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Self-Supervised Deep Learning-Based Physics-Driven Image Reconstruction

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Magnetic Resonance Imaging (MRI) is widely regarded as the gold standard for diagnosing, staging, and monitoring treatment responses across a broad range of diseases. Conventional acceleration techniques such as Sensitivity Encoding (SENSE) and Generalized Autocalibrating Partially Parallel Acquisition (GRAPPA) reduce scan times by utilizing high-density receiver coil arrays. However, their acceleration capability is fundamentally limited by issues such as noise amplification, image artifacts, and reduced signal-to-noise ratio (SNR). In neuro-oncology, MRI protocols often take more than 20 minutes, even with two- to three-fold acceleration by GRAPPA or SENSE, which presents significant challenges in clinical practice.

Recently, deep learning has emerged as a powerful tool for image reconstruction, addressing many limitations of traditional methods, including long reconstruction times and residual artifacts at high acceleration levels. Model-based deep learning (MoDL) combines a convolutional neural network with a parallel imaging forward model to effectively denoise and correct undersampled data. This framework has also been extended to many applications such as multi-shot echo planar imaging for diffusion MRI through the MoDL-MUSSELS framework, which improve the image quality from much reduced data.

One major challenge with supervised deep learning approaches is their reliance on large datasets of high-quality ground truth images, which can be particularly difficult to obtain for echo planar imaging acquisitions.

To overcome this limitation, various self-supervised learning methods have been proposed to eliminate the need for external training data. Zero-shot self-supervised learning (ZS-SSL) is one such approach, in which the measured k-space is divided into three separate subsets for training input, loss calculation, and validation. ZS-SSL has shown strong performance in tasks such as denoising, reconstruction, and quantitative mapping, often achieving results that are on par with or better than supervised methods. Building on the success of ZS-SSL, numerous self-supervised methods have been developed for different MRI applications.

In this lecture, I will introduce physics-driven deep learning methods for image reconstruction based on the MoDL framework, and describe how they can be further enhanced using self-supervised learning approaches inspired by ZS-SSL.

Keywords: Fast MRI, Image reconstruction, Self-supervised learning, Physics-constraints