MRI Image Generation

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Abstract

Magnetic Resonance Imaging (MRI) scans are expensive and time-consuming. Speeding up this process can increase its use and improve the patient experience. Thanks to technology and the availability of large datasets we are now able to implement and test many deep learning models. U-Net is an architecture built on FCNs (Fully Convolutional Networks). In order to solve the problem of slow MRIs, the U-Net model will take an undersampled MRI image and generate the rest of the image. The ability to successfully and accurately reconstruct an MRI image using undersampled data will complete our objective.

Introduction

Magnetic Resonance Imaging (MRI) is a powerful tool that is widely used to diagnose a myriad of disorders and diseases. This technology has revolutionized medical diagnoses. However, it is also very expensive and time-consuming. Furthermore, they are difficult on the patient, and certain conditions preclude the use of MRI's. That means that this potentially life-saving tool isn't utilized nearly as often as would be useful.

The MRI's being utilized were taken using Diffusion Tensor Imaging (DTI). The data set is comprised of anonymous images provided by NYU Langone. This set contains the raw k-space data from more than 1,500 fully sampled knee MRIs obtained on 3 and 1.5 Tesla magnets and DICOM images from 10,000 clinical knee MRIs also obtained at 3 or 1.5 Tesla. While this set isn't considered a ground truth, it has been carefully curated as part of an IRB approved study.

The raw dataset includes coronal proton density-weighted images with and without fat suppression. The DICOM dataset contains coronal proton density-weighted with and without fat suppression, axial proton density-weighted with fat suppression, sagittal proton density, and sagittal T2-weighted with fat suppression. Raw and DICOM data were anonymized via conversion to the vendor-neutral ISMRMD format and the RSNA clinical trial processor, respectively. Further, the study performed manual inspection of each DICOM image for the presence of any unexpected protected health information (PHI).

Our model will be implemented utilizing Google Colab and the previously described dataset. The main focus of effort will be on the replication (decoding) of the image. This is what would be used in the future to speed up the MRI process. This will be measured using Structural Similarity which quantifies changes in the structural information of an image and is given by a percentage score. The challenge itself will then be further reviewed by a team of radiologists.

Related Works

One method used on this dataset is the i-RIM (Recurrent Inference Machine) model which is an invertible version of RIM that has been applied to the FastMRI previously. i-RIM allows the ability to train models that are several hundred layers. Another is using GANs (Generative Adversarial Networks) for unpaired training to reconstruct MRI images. Those utilize under-sampled data to recreate higher resolution images..

Proposed Approach

Our approach will be using a U-NET convolutional neural network (CNN) approach. The model is a medical CNN that uses layers of convolutional blocks for its model. This approach allows the model to determine if it needs to utilize more layers to define appropriate weights. This helps reduce excessive convolutions and pools while increasing the accuracy of the image generation.

This model is, at it's core, an encoder and decoder which uses image segmentation to perform it's functions. The image will first be down-sampled (encoded), to then be up-sampled (decoded). This will mimic the parallel coil images that are taken in MRI's, which will provide the speedup.

The down-sampling path consists of blocks of two 3×3 convolutions each followed by Rectified Linear

Unit (ReLU) activation functions. The blocks are interleaved by down-sampling operations consisting of max-pooling layers to reduce dimensions.

The up-sampling section is essentially the inverse. The goal of this is to re-make the original image without a mask and make it appear as close as possible to the original image with no mask. At the end, there is a final series of convolutions.

The most intensive part is the data transformations that occur. The files themselves are an average of 10GB each. First, the k-space must be segmented into its tensors. This is not to be confused with Tensorflow. An MRI tensor is one snapshot in time during the process an MRI. An MRI can be considered a 4D image. There is a normal length and height. Additionally, the coils themselves can be considered a width, and the tensors themselves are akin to time data. Masks and cropping and normalization are also applied to the image. Additionally, Fourier transformation occurs (utilizing PyTorch). This mimics the actual Fourier transformation utilized by hospitals. In MRI physics, *k-space* is the 2D or 3D Fourier transform of the MR image measured, which comprises each *slice*. Its complex values are sampled during an MR measurement, in a premeditated scheme controlled by a pulse sequence, hence it’s likeness to added time data.

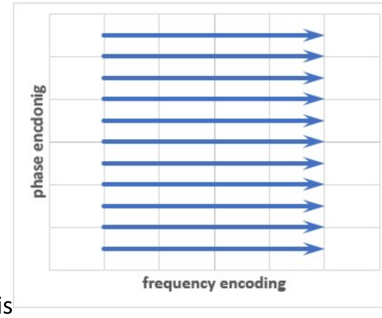
Experiments

Dataset

The dataset that is used for this experiment includes knee MRI scans for two different tracks, Multi-coil and Single-coil. For our research purposes we will only be worried about Multi-coil. The Multi-coil track consists of four different datasets: training, validation, test, and challenge.

The training validation datasets both contain two different tensors: kspace and reconstruction. Kspace tensor is the Multi-coil k-space data, the shape of this tensor is (number of slices, number of coils, height, width). Reconstruction tensor is the Root-sum-of-squares reconstruction of the multi-coil k-space data cropped to the center 320 x 320 region. The reconstruction tensor will have a shape of (number of slices, 320, 320).

The testing and challenge datasets also contain two tensors: k-space and mask. The k-space tensor is the under-sampled multi-coil k-space, the shape is (number of slices, number of coils, height, width). The mask tensor defines the under-sampled Cartesian (vice radial) k-space trajectory. The traditional way of acquiring K-space data is through Cartesian, or rectilinear, phase and frequency encoding. this is done as:



The number of elements is the same as the width of k-space.

Evaluation Metrics

Structural Similarity (SSIM) - Structural similarity is the index measure of similarity between two images. The images are measured by their inter-dependencies of objects in an image and locations by using sliding windows. It is given as a percentage (viewed from 0-1). The SSIM measurement encompasses the NMSE and PSNR.

Normalized mean Square Error (NMSE) - the estimator of overall deviations between predicted and measured values.

Peak Signal-to-Noise Ratio (PSNR) - It compares two images by getting a compressed image and the original in decibels. The higher the ratio in the PSNR the better quality the compressed image is or the reconstructed image.

Results

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SSIM = 0.5986 +/- 0.2733
PSNR = 27.81 +/- 4.773
MSE = 2.488e-10 +/- 5.649e-10 NMSE = 0.0651 +/- 0.06147
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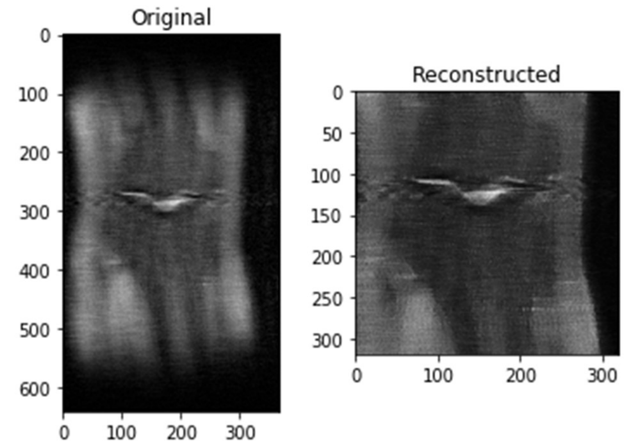
After running our model we got a 59.86% SSIM between the original image and the reconstructed image. This showed the similarity of the image by pixels between both images.



The above image shows the Original and reconstructed image. The image shows there are clear similarities between each other but shows that certain features are different as certain areas of the image are darker in the reconstructed image.

Research paper results

Single-coil classical and U-Net baselines applied to test data				
Model	Acceleration	NMSE	PSNR	SSIM
Classical Model (Total Variation)	4-fold	0.0479	30.69	0.603
	8-fold	0.0795	27.12	0.469
	Aggregate	0.0648	28.77	0.531
U-Net	4-fold	0.0320	32.22	0.754
	8-fold	0.0480	29.45	0.651
	Aggregate	0.0406	30.7	0.699

Our Results with 50 epochs

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PSNR = 28.72 +/- 5.493
SSIM = 0.6236 +/- 0.2861
MSE = 1.867e-10 +/- 3.877e-10 NMSE = 0.05532 +/- 0.06095
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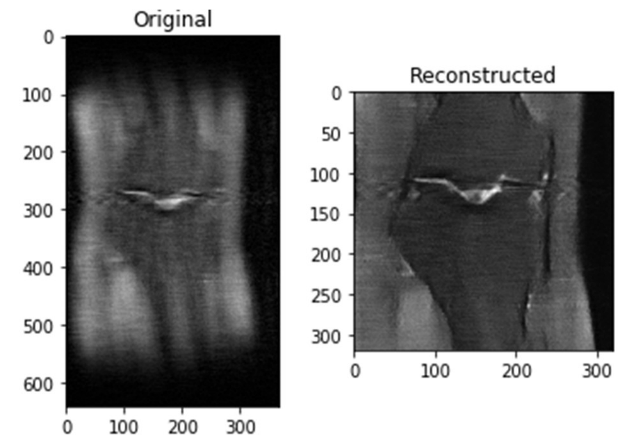
We decided to run the training model with 50 epochs to see if it can improve the SSIM similarity. As you can see above we improved to a SSIM of 62.36% This compared to the research paper results put us in between the average results for the classical models and the U-Net models. Our model is based off the U-Net model but due to data storage problems caused by google colab space our training was limited by the amount of images used.



In the above images we show a reconstructed and original image comparison using 50 epochs as you can see a 3% higher SSIM accuracy increase caused some distinct features that were not in the original as on the right side of the knee is shows a dark line going up and down.

Conclusion

In this project, we have presented one method, utilizing image segmentation within a U-Net architecture to speed up the MRI process utilizing deep learning to "predict" what the next coil snapshot image would be. If perfected, it could easily cut MRI in half by filling each coil image with a predicted value. However, MRI's can be very subtle, and more work must be done to get training accuracy as close to perfect as possible. Some further ideas to expand upon our research would be to utilize a recurrent neural network (RNN) augmented with Adaptive Computation Time to better learn the slice features (which represent the time data as previously discussed).

The most important element of any further work with MRI's will also need the expertise of doctor's and radiologist. This will enable us to have a fully ground truth dataset, suitable for deep learning. Lastly, perfecting the algorithms to mimic the exact functions of the MRI machine could be a final step to the perfection of a model that will eventually speedup the process of an MRI. Hopefully, in the process, this will save lives.

References

[1] Zbontar J, Knoll F, Sriram A, et al. fastMRI: An Open Dataset and Benchmarks for Accelerated MRI. arXiv:1811.08839 [cs.CV] 2018.

[2] Yoseob Han and Jong Chul Ye. Framing U-Net via deep convolutional framelets: Application to sparse-view CT.IEEE Transactions on Medical Imaging, 37(6), 2018.

[3] Patrick Putzky, Dimitrios Karkalousos, Jonas Teuwen, Nikita Miriakov, Bart Bakker, Matthan Caan and Max Welling. i-RIM applied to the fastMRI challenge. arXiv:1910.08952v1 [eess.IV] 20 Oct 2019.

[4] Ke Lei, Morteza Mardani, John M. Pauly, and Shreyas S. Vasawanala. Wasserstein GANs for MR Imaging: from Paired to Unpaired Training. arXiv:1910.07048v1 [eess.IV] 15 Oct 2019.