

# Machine learning for improved diffusion MRI parameter estimation with gradient nonlinearity correction

White matter (WM) degradation is one of the most common lesions causing neurological disorders, where early diagnosis is crucial. Diffusion weighted imaging (DWI) is an imaging technique that measures the movement of water molecules inside the body, allowing the detection of WM associated pathologies more accurately. Microstructural modelling is a strategy that uses mathematical representations to relate the microscopic details of the tissue structures with the DWI signals. Parameter estimation of multiple microstructural components can be challenging and very time consuming, which makes the possibility of real-time mapping almost impossible with traditional optimization methods, such as non-linear Least Squares (NLLS). Additionally, DWI also come with various errors like the so-called gradient nonlinearities (GNL), which need to be corrected for the appropriate interpretation of the maps. Lately, machine learning (ML) networks have proven to be useful for predicting these parameters, getting faster and more accurate results. This project aims to use ML to predict DWI parameter maps of multiple subjects while correcting for GNL.

The methodology involved comparing two ML strategies to the traditional NLLS method to show which one worked better. Moreover, the comparison of correcting and not correcting for GNL was also investigated in each experiment. Four different experiments were carried out using signal and parameter simulations of increasing data complexity. Data simulations are calculations that replicate real-world scenarios to investigate the methodology in a more controlled environment. Experiment 1 used simulations from non-realistic data to test how the methods behaved with simple distributions. Experiment 2 used simulations from one unique real subject to train and test the ML approaches. It was meant to examine if the strategies worked with simulations from real data. Experiment 3 used simulations from four real subjects to train the ML strategies, and utilized data from the same four subjects to test the approaches. It was used as the first attempt to investigate how the ML network worked with multiple datasets at the same time. Lastly, experiment 4 used simulations from three real subjects to train the ML strategies, and took one completely different subject to test the approaches. This last data arrangement was performed to see if the network could predict completely new subjects, which was one of the main goals of the project.

The results demonstrated that ML networks can be used to predict microstructural parameters when training and testing with one unique subject. However, the study also showed that more extensive investigation is needed to obtain optimal results when adding more than one subject to the training. Moreover, the novel GNL correction using ML was properly implemented and included in the methodology, proving to be successful in all the experiments.

In conclusion, the findings proved that ML networks can successfully extract relationships between DWI data, and therefore can help in the near future to obtain faster and more accurate parameter maps from diffusion images. The project also demonstrated that ML networks can be used to correct for GNL, opening the possibility of including such correction in future ML workflows.