CEA NeuroSpin INRIA Parietal Team

Deep learning for Magnetic Resonance Image Reconstruction in the Multichannel Acquisition Setting

Research theme: Deep learning, MR Image reconstruction, fastMRI data set.

Duration/Salary: 5 to 6 months, starting in April 2020.

Teams: CEA/NeuroSpin and Inria/CEA Parietal team.

Supervisors: Philippe Ciuciu (CEA research director, philippe.ciuciu@cea.fr, +33 1 6908 7785) and Zaccharie Ramzi (PhD student, zaccharie.ramzi@inria.fr).

Localization: The successful candidate will be located at NeuroSpin.

Application: Interested candidates should send their CV and motivation letter to the supervisors.

Research topic: Magnetic resonance imaging (MRI) is one of the most powerful imaging modalities for examining the human brain. High isotropic resolution (UHR: 500 μm in 3D) MRI substantially facilitates the early diagnosis of neurodegenerative diseases. Although ultra-high magnetic field systems ($\geq$ 7 Tesla) enable increased spatial resolution, long scan times (i.e. 8 h for UHR imaging) and motion sensitivity continue to impede the exploitation of UHR-MRI. The recent theory of compressed sensing (CS) has offered a solution for reducing the MRI scan time by undersampling the number of measurements in the Fourier space. This breakthrough has been accomplished by combining three key ingredients: (i) variable density sampling, (ii) image representation using sparse decomposition (e.g., wavelets) and (iii) nonlinear image reconstruction. However, CS image reconstruction is an iterative and time consuming process as it must go from an incomplete Fourier transform to the original image. Hence, the time saved at acquisition lost during reconstruction.

The recent raise of the new deep learning (DL) era [1] has allowed the emergence a new generation of MR image reconstruction algorithms, which speed up reconstruction times while maintaining good image quality. Many convolutional neural networks (CNN) architectures have been proposed in the recent literature [2, 3, 4, 5], some of them perform denoising in the image domain, some in the acquisition space and finally others such as the Primal Dual (PD) [3] net alternate between the two. Recently, we have developed a benchmarking study on the fastMRI open data set [6] that compares several 2D DL networks in the single coil acquisition scenario [7]. These results clearly demonstrate the superiority of PDnet architecture. However, when one is interested in high-resolution imaging, a critical concern is to maintain a high signal-to-noise ratio (SNR). For that purpose, one usually collects the NMR signal using a multi-channel phased array coil. The smaller the channel, the higher the SNR in a localized region, hence the larger the number of localized coils required to cover the whole organ. Typically in neuroimaging, one usually performs acquisition with 32 channels in reception. The immediate consequence is that one collects as many data sets in the Fourier space as the number of channels. Therefore, the above mentioned benchmark needs to be further extended to this context. Preliminary DL works have been done in this direction [8], however they are pretty limited to a single variational network that learns the regularizer.

The topic of the current internship thus consists in generalizing the 2D DL network architectures involved in our first benchmark to take multi-channel data into account. This should actually affect both the primal and dual steps in PDnet. For doing so, we will proceed in three steps steps:

- Develop a version of CascadeNet, KIKInet and PDnet architectures [7] compatible with multi-channel MRI data.
- Test and validate these architectures on the fastMRI data set [6] and identify the most accurate.
- Compare the performances between single-channel and multi-channel image reconstruction.

As regards the first step, we will start with the easier case when one assumes the channel-specific sensitivity maps known in advance and given as input parameters to the networks. Next, if time permits, we will try to generalize the proposed contribution by doing calibrationless image reconstruction [9]. In this framework, we no longer need the sensitivity maps and we may reconstruct as many images as the number of channels.

Implementation and validation. All the software developments will be performed in the TensorFlow 2/Keras architecture, already available in open source[1]. Preliminary tests will be conducted on a workstation before running the training steps on supercomputing facilities (Jean Zay, Irene Joliot Curie) we get access to. The fastMRI data set is sufficiently large (more than 1,000 volumes)

Skills. We look for candidates strongly motivated by challenging research topics in machine learning and medical imaging. The applicant should present a good background in signal processing, machine and deep learning. Basic knowledge in MRI would be a plus. As regards software developments, proficiency in `Python` language is expected and a preliminary experience in TensorFlow/Keras will be desirable.

Key-words. Compressed Sensing, MRI, Deep learning, Parallel imaging, Keras/TensorFlow.

References

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