Optimized Subsampling for Fast MRI Segmentation Using U-Net Architecture

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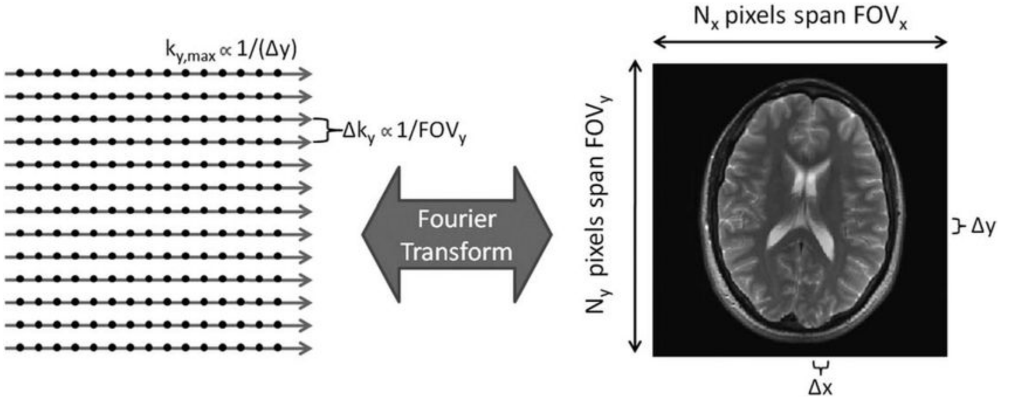
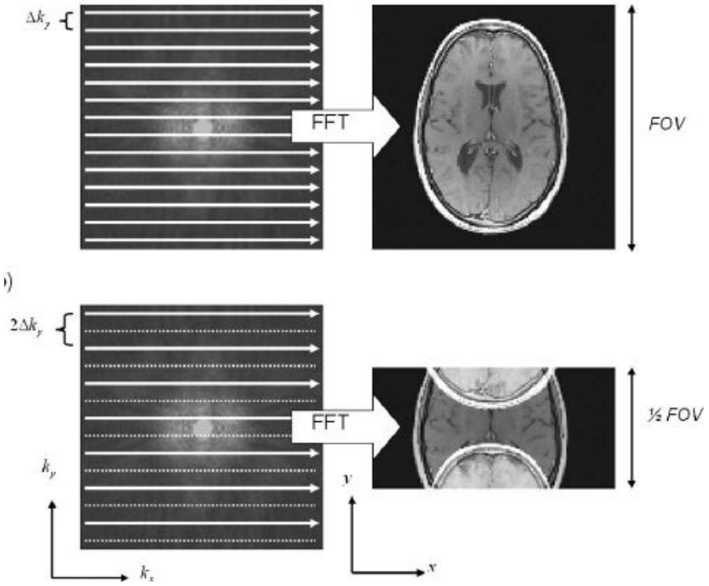
Background

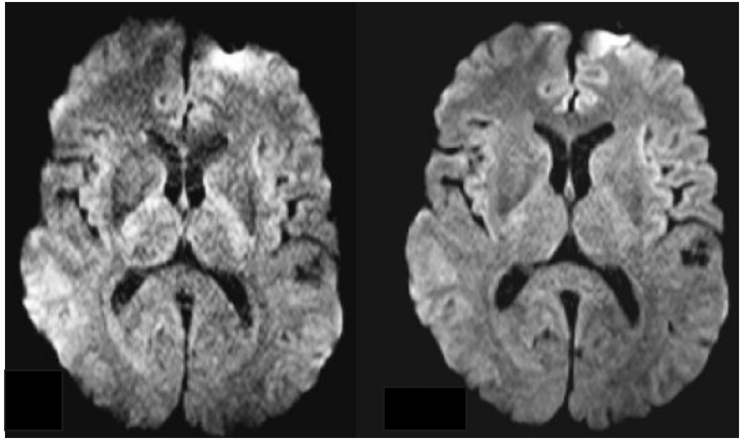


Researchgate

- MRI - the favorite imaging modality
  - Pros - soft tissue contrast, convenient 3D imaging, no radiation
  - Cons - long scan times, patient discomfort, motion artifacts, expensive
- Long scan times
  - Typically 256 phase encodes with 256 frequency encodes each
  - Each phase encode acquired over TR (4sec), for 60 slices, t=60*256*4s=17hrs! (hypothetical)

Compressed sensing : An example





R=2 R=3

Images from Researchgate

Motivation & Methods

GOAL

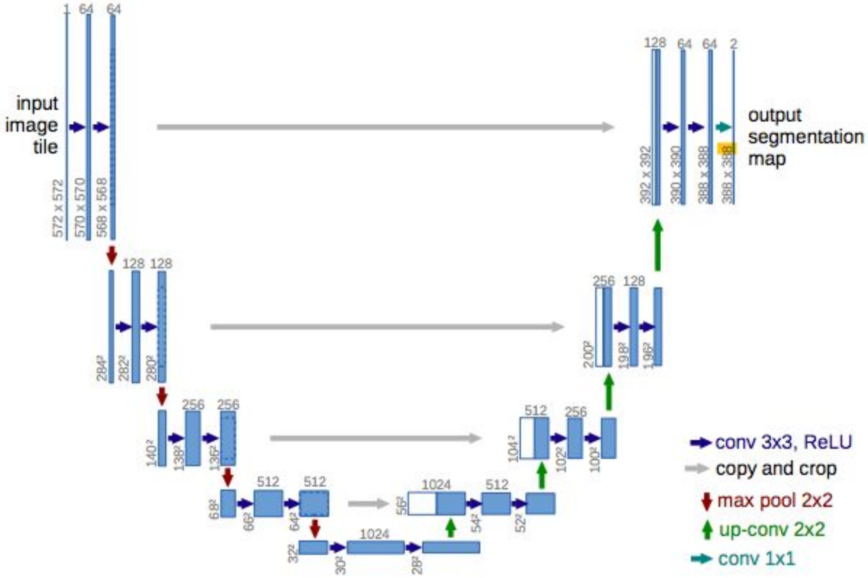
- Optimize selective reduction of MRI data size to acquire images faster.
- Use CNNs to train physical layer to subsample fourier (k) space data, and segment high-resolution reconstructed images accurately

DATASET

- Subset of 2017 Brain Tumour Image Segmentation (BraTS) challenges
- About 750 multiparametric scans - T1, T1 Gd, T2, T2 FLAIR
- Pre-processing steps: (240,240) center crop, Normalization and conversion to numpy arrays

U-Net Architecture

1. U-Net: 4 encoding and decoding layers with 2 convolutional layers each
2. Image augmentation
3. 10 Batch normalizations
4. 2 instances of dropout at .5
5. ReLu activation in all layers with sigmoid used in final Dense layer for logits



arxiv.org/pdf/1505.04597.pdf

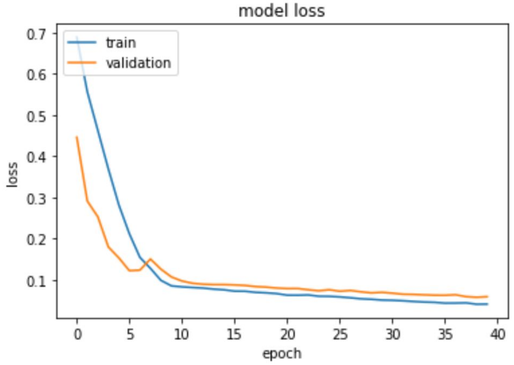
Metrics for Comparison

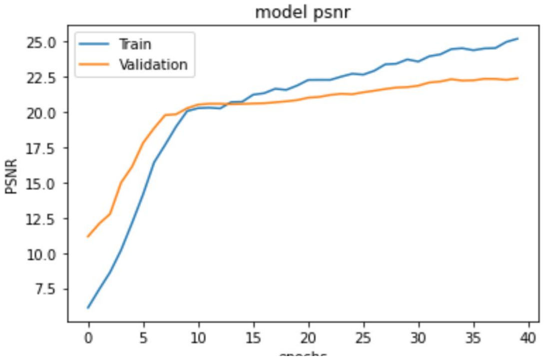
- Binary Cross Entropy Loss
- Accuracy (Pixel to Pixel)
- Peak Signal to Noise Ratio (PSNR)
- Mean Intersection over Union (mIoU)

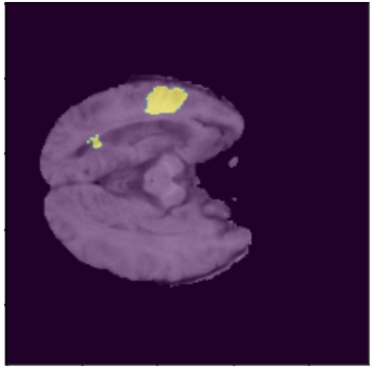
Physical Layer: Optimized Sampling

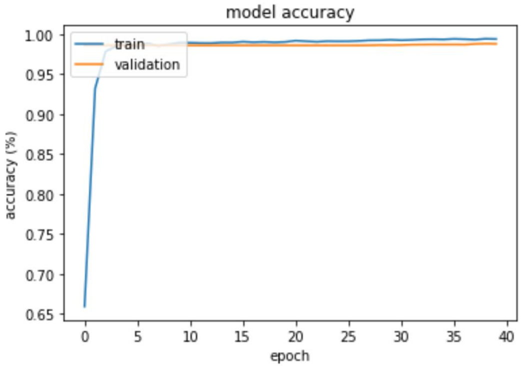
- Create optimizable mask for input k-space data
- Each column of mask either 0 or 1 - Relaxed One Hot Categorical distribution
- Tile columns to create mask same size as image (240,240)
- Update temperature per epoch - lower temperature implies discrete distribution
- Mask k-space data and ifft to reconstruct image
- Input image to U-Net

Results: U-Net alone



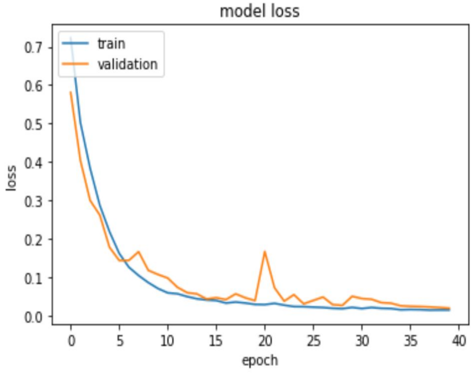


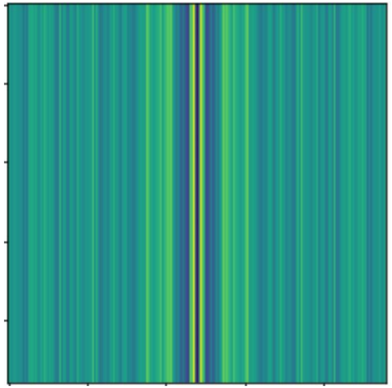


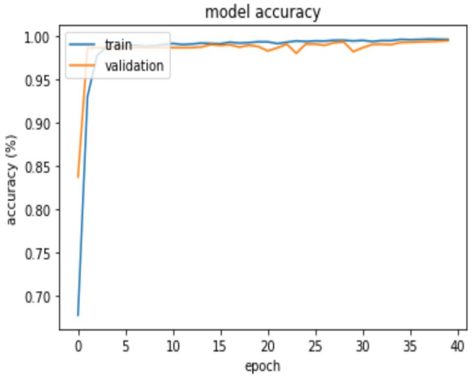


Mean IoU: .4931

Results: U-Net with Optimizable Mask



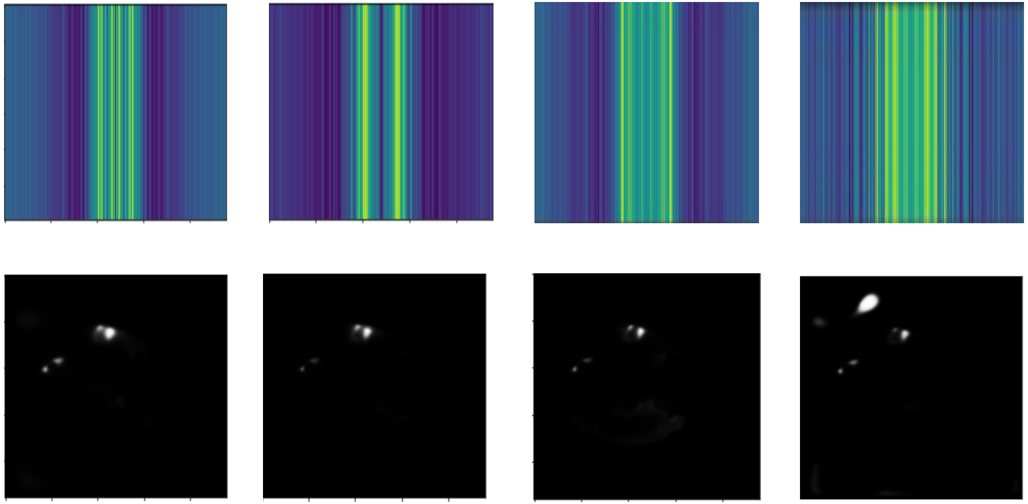




Mean IoU: .4951

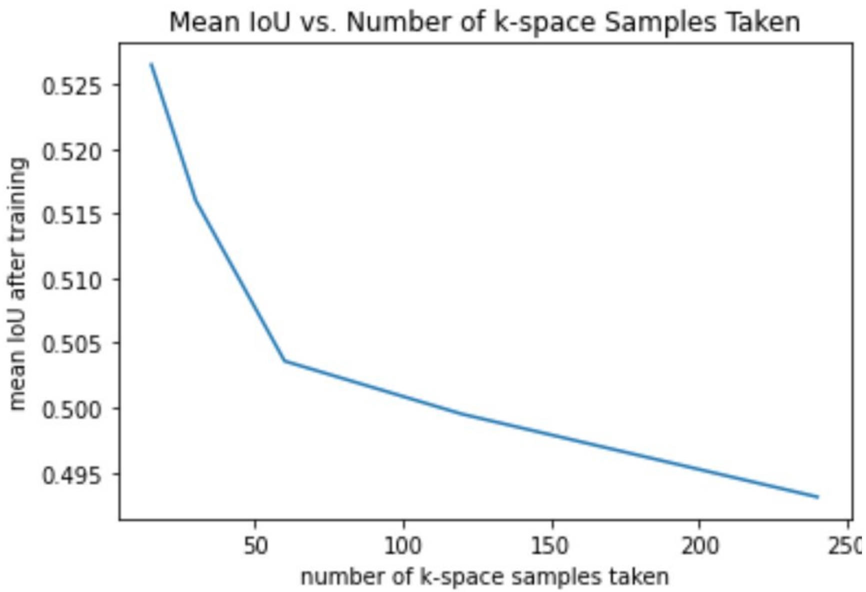
Results: U-Net with Relaxed One-Hot Dist

120 Samples | 60 Samples | 30 Samples | 15 samples



- CNN chooses “important” frequencies first, then goes back to fills in areas
- Preference for areas around DC, and some higher frequencies
- Filtering out middle frequencies
- As less samples are taken, more false negatives and false positives

Comparison of Mean IoU



- Mean IoU seems to decrease with increasing samples
- CNN is potentially overfitting to compensate for lack of k-space data and/or aliasing
- Initial dataset possibly corrupted; lower sampling sizes filter out “unimportant” frequencies
- Changes in MeanIoU could be inconsequential at low values

Conclusions and Further Research

- Investigated optimized k-space subsampling for potential implementation in MRI
- Center frequencies seem to be important, but not DC
- Sampling 60 out of 240 columns of k-space reconstructs images and segments well
- In future, use 3-D data or larger images with more computing resources available
- Investigate IoU to understand decreasing values
- Apply to other, larger datasets, with better initial logits