Data Standardization, Multi-Domain Learning and GRAPPA preprocessing for Improved MRI

Mohamed Amine Ketata
Bachelor's thesis presentation
Supervisor: Prof. Dr.sc ETH Zürich Reinhard Heckel

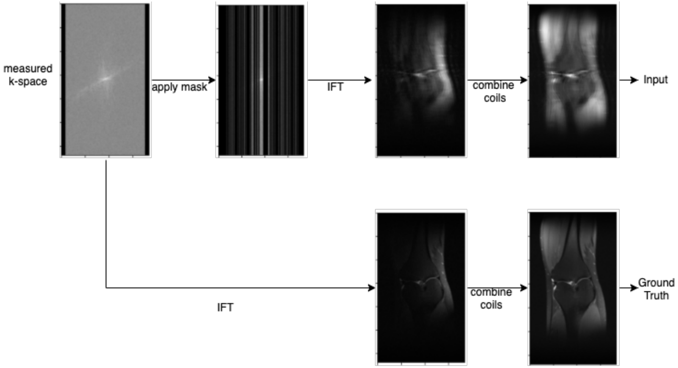
Technical University of Munich

Introduction

- Major goal: Accelerate Magnetic Resonance Imaging (MRI) scans.
- By taking under-sampled k-space measurements.
- fastMRI [1]: research project that provides a large dataset and organizes a yearly challenge.
- Thesis goal: investigate the methods proposed by AIRS medical team, winning team of fastMRI challenge 2020 edition.

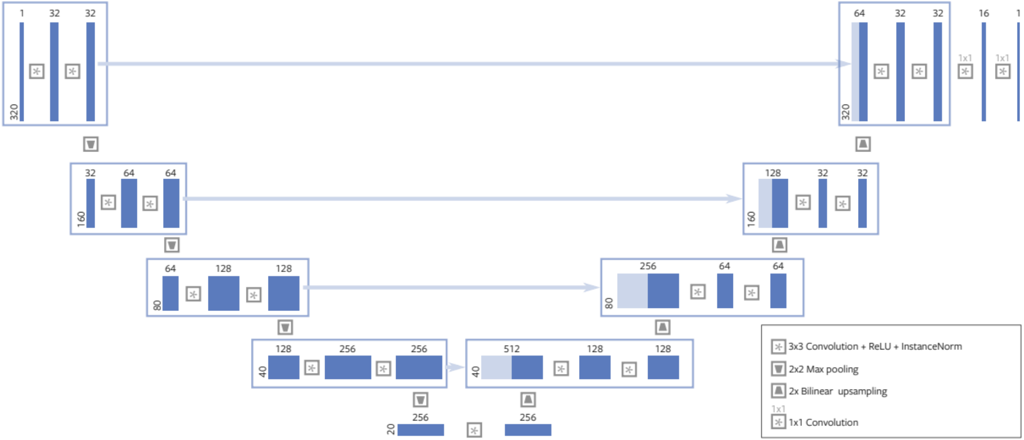
fastMRI dataset

- Measured i-th k-space signal: $y_i = F\left(S_i m\right) + noise$, where S_i is i-th coil sensitivity map and m is the spatial image.
- Image reconstruction: (1) $m_i = F^{-1}\left(y_i\right)$, then (2) $m_{rss} = \left(\sum_{i=0}^{n_c} |m_i|^2\right)^{\frac{1}{2}}$.



Data acquisition process

Baseline model: U-Net [2]



Baseline U-Net architecture. Taken from the paper [1].

Multi-channel data standardization

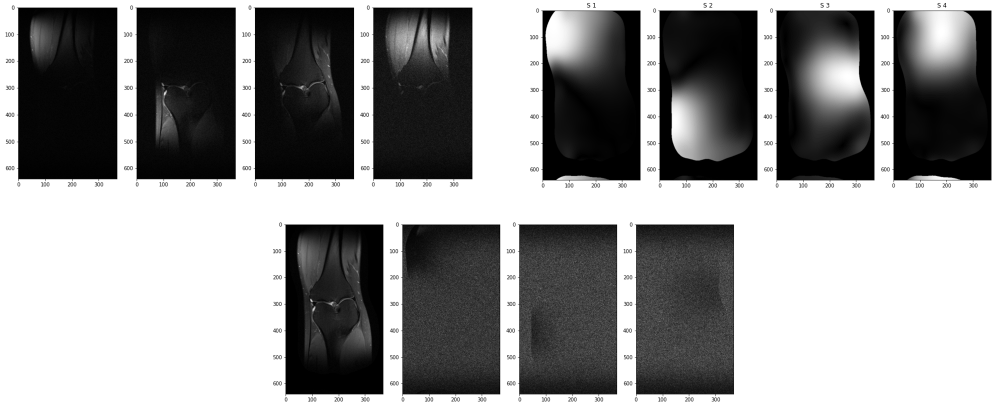
- combined image:

$$
\begin{aligned}
y_i &= F\left(S_i m\right) + noise \\
m_i = F^{-1}\left(y_i\right) &= S_i m \\
S_i^* m_i &= S_i^* S_i m \\
\sum_i S_i^* m_i &= \sum_i S_i^* S_i m \\
\sum_i S_i^* m_i &= m \\
\Rightarrow m_{comb} :&= \sum_i S_i^* m_i
\end{aligned}
\tag{1}
$$

- residual images:

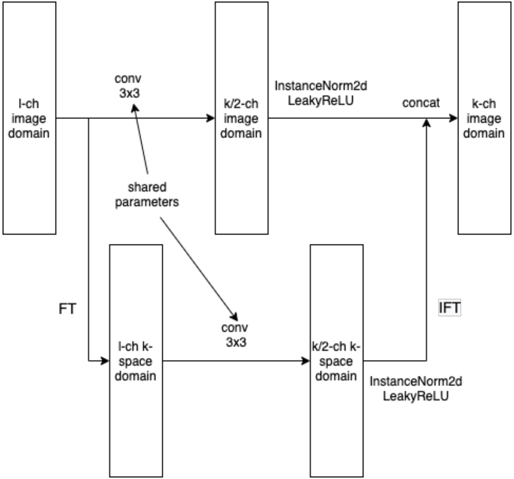
$$
m_{i,res} = m_i - S_i m_{comb} \tag{2}
$$

Multi-channel data standardization (2)



Absolute values of multi-coil images (top left), sensitivity maps given by ESPIRiT [3] (top right), and combined and residual images (bottom).

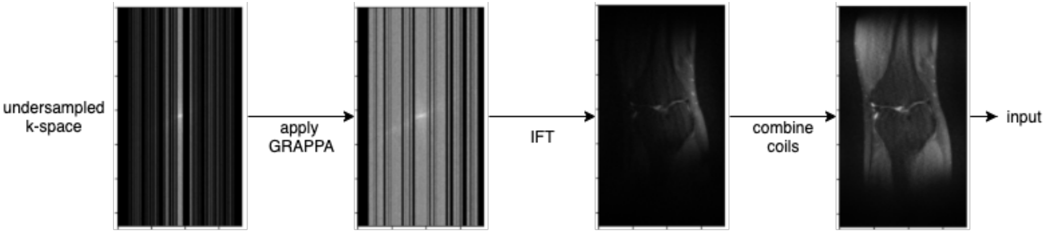
Multi-domain model



Schematic representation of a convolutional layer of MDU-Net

Data preprocessing with GRAPPA

- GRAPPA [5]: Generalized Autocalibrating Partially Parallel Acquisitions.
- Unacquired k-space values are synthesized by a linear combination of acquired neighbouring k-space data from all coils.



GRAPPA preprocessing

Results: Data stnadardization and multi-domain model

- Training on 50% of knee images without fat suppression (PD) and 25% of brain images with sequence AXT2, using RMSProp with learning rate of 0.001 for 10 epochs.
- Baseline model: U-Net model with $\tilde{m}_{rss}$ as input.
- Baseline model + data standardization: U-Net model with $|\tilde{m}_{comb}|$ as input.
- MDU-Net: the multi-domain model with $\tilde{m}_{comb}$ as input.

Model		NMSE	SSIM	PSNR
Baseline model	Knee	0.0076	0.9063	35.34
	Brain	0.0155	0.9000	32.29
Baseline model + data standardization	Knee	0.0092	0.8902	34.44
	Brain	0.0218	0.8615	31.02
MDU-Net	Knee	0.0188	0.8358	30.74
	Brain	0.0283	0.8274	28.16

Results: GRAPPA preprocessing

- Training on 25% of brain images with sequence AXT2, using Adam for 50 epochs
- Baseline model: U-Net model with $\tilde{m}_{rss}$ as input.
- Baseline model + GRAPPA: U-Net model with GRAPPA preporcessed $\tilde{m}_{rss}$ as input.

Model	L1-LOSS	NMSE	SSIM	PSNR
Baseline model	0.1186	0.0107	0.9205	33.8951
Baseline model + GRAPPA	**0.1052**	**0.0101**	**0.9222**	**34.9951**

Conclusion

- GRAPPA preprocessing: helps quite well.
- Multi-Channel Data Standardization: slightly drops the performance. Considering the residual images might help.
- Multi-Domain Model: promising idea that could be further investigated. Performs worse than U-Net with current implementation.

References

[1] Jure Zbontar, Florian Knoll, Anuroop Sriram, Tullie Murrell, Zhengnan Huang, Matthew J Muckley, Aaron Defazio, Ruben Stern, Patricia John- son, Mary Bruno, et al. fastmri: An open dataset and benchmarks for accelerated mri. arXiv preprint arXiv:1811.08839, 2018.

[2] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. In International Conference on Medical image computing and computer-assisted interven- tion, pages 234–241. Springer, 2015.

[3] Martin Uecker, Peng Lai, Mark J Murphy, Patrick Virtue, Michael Elad, John M Pauly, Shreyas S Vasanawala, and Michael Lustig. Espirit: an eigenvalue approach to autocalibrating parallel mri: where sense meets grappa. Magnetic resonance in medicine, 71(3):990–1001, 2014.

[4] Mark A Griswold, Peter M Jakob, Robin M Heidemann, Mathias Nittka, Vladimir Jellus, Jianmin Wang, Berthold Kiefer, and Axel Haase. Generalized autocalibrating partially parallel acquisitions (GRAPPA). Magnetic Resonance in Medicine, 47(6), 2002.