Deep Reconstruction of Undersampled Cardiac MRI Datasets

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Introduction

Scan time and reconstruction time is a key challenge for Magnetic Resonance Imaging (MRI). Scan time can cause discomfort for patients and long reconstruction times can lead to delayed diagnosis by clinicians. Time-efficient k-space sampling techniques can be used to decrease scan times by undersampling and with compressed sensing [1]. This leads to an increase in the computation time required when reconstructing undersampled k-space data. Deep learning has the potential for minimizing reconstruction times for undersampled MRI data.

Dataset & Features

The dataset comprised of 9,760 2D cardiac images (1/2 sagittal, 1/2 coronal slices) acquired using a gradient-echo (GRE) sequence using 12 spiral interleaves (75.6 ms) to achieve 28x28 cm^2 FOV and 3.1 mm in-plane resolution. We utilize 98% for training, 1% for validation, and the remaining 1% for testing. The non-cartesian (spiral trajectory) 2D (navigator) data was first gridded to a cartesian grid. Then, the data was pseudo-randomly undersampled (by a factor of 1-2 in the x and y dimensions) using a variable density sampling mask which would normally be reconstructed using L1-ESPRiT [1]. In Fig. 1, the k-space data, before and after one of the 9 different undersampling masks was applied, is shown with the corresponding iFFT images. The final step for data preparation included generating the coil sensitivity maps for the 8 channels.

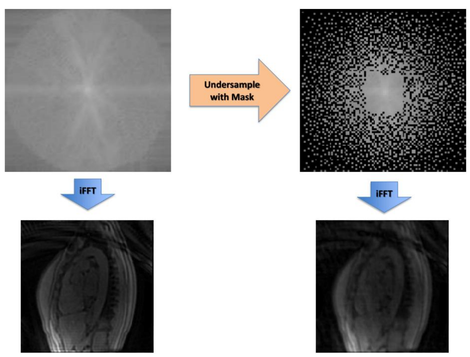
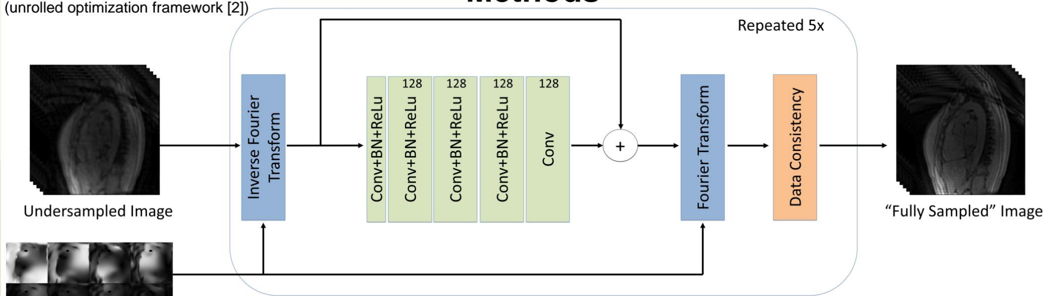


Figure 1: Example images before and after applying an undersampling mask

Methods

Figure 2: Implemented CNN architecture for image reconstruction (unrolled optimization framework [2])



- Complex 3D data real/imaginary channels
- Residual block with 5 convolutional layers
- iFFT, 4 (BN & ReLU), 1 (linear), FFT data consistency (Repeated 5x)
- Implemented in TensorFlow with Tesla K80 GPUs

Results

Figure 3: Comparison of input, CNN output, and ground truth images

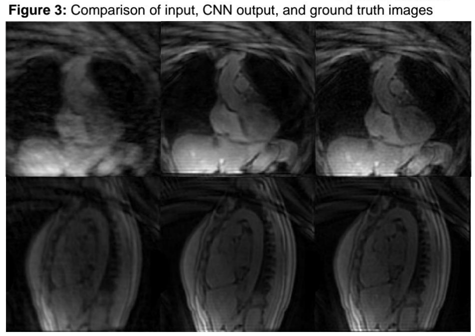
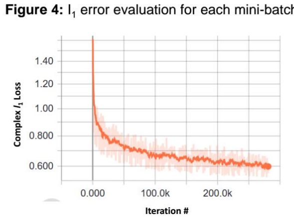


Figure 4: l_1 error evaluation for each mini-batch



- l_1 loss gives significant improvements in reconstructed images in test set
- Works well for both coronal and sagittal cardiac images

- Cardiac images improved by recovering structures and applied denoising/smoothening
- Higher undersampling masks also performed well using the current architecture
- When using the reconstructed images as navigators, similar motion estimates were extracted

Discussion & Future Work

- Qualitative and quantitative results of ResNet "reconstruction" preserved structure and exhibited low complex l_1 loss
- Hyperparameters for the chosen architecture worked well, but can possibly be further tuned for improved performance
- Implementation on undersampled 3D non-cartesian dataset with potentially doing 3D convolutions (instead of 2D convolutions slice by slice).
- Expand training sets using MRI data from different anatomies

References

[1] M Uecker et al., ESPIRiT eigenvalue approach to autocalibrating parallel MRI: where SENSE meets GRAPPA. Magn Reson Med, 71(3):990–1001, 2014.

[2] S. S. Diamond, V. Sitzmann, F. Heide, G. Wetzstein, Unrolled optimization with deep priors, arXiv (2017).