Deep Learning-Assisted Accelerated MRI Reconstruction

EE290 Project Proposal

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1. Research Problem

Magnetic Resonance Imaging (MRI) provides excellent soft tissue contrast but suffers from long acquisition times, affecting clinical throughput and patient comfort[1]. Traditional acceleration methods, including parallel imaging (PI) such as GRAPPA and ESPIRiT, utilize multiple receiver coils to encode spatial information, significantly reducing acquisition times[2]. Furthermore, compressed sensing (CS) methods exploit image sparsity in certain transform domains to reconstruct images from undersampled data[3].

Recently, deep learning (DL) techniques have shown great potential in further accelerating MRI acquisition and improving image reconstruction quality. However, current DL-based methods often fail to fully exploit the inherent relationships between multiple receiver coils and inadequately utilize the comprehensive calibration (reference scan) data routinely acquired alongside undersampled k-space data[4]. This gap in effectively leveraging coil and calibration data constrains achievable acceleration factors and limits reconstruction quality.

2. Rationale

2.1 Challenges in Traditional PI Pipelines

Traditional PI pipelines typically involve coil compression, sensitivity map estimation, coil combination, and phase postprocessing. However, these methods struggle with highly accelerated undersampled data, especially at higher acceleration factors like 2×5, leading to significant image degradation and reconstruction artifacts.[9]

2.2 Improvements with GRAPPA Integration

Previous research has shown that introducing a GRAPPA step between coil compression and sensitivity map estimation can partially alleviate these issues by improving the initial reconstruction quality from highly undersampled k-space data[5].

2.3 Potential of Deep Learning

More recently, DL approaches have demonstrated superior capabilities in repairing undersampled k-space data, surpassing traditional methods.[6] Despite this potential, existing DL methods have yet to fully harness the comprehensive relationship between coils or effectively utilize refscan calibration data. By strategically integrating coil sensitivity maps and calibration data into advanced DL models, there exists a significant opportunity to enhance the accuracy and robustness of reconstructions, particularly in highly accelerated scenarios.

3. Plan

3.1 Dataset and Preprocessing

I will use the publicly available 7T 32-channel brain dataset from Yu et al. (2022)[4], which provides complex-valued fully sampled k-space data. Retrospective undersampling will be applied using AutoSamp[5], a variational information-maximization-based method designed to generate optimal undersampling patterns. Coil compression will be applied where necessary for memory efficiency.

3.2 Coil Sensitivity Map Estimation

Sensitivity maps will be estimated using the ESPIRiT[3] algorithm, implemented via the Berkeley Advanced Reconstruction Toolbox (BART), leveraging the reference scan region of k-space. These maps will be incorporated as explicit inputs to the reconstruction pipeline.

3.3 Deep Learning Reconstruction Framework

I plan to develop a GAN-based deep learning reconstruction model to replace the GRAPPA interpolation step. The design will be inspired by SwinGAN[6] and DGEDD-GAN[7], which incorporate attention-based hierarchical transformers and dual-domain learning strategies for MR image generation. Our model will adapt these mechanisms to better utilize coil sensitivity maps and reconstruct highly undersampled multi-coil k-space data. The network will consist of generator-discriminator pairs optimized for both image-domain and k-space fidelity, and it will support integration with BART-estimated sensitivity information.

3.4 Baseline Comparison with GRAPPA

For comparison, I will implement a baseline pipeline incorporating GRAPPA between coil compression and sensitivity map estimation. This traditional approach will be evaluated under identical acceleration conditions to benchmark the performance of the proposed DL method.

3.5 Evaluation and Metrics

Reconstructions will be evaluated using SSIM, PSNR, and Self-Supervised Feature Distance (SSFD) metrics[8] to assess perceptual and clinical quality. Comparisons will be made against traditional PI methods and baseline deep learning models lacking explicit coil handling.

4. References

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