**Description for the general public**

This research project focuses on a comprehensive statistical modelling of the noise in parallel magnetic resonance imaging (pMRI). Since the noise component in magnitude pMRI data cannot simply be assumed as additive Gaussian distributed, the advanced and computationally intensive statistical models using non central chi and Rician probability distributions have been proposed. These models take signal-dependency and non-stationarity of the noise into account, and they became the fundamental part of modern adaptive noise-driven pMRI data processing, e.g., noise removal procedures, image segmentation methods using mixture models, or diffusion tensor estimation from diffusion-weighted pMRI data.

In this project, however, the author proposes a new computational framework to deal with non-Gaussian distributed images from pMRI examinations using a variance-stabilizing approach. The variance-stabilizing transformation (VST) changes a signal-dependent noise in non-Gaussian signals into a signal-independent one. To put it differently, the noise component in variance-stabilized pMRI data might be considered as additive Gaussian and Gaussian-dedicated algorithms applied. Consequently, the complicated non central chi or Rician models are no longer necessary as they can be replaced by calculations in variance-stabilized domain of the image.

The statistics-oriented thinking about the noise leads to the main application of the proposed VST framework in context of non-stationary signal-dependent noise estimation schemes intended for pMRI examinations, i.e., GRAPPA (GeneRalized Autocalibrating Partially Parallel Acquisition) and SENSE (SENSitivity Encoding). These image reconstruction algorithms, which combine subsampled images from multiple receiver coils, lead to a spatially variant noise component (i.e., a non-stationary) in final magnitude pMRI image (Fig. 1). The author derives new VSTs for non central chi and Rician distribution, and then employs them in context of non-stationary signal-dependent noise estimation in pMRI. The non-stationary noise estimation techniques presented in the literature so far are based on multiple acquisitions, do not handle low signal-to-noise ratios (SNRs) of the image properly and they may produce granular results as long as they use local neighbourhoods to estimate the noise. Moreover, the methods are usually based on Gaussian assumptions and the empirical correction factors to deal with non central chi/Rician distributed data rather than grounded theory. In this project, however, we propose new noise estimation schemes to automatically retrieve the noise patterns from structural and diffusion-weighted GRAPPA/SENSE pMRI examinations. The proposal needs only a single image (or a single set of images for diffusion imaging) to provide the noise estimate, it does not require any additional technical information from the acquisition process, it is not affected by the granular effect and it is robust for the whole range of SNRs. Last but not least, the *blind noise estimation* procedure, as the final part of the project, involves noise estimation without any *a priori* assumptions about the acquisition process, algorithm used to reconstruct the image or even the statistical distribution of the magnitude data.

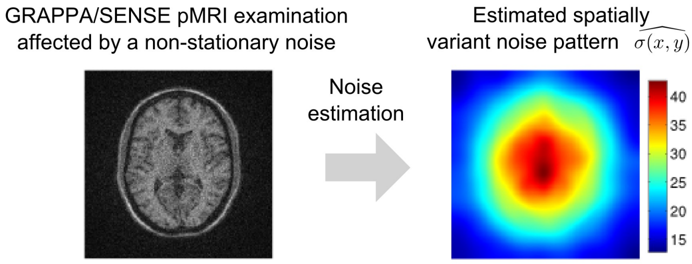


Fig. 1 Non-stationary noise estimation from a single image. The picture on the right presents a spatially variant noise pattern observed in pMRI acquisitions like GRAPPA or SENSE