Boosting MRI Image Quality using Deep Learning

Jordan Greenberg, Avanika Narayan, Alexander Walczak

Stanford University - Department of Computer Science

{jgberg,avanikan}@stanford.edu, awal@berkeley.edu

Motivation

MRI scans are highly effective in diagnosing an abundance of medical conditions. However, if the quality of the MRI scan is low, this can lead to fatal misdiagnoses. Thus, producing MRI images of high quality is of utmost importance. Recent discovery has shown that deep learning neural networks can be used to reconstruct MRI images to be more accurate than the original, leading to increasingly effective medical care.

Introduction

- Standard processes for generating MR images from raw sensor inputs are **timely** and rely heavily on **expert knowledge**.
- Image reconstruction is **difficult** because knowledge of the exact inverse transform between the output image and raw sensor data is unknown a priori.
- Traditional image reconstruction methods involve hand-crafted, sequential modular reconstruction chains composed of several ad hoc signal processing stages.
- **Solution**: a deep learning driven image reconstruction framework that learns the reconstruction relationship between sensor and image domain without expert knowledge. Our model yielded a PSNR of 28.2, which was a significant improvement over existing methods trained on the same dataset.

Data and Features

Primary Data Source: fastMRI Dataset by Facebook AI Research and NYU Langone Health
Details:

- Dataset contains 1,594 knee volumes for a total of 56,987 slices.
- Single-coil track training dataset :
  - k-space: | Shape : (number of slices, height, width) (complex-valued)
  - reconstruction: Shape | (320, 320) (real-valued)
- Single-coil track test dataset :
  - k-space: | Shape : (320, 320) (complex-valued)
  - mask: | Shape : width of k-space tensor (real-valued)

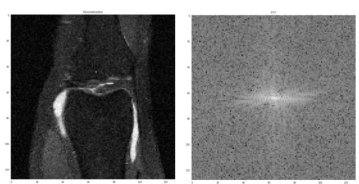

Fig. 1: MRI knee scan (left) and its corresponding k-space image (right) from the fastMRI dataset.

Methods

AUTOMAP (AUtomated TransfOrm by Manifold APproximation) architecture: The state-of-the-art CNN for MR image reconstruction. Our model uses a variation of the AUTOMAP architecture with MSE loss. The original AUTOMAP architecture had 806 million parameters: nearly 4x the number of parameters in our model (201 million).

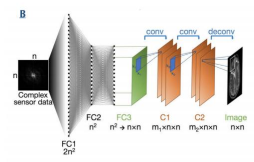

Fig. 2: AUTOMAP architecture.

Key Metric (Peak Signal-To-Noise Ratio):

$$PSNR(\textit{reconstruction}, \textit{ground truth}) = 10 * \log \frac{MAX^2}{MSE}$$

Results

Qualitative : Our final model yielded a **PSNR** = 28.2 on the validation set. A sample of the reconstructed images generated by our model can be seen below.

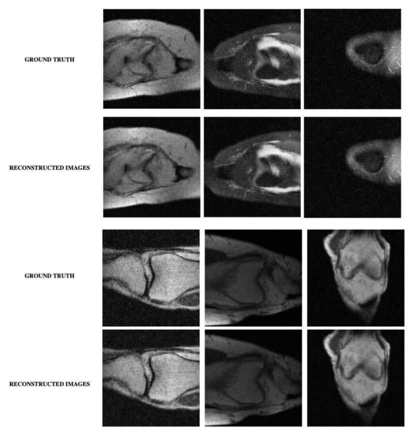

Fig. 3: Qualitative interpretation of results.

Discussion

Our model achieved a PSNR of 28.2 on validation data, outperforming the standard total variational baseline (PSNR 25.9) trained on the same dataset [5]. The paper for the AUTOMAP model did not post PSNR values for single-coil MRI data. These results indicate the significance of our model in producing valid image reconstructions. This being said, a qualitative analysis of our results indicate that the resolution of the reconstructed images can be improved. Due to the high dimensionality of our inputs, we we cannot rely on fully-connected layers in our architecture to improve resolution. Thus, we would need to develop a CNN architecture that does not rely on fully convolutional layers to learn a better mapping or adopt other deep learning architectures such as GANs.

Future Work

- Testing the generalizability of model and ways through which the model can be made more adaptable to different classes of MRI scans.
- Explore ways to increase the stability of our model.
- Work toward making the model work for other healthcare data such as CT scans.
- Collaborate with Dr. Olivier Keunen's lab to further develop the model's effectiveness on brain scans of rats.
- Architect a model capable of reconstructing high resolution MRI images without the limitations of massive fully-connected layers.

References

References

[1] Vegard Antun et al. "On instabilities of deep learning in image reconstruction-Does AI come at a cost?" In: *arXiv preprint arXiv:1902.05300* (2019).

[2] Chang Min Hyun et al. "Deep learning for undersampled MRI reconstruction". In: *Physics in Medicine & Biology* 63.13 (2018), p. 135007.

[3] Jo Schlemper et al. "A deep cascade of convolutional neural networks for MR image reconstruction". In: *International Conference on Information Processing in Medical Imaging*. Springer. 2017, pp. 647–658.

[4] Guang Yang et al. "DAGAN: deep de-aliasing generative adversarial networks for fast compressed sensing MRI reconstruction". In: *IEEE transactions on medical imaging* 37.6 (2017), pp. 1310–1321.

[5] Jure Zbontar et al. "fastmri: An open dataset and benchmarks for accelerated mri". In: *arXiv preprint arXiv:1811.08839* (2018).

[6] Bo Zhu et al. "Image reconstruction by domain-transform manifold learning". In: *Nature* 555.7697 (2018), p. 487.