FRIEDRICH-ALEXANDER
UNIVERSITÄT
ERLANGEN-NÜRNBERG
TECHNISCHE FAKULTÄT

Computational Imaging Project

Zhengguo Tan, Marc Vornehm, Jinho Kim, and Florian Knoll
Friedrich-Alexander-Universität Erlangen-Nürnberg
Summer Semester 2023

Outline

1 Introduction

Who we are?

- Dr. Zhengguo Tan
  - Postdoc in CIL
- M.Sc. Marc Vornehm
  - PhD student in CIL and Siemens Healthineers
- M.Sc. Jinho Kim
  - PhD student in CIL and Siemens Healthineers
- Prof. Dr. Florian Knoll
  - W3 professor of CIL

What is CIL/CIP about?

- Semester period: 01. April 2023 – 30. September 2023
- **10 ECTS $=$ 300 working hours**
- Prerequisite - You should have taken one of these courses:
  - pattern analysis or pattern recognition
  - magnetic resonance imaging (MRI) 1/2
  - **computational MRI** (given by Prof. Knoll every winter semester)
- **Hands-on**: learning by doing

Effort & Attendance

- 1 project per student
- effort:
  - reading and understanding papers
  - implementing ideas (coding)
  - analyzing results — 50 %
  - final presentation (about 20 minutes) — 20 %
  - written report (about 10 pages) due in three weeks after your presentation — 20 %
- attendance:
  - ≥ 60 % final presentations: — 10 %

```
np.ceil(num_presentations * 0.60)
```

Office Hours

- Zhengguo: Tue, Wed, Thu 10:00 – 11:00
- Marc: Mon 08:30 – 10:00, Tue 08:30 – 09:30
- Jinho: Mon 09:00 – 10:00

- Book 30 min slots via StudOn: https://www.studon.fau.de/book5115803.html
- Location: Meet at our office (Room 2.02, Werner-von-Siemens-Str. 61)
- Please come to an office hour every $\sim$2 weeks

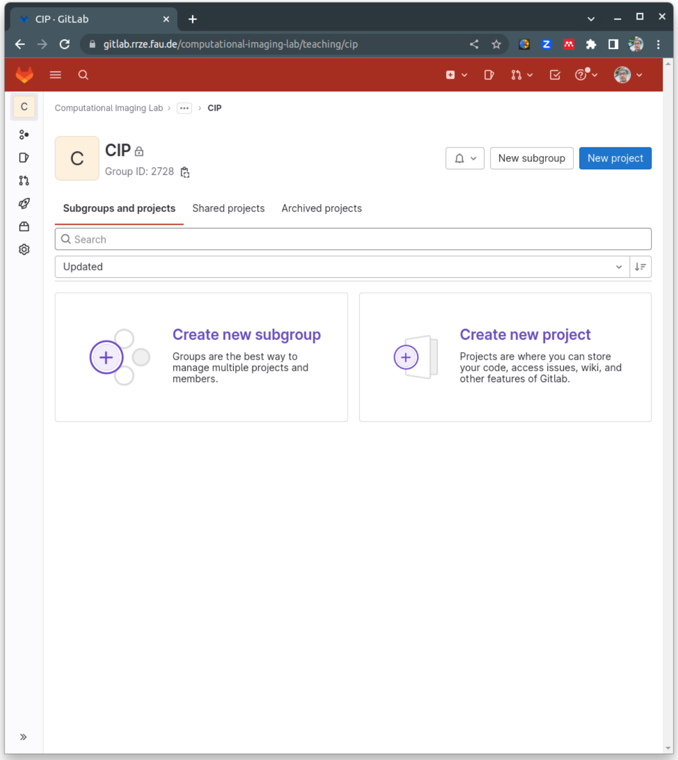
Mid-term presentations

- tentative date: 15.06.2023 starting at 10 AM.
- everyone needs to give a 5 to 10 minutes presentation about his/her project.

- **Registration for the final exam via CAMPO (29.05.2023 – 19.06.2023)**

Management on Codes, Presentations, and Reports

1. unified environment: `https://gitlab.rrze.fau.de/computational-imaging-lab/teaching/cip`
2. please request the FAU GitLab service via IdM-Portal.
3. I will then invite you to the your project repository.



Oral Presentation and Written Report

Presentation

- Format:
  - Motivation and Introduction
  - Theory
  - Methods
  - Results and Discussion
  - Conclusion

Report

- Format:
  - Introduction
  - Theory
  - Methods
  - Results and Discussion
  - Conclusion

- No template for presentation;
- there will be a LaTeX template for the report.

Computing Options

- **HPC @ FAU**:
  - requires knowledge on bash script in Linux terminal, anaconda, and python.
  - requires account application, so please let me know soon.
- **JupyterHub @ FAU**:
  - this is a new offer from NHR@FAU!
  - GTX1080Ti GPU
- **CIP-Pool @ FAU**:
  - requires account application, and <u>you need to do it</u>.
- **Google Colab**:
  - usually you can get a Tesla T4 GPU for free.
  - requires knowledge on jupyter notebook (bash script and python).
- **Your own computer**.

Computing Environments

- **Anaconda** $\rightarrow$ conda
  - flexible
  - reproducible
  - learning material:
    https://conda.io/projects/conda/en/latest/user-guide/index.html
- **Jupyter Notebook**
  - learning material:
    https://jupyter-notebook-beginner-guide.readthedocs.io/en/latest/
- Spyder, Visual Studio Code, PyCharm

Questions?

Self Introduction

- who I am?
- study program / semester / courses
- what you want to learn/do in the CIL/CIP?

Pause

Let’s make a 10-minutes break ...

2 Projects

My plan about this session

- Go through the projects by yourself – 15 minutes;
- Raise questions you have in mind;
- I will give an brief introduction.

→ Projects supervised by Marc Vornehm and Jinho Kim will be noted.

Revisit ℓ_1-wavelet compressed-sensing MRI in the era of deep learning

- Articles:
  - Gu H, Yaman B, Moeller S, Ellermann J, Ugurbil K, Akçakaya M. Revisiting ℓ_1-wavelet compressed-sensing MRI in the era of deep learning. *Proc Natl Acad Sci USA* (2022). doi: 10.1073/pnas.2201062119
  - Lustig M, Donoho D, Pauly JM. Sparse MRI: The application of compressed sensing for rapid MR imaging. *Magn Reson Med* (2007). doi: 10.1002/mrm.21391
- Codes: `https://zenodo.org/record/6808387`
- Suggested computing options: HPC
- hands-on tasks:
  - set up environments to run the codes (training and testing)
  - analyze results that you obtain

Dynamic contrast enhanced (DCE) MRI reconstruction

- Articles:
  - Feng L, Grimm R, Block KT, Chandarana H, Kim S, Xu J, Axel L, Sodickson DK, Otazo R. Golden-angle radial sparse parallel MRI: Combination of compressed sensing, parallel imaging, and golden-angle radial sampling for fast and flexible dynamic volumetric MRI. *Magn Reson Med* (2014). doi: 10.1002/mrm.24980
  - Guo Y, Lingala SG, Zhu Y, Lebel RM, Nayak KS. Direct estimation of tracer-kinetic parameter maps from highly undersampled brain dynamic contrast enhanced MRI. *Magn Reson Med* (2017). doi: 10.1002/mrm.26540
- Basic codes:
  - from me; from USC: `https://github.com/usc-mrel/DCE_direct_recon`
- Suggested computing option: JupyterHub or Google Colab, and MATLAB
- Hands-on tasks:
  - Implement the analytical non-linear inversion equation in Python
  - Compare its result and computing time with the PyTorch auto-differentiation version
  - Integrate the SENSE model into PyTorch and test

Coil compression for in-plane and slice accelerated data

- Articles:
  - Buehrer M, Pruessmann KP, Boesiger P, Kozerke S. Array compression for MRI with large coil arrays. *Magn Reson Med* (2007). doi: 10.1002/mrm.21237
  - Huang F, Vijayakumar S, Li Y, Hertel S, Duensing GR. A software channel compression technique for faster reconstruction with many channels. *Magn Reson Imaging* (2008). doi: 10.1016/j.mri.2007.04.010
  - Chu A, Noll DC. Coil compression in simultaneous multislice functional MRI with concentric ring slice-GRAPPA and SENSE. *Magn Reson Med* (2015). doi: 10.1002/mrm.26032
- Basic codes: from me.
- Suggested computing options: JupyterHub or Google Colab or your own computer
- Hands-on tasks:
  - test coil compression for fully-sampled data
  - extract in-plane undersampled data for coil compression
  - explore coil compression for slice accelerated acquisition

GRAPPA and slice GRAPPA

- Articles:
  - Griswold M, Jakob PM, Heidemann RM, Nittka M, Jellus V, Wang J, Kiefer B, Haase A. Generalized autocalibrating partially parallel acquisitions (GRAPPA). *Magn Reson Med* (2002). doi: 10.1002/mrm.10171
  - Setsompop K, Gagoski BA, Polimeni JR, Witzel T, Wedeen VJ, Wald LL. Blipped-controlled aliasing in parallel imaging for simultaneous multislice echo planar imaging with reduced g-factor penalty. *Magn Reson Med* (2012). doi: 10.1002/mrm.23097
- Basic codes:
  - GRAPPA from CMRI, slice GRAPPA and simulation from me.
  - MATLAB: GRAPPA from Prof. M Chiew@Oxford
- Suggested computing option: JupyterHub or Google Colab or your own computer
- Hands-on tasks:
  - Implement both GRAPPA and slice GRAPPA in Python
  - Test GRAPPA for 2D undersampling data
  - Test slice GRAPPA + GRAPPA for 3D undersampling data
  - Apply your implementation to in vivo data

Polarity-informed SENSE for EPI image reconstruction & Phase filtering

- Articles:
  - Chen NK, Guidon A, Chang HC, Song AW. A robust multi-shot scan strategy for high-resolution diffusion weighted MRI enabled by multiplexed sensitivity-encoding (MUSE). *NeuroImage* (2013). doi: 10.1016/j.neuroimage.2013.01.038
  - Hoge WS, Polimeni JR. Dual-polarity GRAPPA for simultaneous reconstruction and ghost correction of echo planar imaging data. *Magn Reson Med* (2016). doi: 10.1002/mrm.25839
  - Xie VB, Lyu M, Liu Y, Feng Y, Wu EX. Robust EPI Nyquist ghost removal by incorporating phase error correction with sensitivity encoding (PEC-SENSE). *Magn Reson Med* (2018). doi: 10.1002/mrm.26710
- Basic codes: from me
- Suggested computing option: JupyterHub or Google Colab
- Background: understand **polarity** and **shots** in EPI
- Hands-on tasks:
  - split EPI k-space data into two sets: one for each polarity
  - perform SENSE or GRAPPA recon on each set
  - compare with the recon without splitting
  - explore different filters: Hanning, Gaussian, Bilateral, ...

Semi-supervised Learning for MRI Reconstruction using VORTEX

- Supervisor: Marc Vornehm
- Articles/Data:
  - Desai AD, et al. VORTEX: Physics-Driven Data Augmentations Using Consistency Training for Robust Accelerated MRI Reconstruction. *MIDL* (2022). url: https://openreview.net/pdf?id=WjwUeGh0yMK
  - Sriram A, et al. End-to-End Variational Networks for Accelerated MRI Reconstruction. *MICCAI* (2020). doi: 10.1007/978-3-030-59713-9_7
  - Chen C, et al. OCMR (v1.0)–Open-Access Multi-Coil k-Space Dataset for Cardiovascular Magnetic Resonance Imaging. *arXiv* (2020) 2008.03410. ocmr.info
- Code basis: provided
- Suggested computing options: HPC
- Tasks:
  - Implement VORTEX for a DL reconstruction framework based on the VarNet
  - Evaluate the approach on cardiac cine data
  - Compare reconstruction quality with vs. without leveraging prospectively undersampled data

Dynamic MRI Reconstruction with Time-resolved Coil Profiles

- Supervisor: Marc Vornehm
- Articles:
  - Uecker M, et al. ESPIRiT-an eigenvalue approach to autocalibrating parallel MRI: Where SENSE meets GRAPPA. *MRM* (2014). doi: 10.1002/mrm.24751
  - Ramachandran S, et al. Compact Maps: A Low-Dimensional Approach for High-Dimensional Time-Resolved Coil Sensitivity Map Estimation. *ISMRM* (2021). url: https://index.mirasmart.com/ISMRM2021/PDFfiles/0065.html
- Code basis: provided
- Suggested computing options: HPC
- Tasks:
  - Investigate impact of time-resolved vs. time-averaged coil sensitivity maps on reconstruction quality in cardiac cine MRI
  - Implement and evaluate the “Compact Maps” approach

Low-field DL reconstruction: fastMRI vs M4Raw

- Supervisor: Marc Vornehm
- Articles/Data:
  - Lyu M, et al. M4Raw: A multi-contrast, multi-repetition, multi-channel MRI k-space dataset for low-field MRI research. *Zenodo* (2023). doi: 10.5281/zenodo.7523691
  - Sriram A, et al. End-to-End Variational Networks for Accelerated MRI Reconstruction. *MICCAI* (2020). doi: 10.1007/978-3-030-59713-9_7
  - Knoll F, et al. fastMRI: A Publicly Available Raw k-Space and DICOM Dataset of Knee Images for Accelerated MR Image Reconstruction Using Machine Learning. *Radiol Artif Intell* (2020). doi: 10.1148/ryai.2020190007
- Code basis: https://github.com/facebookresearch/fastMRI/
- Suggested computing options: HPC or Google Collab
- Tasks:
  - Explore low-field dataset
  - Evaluate domain gap between high field (fastMRI) and low field (M4Raw) datasets
  - Compare performance of network trained on fastMRI vs. finetuned on M4Raw vs. trained on M4Raw, when evaluated on M4Raw data

Low-field DL reconstruction: Test-time training

- Supervisor: Marc Vornehm
- Articles/Data:
  - Lyu M, et al. M4Raw: A multi-contrast, multi-repetition, multi-channel MRI k-space dataset for low-field MRI research. *Zenodo* (2023). doi: 10.5281/zenodo.7523691
  - Sriram A, et al. End-to-End Variational Networks for Accelerated MRI Reconstruction. *MICCAI* (2020). doi: 10.1007/978-3-030-59713-9_7
  - Darestani M, et al. Test-Time Training Can Close the Natural Distribution Shift Performance Gap in Deep Learning Based Compressed Sensing. *ICML* (2022). url: https://proceedings.mlr.press/v162/darestani22a.html
- Code basis: https://github.com/facebookresearch/fastMRI/
- Suggested computing options: HPC or Google Collab
- Tasks:
  - Implement test-time training in the fastMRI framework
  - Evaluate performance of test-time training when evaluated on M4Raw data

SPA-LLR

- Articles:
  - Hu Y, Wang X, Tian Q, Yang G, Daniel B, McNab J, hargreaves B. Multi-shot diffusion-weighted MRI reconstruction with magnitude-based spatial-angular locally low-rank regularization (SPA-LLR). *Magn Reson Med* (2020). doi: 10.1002/mrm.28025
  - Chen H, Dai K, Zhong S, et al. High-resolution multi-shot diffusion-weighted MRI combining markerless prospective motion correction and locally low-rank constrained reconstruction. *Magn Reson Med* (2023). doi: 10.1002/mrm.29468

- Basic codes: `https://github.com/zzgroupsjtu/PMCmsDTI`
- Computing option: MATLAB

- Tasks:
  - reproduce the results in the repository
  - Apply this to in vivo 7 T data

Tensor denoising of multidimensional MRI data

- Articles:
  - Olesen JL, Ianus A, Østergaard L, Shemesh N, Jespersen SN. Tensor denoising of multidimensional MRI data. *Magn Reson Med* (2023). doi: 10.1002/mrm.29478
  - Christodoulou AG, Shaw JL, Nguyen C, Yang Q, Xie Y, Wang N, Li D. Magnetic resonance multitasking for motion-resolved quantitative cardiovascular imaging. *Nat Biomed Eng* (2018). doi: 10.1038/s41551-018-0217-y
- Codes: https://github.com/sunenj/MP-PCA-Denoising
- Computing option: MATLAB
- Hands-on tasks:
  - understand higher-order singular value decomposition (**HOSVD**)
  - reproduce results from the repository
  - test the repository on in vivo 7 T data

Train a variational autoencoder (VAE)

- Articles:
  - Kingma DP, Welling M. Auto-encoding variational bayes. *ICLR* (2014). doi: 10.48550/arXiv.1312.6114
- Basic code: from me
- Suggested computing option: HPC
- Tasks:
  - Understand the **reparameterization** trick!
  - Go through the paper with me
  - Apply VAE to a MRI problem

A diffusion model from scratch in Pytorch

- Articles:
  - Ho J, Jain A, Abbeel P. Denoising diffusion probabilistic models. *arxiv* (2020).
- Learning source: "Stop thinking, just do!" – from Sung-Soo Kim's Blog
- Code: Google Colab
- Google Colab or HPC
- Hands-on tasks:
  - Learn and work together with me on the jupyter notebook on Google Colab
  - Understand the architecture of a diffusion model
  - Understand **positional encoding**
  - Try to apply the diffusion model to a MRI problem

Self-supervised learning via data undersampling (SSDU)

- Supervisor: Jinho Kim
- Article:
  - Yaman B, Hosseini SAH, Moeller S, Ellermann J, Uğurbil K, Akçakaya M. Self-supervised learning of physics-guided reconstruction neural networks without fully sampled reference data. *Magn Reson Med* (2020). doi: 10.1002/mrm.28378
- Basic code: https://github.com/byaman14/SSDU
- Suggested computing option: HPC
- Tasks:
  - Understand the main concept of the SSDU architecture: ResNet
  - Reproduce the existing implementation
  - Apply different types of SSDU masks
  - Analyze training and testing results

Train U-Net for 2D image denoising and for image regularization

- Articles:
  - Ronneberger O, Fischer P, Brox T. U-Net: Convolutional Networks for Biomedical Image Segmentation. *CVPR* (2015). doi: 10.48550/arXiv.1505.04597
  - Hammernik K, Klatzer T, Kobler E, Recht MP, Sodickson DK, Pock T, Knoll F. Learning a variational network for reconstruction of accelerated MRI data. *Magn Reson Med* (2018). doi: 10.1002/mrm.26977

- Basic code: `https://github.com/facebookresearch/fastMRI`
- Suggested computing environment: HPC

- Tasks:
  - load fastMRI data and add Gaussian noise
  - train a U-net for image denoising
  - train a U-net for image regularization in iterative reconstruction

3 Homework before our next meeting

Homework

- read the slides and papers again;
- think about which project you want to work on;
- sign up for a project here:
  https://www.studon.fau.de/book5116502.html
  (available period 19.04.2023 – 23.04.2023)
- read the articles (and codes) related to your project;
- **please sign up for the office hours:**
  https://www.studon.fau.de/book5115803.html

Let’s get started ...

- Thank you for your interest and attention!

Let's get started ...

- Thank you for your interest and attention!
- However, attention is not all you need - you also need to accomplish the project.