generator is an under-sampled CS-MRI image and the generator U-Net tries to output a reconstructed image which is then examined by the Discriminator having a CNN network architecture. The 4 losses Pixel-wise loss, Frequency-domain loss, Perceptual loss and Adversarial loss are minimized to obtain the optimized model.

Reconstruction time of about 0.2 seconds for a 2D image on a CPU was achieved using DAGAN proving to be a promising reconstruction technique for CS-MRI.

One important argument that pops up on using GANs is that does the synthetic data generated have any unrealistic generations in the image. This is important because we do not want our reconstructed images to be anything different from what is actually there in the image scan. Any faulty synthesis can cause wrong diagnosis of the patient and can prove to be dangerous. However, DAGAN researchers note that they didn't receive any unnatural image details in the synthesized images because the input to the GAN was not completely random, instead it was derived from the ZF reconstruction which provided a good initialization for DAGAN to perform the de-aliasing. This initialization also helped in stabilizing the training of the GAN which can be problematic in many cases.

Refinement learning is used in DAGAN training which can constrain the generator to only reconstruct the missing details rather than something completely arbitrary and unnatural that may not be present in real MRI images.

3.2 SARA-GAN (Self-Attention and Relative Average Discriminator Based GANs)

Self-Attention and Relative Average Discriminator Based GANs as introduced in [5] are one of the best fast CS-MRI reconstruction networks that are there in the world today. SARA-GANs are a type of GAN that have 2 additional mechanisms are compared to a normal GAN, a Self-attention mechanism and a Relative Average Discriminator which make it the ideal candidate for CS-MRI reconstruction.

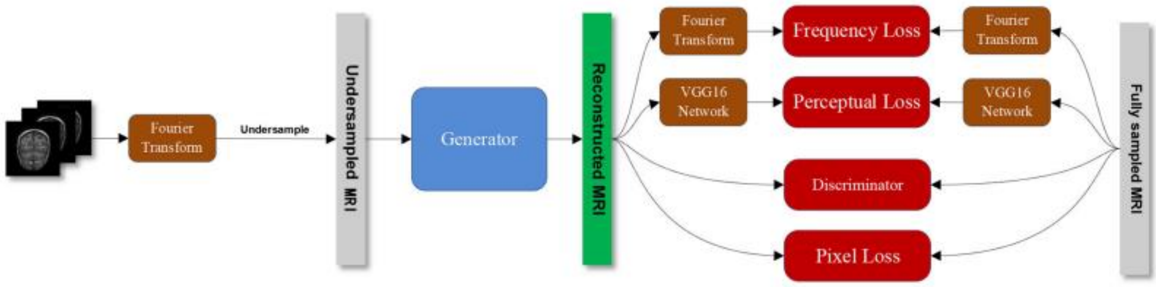

Figure 9 The architecture of SARA-GAN.[4]

Figure 9 depicts the architecture of SARA-GAN. Fully sampled MRI scans which are complete images are taken and the Fourier transform is calculated and then k-space under sampling is done. This under sampled image is passed through a generator which outputs a reconstructed MRI. Like the previous case with DAGAN, the generator output is judged by the discriminator to calculate the adversarial loss and the frequency, pixel and perceptual loss are also calculated.

Design of the generator model

The generator model comprises of a U-Net like architecture as depicted in Figure 10 comprising of a down sampling block, a residual block (skip connection) and an up-sampling block. The down sampling block consists of 3 convolutional layers that are used to extract the features from the image. The residual block contains 7 small residual blocks as defined in ResNet models with each block having 2 convolutional layers. The up-sampling block has three transposed convolutional blocks whose functions is to expand the feature map and generate an output image (MRI scan). Spectral normalization is used in the generator architecture to satisfy the Lipschitz constraint and the activation function used is PReLU (Parametric Rectified Linear Unit). A self-attention later is added to the high layer of the generator which can calculate the correlation between the image pixels and build long range dependencies among the feature layers which means that the reconstructed image is more detailed. The residual network that is used has multiple skip connections to reduce the loss of the original features from the earlier convolutional layers. This can also help in preventing the generator to perform awfully in the initial stage, hence making the training process more efficient.

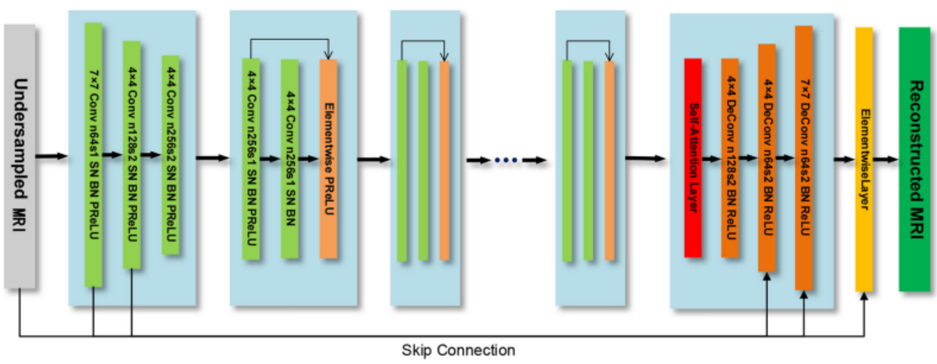

Figure 10 Architecture of the generator module[4]

Design of the discriminator module

The discriminator module as shown in Figure 11 is an 11-layer CNN network which uses Leaky ReLU as the activation function and the last layer being a fully-connected layer and sigmoid activation. Again, like the generator, spectral normalization is used in the discriminator as well. In the actual formula of the original GAN, the prior information of the discriminator's input data is ignored whereas in the SARA-GAN, a relative average discriminator is used which transforms the absolute true and false discrimination into relative true or false discrimination. This helps the model to make full use of the prior information and hence can improve the discriminator's performance on the actual data yielding better results. When the generator generates realistic samples, the discriminator is unable to differentiate between the true and the synthetic samples and should output a probability of 0.5 which means the discriminator is confused. However, in our MRI reconstruction case, the expected output of the discriminator will be 1 when it is totally confused due to the relative averaging.

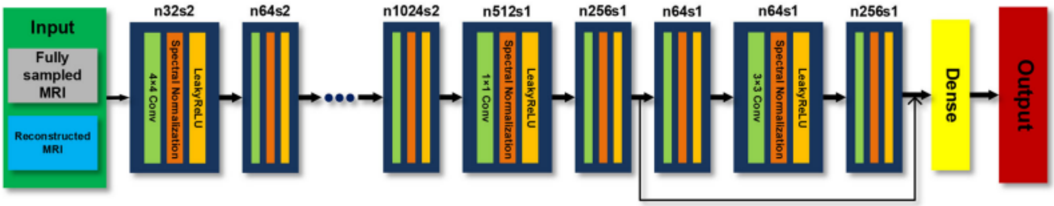

Figure 11 Architecture of the discriminator module[4]

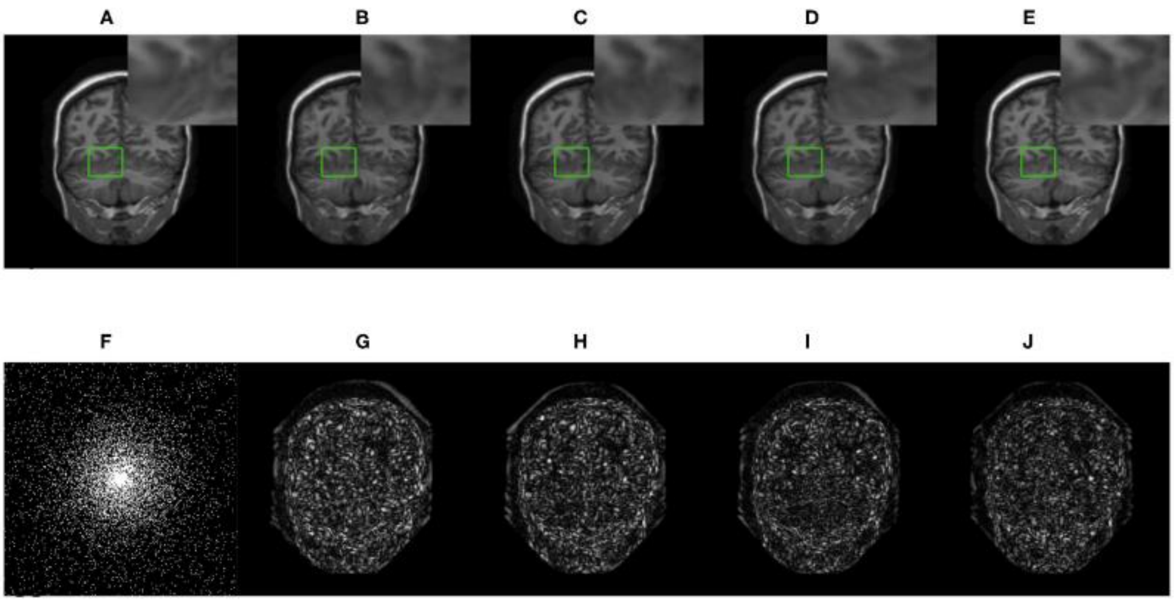

Figure 12 Using a 2D Gaussian mask as depicted in (F) and (A) being the ground truth, wehere observe different outputs for different GANs with a 10-fold acceleration. (E) is the output of SARAGAN and (B) is the output of DAGAN with (G) being its error and (J) being SARA-GAN's error. [4]

As we can observe from Figure 12, SARA-GAN error is the least and the reconstruction is the closest we could get to the ground truth hence we can say it has the best result. Finally, this proves to us that with the usage of a self-attention mechanism, we are able to get the best results and the visual effects is improved.

Discussion:

From this review project, I have learned lots of things. Compressed-sensing MRI, applications of neural networks in reconstruction of under-sampled images to remove aliasing, usage of deep learning to get optimized masks for under-sampling of k-space. I also learned about various deep learning architectures like a convolutional neural network, a U-Net, cascading of CNNs, usage of Generative Adversarial Networks and different special GANs like DAGAN and SARA-GAN which are optimized for MRI reconstruction. I understood the nuances of designing a model for MRI reconstruction and how critical it is to get a good model to get a good reconstruction which looks almost the same as the fully sampled image. I also learned about how using these techniques, we can reduce the time overhead of the whole MRI acquisition process and how reducing the time can benefit us to take faster MRI scans and how this can help in saving more lives.

When I started doing this literature review project, I was completely unaware of what Compressed-sensing MRI is and how deep learning can be leveraged for MRI acquisition and reconstruction. I was aware of applications of Deep Learning for classification, object detection, semantic and instance segmentation on MRI scans to detect abnormalities like tumors, cancers and other diseases. I had also previously done a project in my undergrad which was to detect Low Grade Gliomas in Brain MRI scans and implemented a ResNeXt U-Net on it to achieve very good results. I assumed I would write a review paper on the segmentation applications of deep learning on the MRI scans. However, when I talked about deep learning to Professor Wang, he assigned me a topic of Deep learning in MRI reconstruction and acquisition which was a completely new topic to me and frankly I thought it would be a piece of cake since I was already well-versed with the segmentation aspects. However, when I started searching for the papers on this topic I realized I had struck a goldmine and I had a very good opportunity to write a good review paper. I started off with not knowing anything about under-sampling of MRI scans since in the class we had always talked about full k-space sampling and not under-sampling. I read some articles online and papers and found out that under-sampling and image reconstruction using deep learning is a new application in MRI. Initially, when I was unable to find any research papers related to MRI acquisition, I asked Professor Wang that I wasn't able to get any papers on that topic. He suggested me to look for Professor Sabuncu's paper on the topic and when I read it I found out it was a combination of deep learning optimization for both MRI acquisition and reconstruction. After that, I read some more papers and I was able to write a review paper quite easily. This MRI course has been very beneficial to me in doing this term paper and overall for my understanding and knowledge. When I joined this course, I never knew how deep the MRI physics are and this caused me to revise all of my undergraduate concepts of Magnetism, Linear Algebra, Probability and Signal Processing. Professor Wang's lectures were always very informative and though sometimes I could not comprehend them completely, it was a delight to learn new things. The guest lectures that we had from doctors at Weill Cornell and other places were extremely informative and they told us about the actual ground reality in the hospitals and it is important for us to know that since sometimes, there is a disconnect between research and industry. From one of the guest lectures, I learned that there is a very short span of time for a person who has got a stroke and sometimes long MRI sequences can be very dangerous as the person can die in that timespan. This got me thinking about fast MRI and how to speed up the MRI pipeline which eventually led me to take the topic of Deep Learning applications in MRI acquisition and reconstruction. From the MRI lectures, I learned about k-space and 2-D Fourier Transform and how sampling all frequencies on the k-space can get us a full image and how if we under sample below the Nyquist rate, we get aliasing effects. This MRI course was very advanced in my opinion and that made it a bit hard for the students to follow sometimes. It was perfect in terms of how the material was covered in class, however, I think that in the future if current advancements in MRI are also taught in class like the applications of Deep Learning in MRI acquisition and reconstruction which can also help people who are not going to go into MRI research learn about some complementary domains connected to MRI and how those areas can also be explored in the future. This MRI course was overall very beneficial to me and it was an eye-opener. I loved going to the MRI scanner in our campus in Ithaca and the experience that I got while scanning fruits and one of my classmates was extremely informative. I was also allowed to use the MRI software of the scanner and also saw the wonders of fMRI.

Conclusion

In this term paper project, I started off with exploring the use of deep learning in CS-MRI where I reviewed LOUPE, which is a technique to find the best optimized under sampling mask for CS-MRI which can give us great reconstructions. This can in turn give us the optimal sampling masks for different applications like for MRI of the knee or MRI of the chest or MRI of the brain. I also explored the concept of a deep cascaded CNN in MRI reconstruction which involves many CNNs which are arranged one after the other with k-space under-sampled mask injections at all the stages. This deep cascaded CNN was able to get great and fast results for MRI reconstruction and thus this technique can be a good implementation in the industry. After that, I moved on to 2 GAN based architectures for MRI reconstruction with the first one being DAGAN. DAGAN uses a U-Net based architecture for the generator and the discriminator tries to differentiate between the true samples and the fake samples and on minimizing that loss, we were able to get good results closely resembling the actual ground truth. Finally, I reviewed SARA-GAN which is a self-attention and relative average discriminator-based GAN which also has a somewhat U-Net like architecture and which showed us the best results due to the self-attention mechanism and the relative average discriminator instead of the normal discriminator like in normal GANs. What remains to be seen is what we can do to improve the results beyond these models. Perhaps a combination comprising of a LOUPE like front-end for the optimization of the mask followed by a SARA-GAN like GAN can yield us an improvement over these results.

Overall, from this MRI course, I have learned lots about the different types of gradient fields, the MRI scanner, how the different imaging is done like Echo Planar Imaging, Gradient Echo and Spin-Echo. Apart from these, I also learned about T1 weighted, T2 weighted, DWI imaging and when it is suitable to use each technology. I also learned about Gadolinium and how it can help gain better contrast images. I also learned about various medical aspects of MRI through the various guest lectures that we had that taught me how to think about problems from a holistic point of view.

My learning in this course may impact my future greatly because I want to make a career at the intersection of Medical Imaging and Deep Learning. With the knowledge that I gained in this course and the exposure to advanced topics, I found potential applications of deep learning in this field and I would like to create solutions for the hospitals which can actually improve the medical imaging technologies or the diagnosis thereafter. Ultimately, I aim to become an entrepreneur and make AI enabled products and integrate AI into existing scanners which can bring down the imaging time and diagnosis time drastically which can improve the patient’s experience in the hospital along with better treatment opportunities.

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