Task-Based Assessment for Neural Networks: Evaluating Undersampled MRI Reconstructions based on Signal Detection

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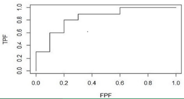


Mathematics of Medical Imaging (MoMI) at Manhattan College

Introduction

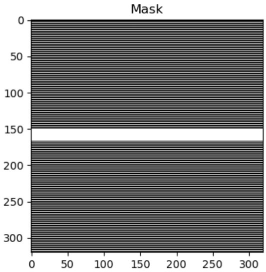
- Magnetic Resonance (MR) Imaging is time consuming
- Omitting frequencies during scanning (under-sampling) speeds up data acquisition
- Neural Networks have recently been applied to reconstruction
- Standard metrics of image quality do not incorporate the task
- In this research a task-specific evaluation method is introduced

Goals

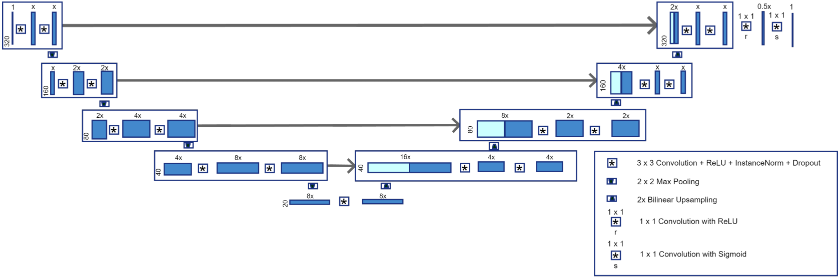
- Introduce 2AFC-task based evaluation of network reconstruction
- Pick ideal undersampling factor using new and standard metrics

Undersampling

- The FastMRI FLAIR (Fluid Attenuation Inversion Recovery) dataset is used to generate a set of fully sampled images
- The images are 320 by 320 pixels
- MR data in k-space (Fourier Transform of Image Space)
- Keep 16 middle k-space lines and sample every k outside of middle
- e.g. 3x sampling mask



Reconstruction



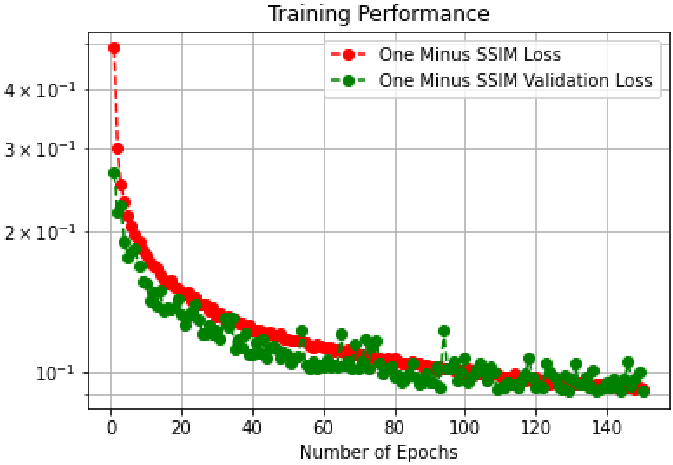
Unet with x channels

- 1-SSIM is used as the loss function
- RMSProp is used as the optimization algorithm

Computational Methods

- Used the Kakos Center's Linux workstation Athena
- Used a Quadro P5000 16 GB CUDA GPU.
- Used TensorFlow in Python to code the neural networks

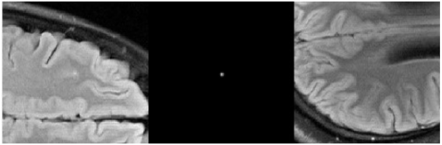
Training



Example Convergence Plot: 2x, split 2

2AFC task, observers and metrics

- Task: Pick correct image that has artificially placed tumor in center
- Sample 2AFC image



- Human observer study: given measure of human performance (200 trials per condition)
- Channelized Hotelling observer with Laguerre Gauss Channels: estimate of ideal machine performance
- NRMSE as general measure of pixel error
- SSIM as measure of image structural similarity

Cross Validation Results

Unet 64 channels 0.1 dropout	SSIM	NRMSE
2x	0.907/0.004	0.142/0.014
3x	**0.905/0.006**	**0.137/0.007**
4x	0.831/0.008	0.179/0.011
5x	0.807/0.021	0.196/0.013

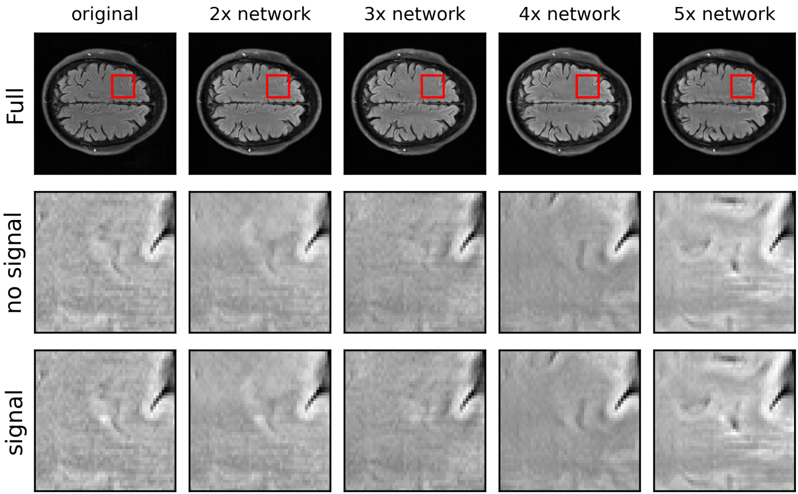
- Table containing 5-fold cross validation SSIM and NRMSE scores
- Format is mean/standard deviation of the 5 splits
- A reasonable undersampling factor would be 3x, since large performance drop from 3x to 4x

Testing Results

Unet 64 channels 0.1 dropout	LG AUC	Human Observer
Full recon	98.2/0.7	96.3/1.8
2x network	95.7/1.1	**93.5/1.6**
3x network	**94/1.4**	83.9/2.8
4x network	86.7/2.1	74.5/2.1
5x network	83/2.7	60.3/5.3

- Table containing Single Run LG AUC and Human Observer PC
- Format is mean/standard deviation
- Human observer means and standard deviations are calculated across the 4 participants, while LG AUC using bootstrap
- Based on LG AUC, a reasonable undersampling factor would be 3x
- Based on Human Observer, a reasonable undersampling factor would be 2x

Visual Comparison

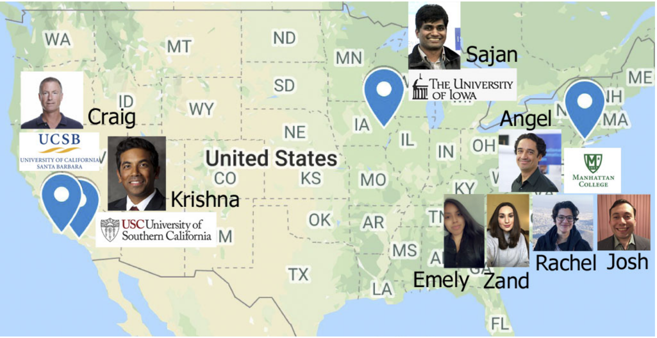


Picture 22 out of 0 -199

Conclusion and Future Work

- SSIM , NRMSE and Laguerre-Gauss metrics predict 3x undersampling factor to be best compromise between speed and performance
- Human observer predicts 2x undersampling factor as best compromise
- Preferred undersampling factor depends on the observer e.g. Human Observer PC may predict the undersampling better for a human
- Future work may include
  - model human observer
  - variable tumor location detection
  - larger dataset
  - MSE Loss for Unet
  - incorporate the physics of MRI to the neural network

Acknowledgments



Collaboration Map

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Appendix

- Cross-validation done using crossvalmag111320/unet_run_cross_val_mag_110220.py