Titre : **Échantillonnage actif pour la correction de mouvement en IRM cérébrale accélérée à haute résolution à 7 et 11.7 Tesla**

Mots clés : très hauts champs magnétiques ; neuroimagerie; échantillonnage compressif; apprentissage par renforcement; apprentissage profond; contrôle temps réel.

Title: **Active sampling for motion correction in accelerated high resolution brain imaging at 7 and 11.7 Tesla**

Key words: ultra-high magnetic fields; neuroimaging; compressed sensing; reinforcement learning; deep learning; real time monitoring.

Résumé: L'imagerie par résonance magnétique (IRM) est devenue la modalité de référence pour sonder le cerveau de façon non invasive mais son usage clinique reste contraint à une résolution spatiale millimétrique pour limiter la durée des examens. De nouvelles techniques d'acquisition accélérée en IRM s'appuyant sur la théorie de l'échantillonnage compressif ont été développées à NeuroSpin (technologie SPARKLING), permettant ainsi d'accéder à 7 Tesla à une imagerie 3D pondérée en susceptibilité en 3min à une résolution isotrope de 500µm. A cette échelle, les mouvements du sujet dans l'IRM peuvent avoir un impact délétère sur les images en induisant du flou, une perte de contraste ou des artefacts fantômes. Les stratégies usuelles de compensation de mouvement s'attachent à effectuer une *correction rétrospective*, une fois l'examen terminé, pendant la phase de reconstruction d'images, soit par des techniques variationnelles soit à l'aide de réseaux de neurones entraînés à corriger des mouvements simulés sur des données de référence. Dans cette thèse, nous proposons de nouvelles stratégies de *correction prospective*, i.e. durant l'examen, qui s'appuient à la fois sur la capacité de SPARKLING à détecter les mouvements (rotation et translation) en 3 dimensions, puis à prédire quelles sont les nouvelles données à collecter dans l'espace d'acquisition (espace k) pour compenser celles corrompues par le mouvement détecté. Ces stratégies se veulent non-supervisées car elles procèdent sans données de référence. Elle s'appuient sur des méthodes d'apprentissage par renforcement permettant de construire de nouvelles règles d'échantillonnage actifs. Les méthodes seront d'abord validés in silico puis expérimentalement sur l'IRM à 7Tesla de NeuroSpin sur fantôme à l'aide de mouvement induits contrôlés, et enfin sur volontaires sains sur lesquels nous réaliserons des examens d'imagerie de susceptibilité à une résolution isotrope de 500µm.

Abstract:
Magnetic resonance imaging (MRI) has become the reference modality to probe the brain non-invasively, but its clinical use remains constrained to a millimetric spatial resolution to limit the duration of the examinations. New accelerated MRI acquisition techniques based on the theory of compressive sampling have been developed at NeuroSpin (SPARKLING technology), allowing access to susceptibility-weighted 3D imaging at 7 Tesla in 3 minutes at an isotropic resolution of 500µm. At this scale, the subject's movements in the MRI can have a deleterious impact on the images by inducing blur, loss of contrast or ghosting artifacts. The usual strategies for motion compensation focus on

retrospective correction, once the examination is completed, during the image reconstruction phase, either by variational techniques or by using neural networks trained to correct simulated motions on reference data. In this PhD thesis, we propose new prospective correction strategies, i.e. during the examination, which rely on both the ability of SPARKLING to detect movements (rotation and translation) in 3 dimensions, and then to predict which new data to collect in the acquisition space (k-space) to compensate for those corrupted by the detected movement. These strategies are intended to be unsupervised because they proceed without reference data. They are based on reinforcement learning methods allowing to build new active sampling rules. The methods will first be validated in silico, then experimentally on the 7Tesla MR system at NeuroSpin on phantom using controlled induced motion, and finally on healthy volunteers on whom we will perform susceptibility imaging at 500µm isotropic resolution.

Theme/Disciplines: Imagerie médicale et intelligence artificielle

Field: Sciences du numérique, IRM et neuroimagerie

Context: Subject motion during MRI has been problematic since its introduction as a clinical imaging modality. Bulk motion in particular induces various deleterious effects on MR images such as blurring of sharp contrast, ghosting originating from moving structures or the appearance of undesired strong signals, see Fig. 7[top]. To obtain the correct image for diagnosis, the scan is often repeated, elongating exam duration and increasing patient discomfort. Preventive (i.e. physically-restraining), prospective (adjusting data acquisition) and retrospective (correcting collected data) motion correction methods coexist as no single method can yet be applied to all imaging situations (Zaitsev et al, 2015). Retrospective correction intervenes during image reconstruction to correct the sampling mask involved in the Fourier operator, see Fig. 7[bottom]. In CS acquisitions, retrospective correction is insufficient as parts of the k-space remain void, hence prospective correction must be used. Importantly, non-Cartesian VDS trajectories used in CS are already motion-resistant as they traverse the k-space center across each shot and thus preserve the imaging contrast. Modeling rigid head motion requires 3 rotation and 3 translation parameters. Therefore 3D non-Cartesian MR pulse sequences potentially offer all the degrees of freedom to estimate and compensate arbitrary rigid head motion. Compensation strategies come first from measuring the position and orientation of the head in real time using MR navigators (White et al, 2010; Brown et al, 2010) in the pulse sequence or external tracking devices (Zaitsev et al, 2006) and then from updating the encoding gradients. However, compensation does not adapt the sampling to fill up the void portions of k-space. In this PhD thesis, we will introduce 3D learned motion-resistant trajectories that will optimally complement previously collected data using an appropriate policy.

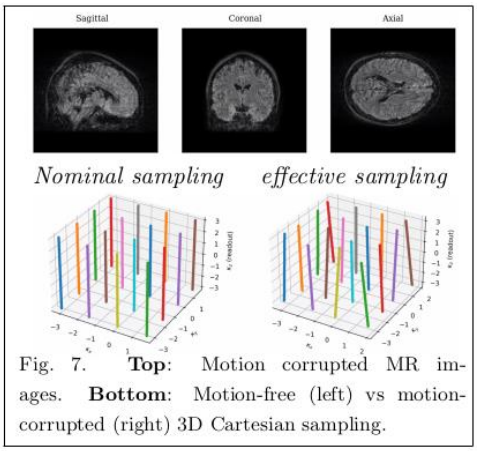

Fig. 7. **Top**: Motion corrupted MR images. **Bottom**: Motion-free (left) vs motion-corrupted (right) 3D Cartesian sampling.

Objectives: The Challenges we tackle in this PhD project aim to transform any 7T MRI scanner into a SMART system by developing **first 1)** methodological contributions related to learning a sampling policy in non-Cartesian MR imaging and **second 2**) by extending them to deal with motion-related artifacts in order to predict how to optimally compensate the acquisition of corrupted MR data.

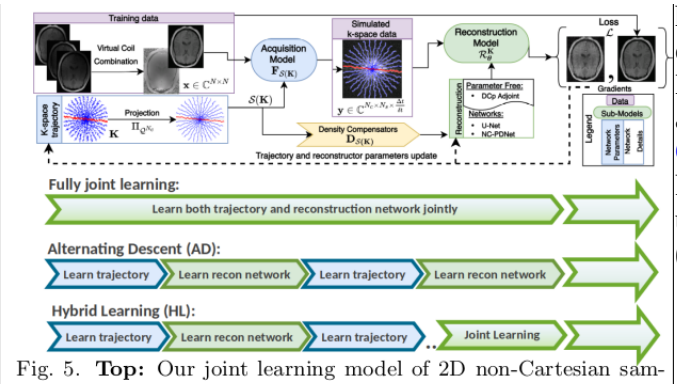

Fig. 5. **Top:** Our joint learning model of 2D non-Cartesian sampling trajectories and image reconstruction CRC22. **Bottom**: HL as a continuum moving from alternating to joint learning.

My team has recently introduced a new framework for accelerated MRI, called hybrid learning (HL) (Chaithya GR et al, 2022), to eventually perform joint learning of k-space sampling trajectories and parameters of an unrolled neural network (e.g. the XPDNet/NC-PDNet (Ramzi et al, 2020, 2022)) for artifact-free and

improved image quality both on the data acquisition and image reconstruction sides (see Fig. 5).

This framework is general enough to be instantiated in multiple MR imaging anatomical contrasts (e.g. T_1 or T_2 weighting). The motivation of this PhD project is to go further by proposing online adaptation of this framework to handle subject's motion during the examination and relevant solutions to perform accurate corrections. This will be validated in vivo prospectively in anatomical and functional MRI at 7T and potentially at 11.7T.

1) Online adaptation of hybrid learning or active sampling

HL provides a fixed sampling pattern of k-space MR data which is agnostic to the sequential ordering. Consequently, the goal here is to provide the best order of sampling shots to maximize image quality in a given scan time. To do so, we plan to explore sampling policies of increasing complexity. First, in a *supervised learning* context, we will consider a simple sampling policy that sequentially picks up the recently proposed SPARKLING trajectories (Chaithya GR et al, 2022b) with minimum mean squared error (MSE) as compared to the reference image. Second, moving to a more realistic unsupervised setting, we will replace the NC-PDNet architecture proposed in (Ramzi et al, 2022) with a probabilistic neural network like a generative adversarial network (GAN), see (Adler and Öktem, 2018; Quan et al, 2018) or a variational autoencoder (VAE) (Cai et al, 2022) that approximates the posterior distribution of the image to be reconstructed. VAE and GAN offer the possibility to perform Monte Carlo sampling and thus output multiple images from which we can quantify variance maps and model uncertainty. As suggested in (Sanchez et al, 2020) we could incrementally pick up the offline-learned trajectory with the largest posterior variance in k-space. To go further and approximate the MSE, a useful statistical technique for risk assessment when the ground truth is unknown, is Stein's Unbiased Risk Estimator (SURE) (Tibshirani and Rosset, 2018). SURE then serves as a proxy for MSE. This idea has been explored in (Edupuganti et al, 2020) for quantification of uncertainty in MR image reconstruction but not as a sampling policy. Here, we plan to investigate this research avenue as it should outperform the GAN-based alternative, simply because the VAE model embeds a data consistency step which is critical to maintain fidelity to the actual measurements. We will test this idea first retrospectively on data already collected at 7T at NeuroSpin and then prospectively in combination with the next task.

2)Adaptation of active sampling to patient-related artifacts

In real MR exams, motion impacts the collected data and may leave empty portions of k-space. The goal therefore is to compensate the missing data by predicting the next k-space trajectory along which to sample. For doing so, here we propose robust-to-motion acquisition strategies that do not significantly increase acquisition times. The work consists of two separate subtasks. First, online motion-detection and estimation is addressed. adetection will be tackled by reconstructing low resolution images from partially collected data in the central region of k-space (navigators). Motion estimation will be automatically performed by minimizing the registration error between the 3-plane (sagittal, coronal and axial) localizer used to adjust the field of view and the images reconstructed in the course of the scan. Then motion parameters will be back-propagated in the pulse sequence to update the magnetic gradient profiles (phase shifts, rotations) and ensure we collect relevant k-space data. The second stage embodies the innovation and the connection with Task 1). It first consists in learning sampling trajectories in the presence of 3D simulated motions for a fixed parameter-free image reconstruction (faster approach than HL). We anticipate that these new trajectories will have an improved robustness to motion and potentially a better k-space coverage. Second, the most promising sampling policies uncovered in the first part of this PhD will be interfaced with these sampling trajectories instead of the original ones. Special attention will be paid to match their acquisition parameters. Validation of these motion-compensation strategies will be performed on 10 healthy volunteers using the same pulse sequences as before, with instruction to the participants to undertake specific movements.

3) Implementation of the SMART system on a 7T scanner (at least)

Real time active sampling during scanning is not available in current MR systems. The goal here is to implement the solutions described in 1) and 2) on a true MR system, notably within 3D pulse sequences. For doing so, we will design a **SMART** workflow on the 7T MAGNETOM scanner at NeuroSpin. The self-monitoring (SM) feature will be implemented directly into the pulses sequences using the IDEA sequence programming environment that work on Siemens-Healthineers (Erlangen, Germany) systems, through a communication loop

established between the readout module and image reconstruction. It will be fed by the analytical and technological (AT) components that will detect, estimate and compensate artifacts online, notably motion, to monitor the ongoing scan without elongating scan time. Specific fast CUDA implementation is targeted for the AT module to be optimally interfaced with the SM one using IDEA. The reporting (R) module will be designed in a way to warn the MR radiographer at the end of the scan about the potential issues (e.g. type of artifacts and grade) that occurred during data acquisition. In the interest of feasibility, we already have access to the source code of the pulse sequences we are targeting on the current SyngoMR VB17 version of the 7T MAGNETOM. In case of success, our intention will be then to transfer these developments to VE12, the software running on the clinical 7T Terra system and on our 11.7T MR system at NeuroSpin.

Results

Obtain new sampling policies for ultra-high resolution accelerated MRI that prospectively correct for the subject's motion in order to yield artifact-free image quality.

Refs:

(Adler and Öktem, 2018) Adler J and Öktem O. arXiv:1811.05910 (2018)
(Brown et al, 2010) Brown T et al. *Neuroimage* 53.1 (2010): 139–145
(Cai et al, 2022) Cai L et al. Proc. of the 2019 *SIAM Intern. Conf. on Data Mining*. (2019): 630–638
(Chaithya GR et al, 2022) Chaithya GR et al. *2022 IEEE 19th ISBI*. IEEE, 2022
(Chaithya GR et al, 2022b) Chaithya GR et al. *IEEE Trans. on Med. Imag.* (2022); 41(8):2105-17
(Edupuganti et al, 2020) Edupuganti V et al. *IEEE Trans. on Med. Imag*. (2020); 40(1): 239–250
(Quan et al, 2018) Quan TM et al. *IEEE Trans. on Med. Imag.* (2018); 37(6):1488–1497
(Ramzi et al, 2020) Ramzi Z et al. Appl. Sci. 2020; 10(5)
(Ramzi et al, 2020b) Ramzi Z et al. NeurIPS 2020 Deep Learning and Inverse Problems WS
(Ramzi et al, 2022) Ramzi Z et al. *IEEE Trans. on Med. Imag.* (2022); 41(7):1625-38
(Sanchez et al, 2020) Sanchez, Th et al. NeurIPS 2020 Deep Learning and Inverse Problems WS
(Tibshirani and Rosset, 2018) Tibshirani R and Rosset S. *JASA*(2018)
(White et al, 2010) WhiteN et al. *Magn. Reson. Med*. 63.1 (2010): 91–105
(Zaitsev et al, 2006) Zaitsev M et al. *Neuroimage* 31.3 (2006):1038–1050
(Zaitsev et al, 2015) Zaitsev M et al. *J Magn. Reson. Imag.* 42.4 (2015): 887–901

Profil et compétences recherchées:

Nous recherchons des candidats qui sont fortement motivés par des défis scientifiques majeurs à l'interface entre l'imagerie médicale (et plus précisément l'IRM) et l'apprentissage profond.
Les candidats doivent posséder une fort niveau en mathématiques appliquées (problèmes inverses, optimisation) et en apprentissage machine/statistique.
Des connaissances en IRM sont les bienvenues et constituent un plus même si elles ne pas indispensables.
Les candidats doivent avoir démontré dans leur parcours un haut niveau de programmation en langage Python, attesté par des projets réalisés (par exemple visibles sur Github) et une expérience en apprentissage profond s'avère indispensable soit sur PyTorch soit sur TensorFlow/Keras.

Profile and skills required:

We seek candidates that are strongly motivated by challenging research topics at the cross-road between medical imaging (notably MRI) and deep learning.
Applicants should have a strong mathematical background with knowledge in numerical optimization and machine/deep learning. Basic knowledge in MRI are welcome and will be graded as a plus but are not mandatory.
In regards to software engineering, proficiency in Python is expected and should be demonstrated through projects for instance visible on Github. A preliminary experience in a deep-learning library such as TensorFlow/Keras or Pytorch is mandatory.