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Robust ML-based quantitative MRI

Background

Quantitative MRI provides a wide range of different physical and biophysical parameter such as relaxation times (T1, T2) or blood perfusion measurements[1]–[3]. Commonly, quantitative parameters are obtained from reconstructed images. Model-based image reconstruction allows to directly reconstruct quantitative parameters from the raw MR data and enables accurate quantification even from highly undersampled data[4]–[6]. Nevertheless, this approach has so far not found widespread use due to long reconstruction times.

Recently, ML has also been proposed for quantitative MRI. One of the main challenges of ML for quantitative MRI is the lack of ground truth experimental data. In addition to the common confounding factors such as physiological motion, scan duration of quantitative MRI can be further limited by contrast dynamics. Therefore, fully sampled reference data cannot be acquired.

In quantitative MRI, ML is commonly used instead of the data fit to allow for fast parameter estimation[7]–[10]. Although this leads to a speed-up of the parameter estimation, it does not ensure any data consistency with the raw data. This can be problematic if simulated data has to be used for training. Any differences between the signal model used for data simulation and the actual data acquisition can lead to unpredictable results. Several ML approaches have been presented which add a physics-based model to the training to overcome this challenge[11], [12]. Nevertheless, this can be computationally very demanding and hence is often only applied for proof-of-principle examples.

Most ML-based approaches for quantitative MRI only yield a point estimate and without information about the uncertainty or reliability of the obtained parameters. Especially for applications in the heart or liver this is important, because the accuracy of parameter estimation can highly differ between patients due to strongly varying anatomy or uncompensated physiological motion.

Project Aim, Objectives and Program

In this project, we want to develop a robust physics-guided ML approach for MR parameter estimation for clinically relevant 2D and 3D non-Cartesian data acquisition by completing the following tasks:

- Based on our previous work on ML-based image reconstruction for dynamic cardiac cine MRI[13], [14], we will combine MR image reconstruction and parameter estimation as a task-based ML approach with a physics-based data consistency term.
- Explore different approaches for transfer-/refinement-learning in order to overcome the challenge of limited training data by pre-training the network with simulated data.
- Extend the ML approach to allow for the estimation of a measure of uncertainty.

WP1: Tasked-based ML combines two or more networks such that the output of the intermediate networks is the optimal input of the subsequent network[12]. In this case here, we will combine a reconstruction network for 2D non-Cartesian scans with a network for parameter estimation. This joint end-to-end training ensures images which provide the best image features for parameter estimation.

WP2: Initial training will be carried out based on simulated data. Different strategies to adapt this pre-trained model for experimental data will be compared.

WP3: The developed model will be evaluated for 2D cardiac T1 mapping and MRF parameter estimation.

WP4: The approach will be extended from 2D non-Cartesian to a 3D non-Cartesian data acquisition to ensure these large datasets can be handled on a GPU and that training is still carried out in an efficient way.

WP5: In addition to providing quantitative parameters, the developed ML approach will be extended to also yield a measure for uncertainty.

WP6: The uncertainty estimate will be utilised to detect any outliers in the data (e.g. due to incomplete respiratory motion compensation).

The work packages defined above are aimed for a post doc. For a PhD student, the focus will be on WP1, 2, 3 and 5.

Principal investigators

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