**Project Title**

*Deep-learned brain MRI super-resolution for improving the accuracy of deep-brain stimulation of Parkinson disease*

**Institution**

Radboud University Medical Center
Functional & Stereotactic Neurosurgery
Nijmegen, The Netherlands

**Supervisors**

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**Background**

Parkinson's disease (PD) is the fastest growing neurodegenerative disease worldwide and its incidence has doubled over the past 25 years. The disease is characterized by its cardinal motor symptoms bradykinesia, rigidity, resting tremor and postural instability, which are related to dopamine deficiency as a consequence of degradation of dopaminergic neurons in the substantia nigra (SN) pars compacta. Although PD can initially be well-treated with medication, motor fluctuations and medication side-effects will develop as the disease progresses. Deep Brain Stimulation (DBS) has become a cornerstone in the treatment of advanced PD. Typically two electrodes (left and right) are stereotactically implanted in deep brain structures, such as the subthalamic nucleus (STN). Stimulation of the STN is known to give a relief of motor symptoms and motor fluctuations, a reduction in anti-parkinsonian medication and it improves quality of life significantly. Traditionally, the DBS-procedure is performed with the patient awake to allow for microelectrode recording (MER) and intra-operative clinical testing as indirect markers for a correct lead position. However, with the advancements in MR imaging, there is a paradigm shift towards asleep MRI-guided and image-verified DBS-surgery.

**About the Research Group**

The Functional and Stereotactic Neurosurgery Research Group is world renowned in MRI-guided and image verified DBS. One of the group's focusses is the application and translation of computational neuroimaging into daily clinical practice to further improve patient outcomes and patient safety in DBS surgery. The lab is uniquely equipped with its own and independent heavy computational facilities.

**Problem**

The STN is a relatively small and double-obliquely orientated diencephalic structure with a total volume around 100 $mm^3$. Anatomically, the STN is located cranial to the SN. Both the STN and the SN contain iron, and can therefore be visualized by using their susceptibility. However, the location, size and orientation of the STN and the lack of contrast to the adjacent SN, make the STN a challenging target to be imaged reliably. The degree of clinical benefit is proven to be dependent on the localization of the DBS-electrode in the MRI-defined STN. Therefore, it is extremely important to visualize the borders of the STN as reliable as possible. Our current clinical sequence has a resolution of 1.1mm isotropic, which means there are approximately 75 voxels in the STN. This relatively low amount of voxels in the STN gives rise to a partial volume effect, especially at the borders of the STN. By increasing the number of voxels in the STN, we can lower the partial volume effects and better delineate the STN. Therefore, there is a need for increasing resolution in brain MRI for DBS in PD.

**Rationale**

Different methods exist to increase MRI resolution, such as interpolation and windowed sinc interpolation. The downside of these methods is that, although they increase resolution, they do not add details (e.g. high frequency data) to the image.

A technique that does add high frequency data to images, is super-resolution. Super-resolution is a deep-learning technique which predicts high-resolution (HR) output based on low-resolution (LR) input. This can be used for natural images, but also has been applied to medical imaging. The difficulty in training a super-resolution model, as for many other deep-learning applications, is the acquisition of proper training data. A common method for obtaining proper training data, is to collect HR images and artificially create the LR by applying some degradation function. This degradation function could be a downsampling in the spatial domain, or a truncation in the frequency domain. The problem with these degradation functions, is that they never truly capture the difference between the LR MRI acquisition and the HR MRI acquisition. The other method for obtaining training data is to obtain both the HR MRI and the LR MRI from the same patient. When using this method, it is paramount that the physical locations are exactly aligned. In practice, this is intricate since patients move and even submillimetre movements can make the dataset faulty.

**Dataset**

Our dataset consists of LR MRI and HR MRI images of 10 Parkinson's patients scanned in one session, see also Figure 1. This dataset is unique in three ways. 1) The dataset has the highest resolution in-vivo Parkinson brains available with voxels of volume 0.5mm$^3$. 2) The patients are scanned under general anaesthesia, which means there are no movement artefacts present. 3) The patients are scanned with a stereotactic frame in place, which makes it possible to align physical locations almost perfectly.

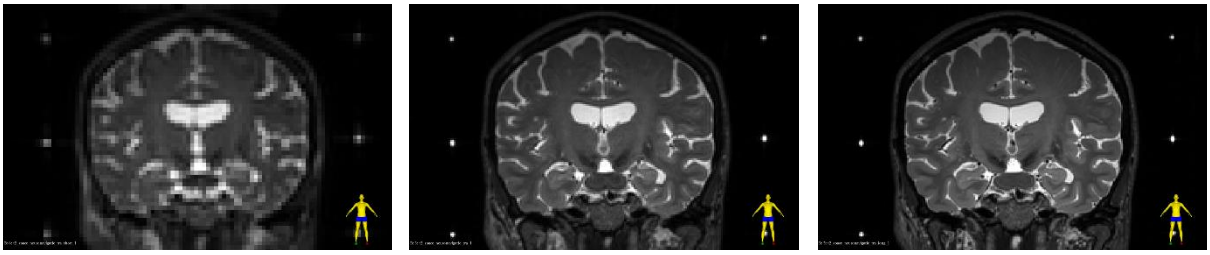

*Figure 1; From left to right: A low resolution, clinical resolution, and high resolution sagittal slice, with respective voxel volumes of 13.824 mm$^3$, 1.331 mm$^3$ and 0.512 mm$^3$*

**Objective**

To determine whether existing degradation functions are sufficient for creating the LR counterparts when compared to LR acquired images for training super-resolution models.

**Study design**

Within this project, different degradation functions will be used to generate the LR images. These functions will be compared to an actual LR acquired MRI. For all combinations of HR and LR images, deep-learned super-resolution models will be trained and compared. These models will preferably be written in Python (MONAI). However, if the student is more comfortable in any other language, this can be discussed.

**Required skills**

- Medical image analysis (courses 8DC00, 8DM20)
- Experimental design (for algorithm validation) (course 8DM20)
- Programming in Python
- Machine learning (course 8DM50)
- Independent working
- Good communication (oral and written)

This project fits best to a BME MSc student (60 ECT)

**Contact**

To learn more about this project, you can contact:

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