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Incorporation of spatial regularization and uncertainty estimations into MR parametric mapping

Background

Many quantitative medical imaging techniques rely on a pixel-by-pixel based evaluation of image series. Typical examples include time-dependent signals as in dynamic contrast enhanced (DCE) MRI and dynamic positron emission tomography (PET), frequency-dependent signals as in Chemical Exchange Saturation Transfer (CEST) MRI or more sophisticated dependencies as in magnetic resonance fingerprinting (MRF). Commonly, signal models are fitted to the pixel-based 1D data series or dictionary matching approaches are used to obtain estimates of the underlying quantitative parameters like relaxation times, metabolite concentrations or rate constants.

Recently, neural networks (NN) have been proposed to replace these time-consuming and/or computationally demanding approaches and speed up the parameter estimation[1–3]. Further, the use of NNs allows to obtain uncertainty estimations indicating how confident the NN is about predictions for a certain parameter in a certain pixel[1,3]. Other approaches incorporate spatial regularization into NNs to make use of the high correlation between neighboring pixels and employ these highly valuable information to improve the parameter estimations[4,5].

PTB-8.13 focuses on the development and evaluation of novel approaches to make quantitative MRI (qMRI) more accurate and reliable. In this context, we successfully implemented and tested different AI-based uncertainty estimation approaches for qMRI as well as different regularization approaches for image reconstruction.

Project Aim, Objectives and Program

The goal of this project is to develop a framework for the creation of synthetic multi-dimensional MRI data and their utilization in AI-based MR parametric mapping approaches that incorporate both, spatial regularization, and uncertainty estimations. This requires the following tasks:

- Continued development of a simulation tool for the generation of synthetic multi-dimensional MRI data for supervised learning
- Investigation of different uncertainty estimation approaches and exploration of the universal applicability of these approaches for various MR parametric mapping methods
- Exploration of different regularization methods for neural networks with uncertainty estimation to take spatial correlations into account

Work Program:

• Extension of self-developed simulation tools for MR and MR-PET data[6,7] to simulate various MR signal series (e.g., T_1, T_2, CEST) and creation of virtual MR phantoms with different (anatomical) geometries. Using the extensive know-how of PTB-8.13 about qMRI[8–10] and motion correction[10,11], the option to incorporate realistic noise and artificial motion (artifacts) shall be provided.

• Initial design and training of different Artificial Neural Networks (ANN) with uncertainty estimation using the generated synthetic data and exploration of the universal applicability of the network for various MR parametric mapping tasks.

• Exploration of various approaches like convolutional neural networks (CNN) to incorporate spatial regularization and investigation of their impact on the performance of the parameter quantification and uncertainty estimation in MR parametric mapping.

• Application of the developed and optimized framework to existing and newly acquired multi-dimensional *in vivo* MRI data and investigation of the transferability to other imaging techniques

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