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Comparative Evaluation of Deep Learning and Compressed Sensing Methods for Dynamic Contrast-Enhanced MRI Reconstruction

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Synopsis

Keywords: AI/ML Image Reconstruction, AI/ML Image Reconstruction

Motivation: Deep Learning (DL) techniques have recently shown considerable promise in addressing MRI reconstruction challenges, frequently surpassing conventional methods. However, their effectiveness for Dynamic Contrast-Enhanced MRI (DCE-MRI) - where precise estimation of pharmacokinetic parameter is critical - remains unclear.

Goal(s): The goal is to compare DL-based reconstruction with established compressed sensing techniques to find out whether the superiority of DL-based reconstructions and their quantitative results still holds true for the more challenging DCE-MRI data.

Approach: We use synthetic and in-vivo DCE-MRI data. Both DL (VarNet) and conventional (TTV-SENSE) methods will be applied, and their performance will be assessed using quantitative metrics.

Impact: DCE-MRI is the most accurate tool for diagnosing breast cancer, but its potential is limited by acquisition techniques that cannot achieve high spatial and temporal resolution simultaneously. This work explores whether DL or conventional compressed sensing can overcome these limitations.

Introduction

Deep Learning (DL) techniques have gained substantial traction for solving MRI reconstruction problems, often outperforming conventional approaches. However, it remains unclear if DL-based reconstruction methods are equally effective for Dynamic Contrast-Enhanced MRI (DCE-MRI), which requires precise pharmacokinetic parameter estimation. Especially, accurate breast cancer diagnosis requires DCE-MRI with high spatial and temporal resolutions (1,2). Existing data acquisition techniques struggle to meet these requirements, presenting an opportunity for innovative reconstruction methods. This study investigates whether DL-based reconstructions can match or exceed conventional compressed sensing (CS) methods in breast DCE-MRI reconstruction. To address potential biases of current DL trends, the research offers fully reproducible experiments with open access to data, code, and tools, ensuring an objective comparison between DL- and CS methods.

Methods

To answer this research question, we use synthetic and in-vivo breast DCE-MRI data. Synthetic data is generated using a Digital Reference Object (DRO) toolkit (3), which utilizes a library of pre-contrast breast MRI images of 53 breast cancer patients and their estimated pharmacokinetic parameters ranges. By selecting pharmacokinetic parameters and anatomical images randomly, we simulate contrast agent uptake across arbitrary temporal resolutions in breast tissue. As in-vivo breast data, we use the publicly available fastMRI breast dataset (4), which contains radial k-space data for DCE-MRI of 300 patients. We follow a supervised and a self-supervised learning approach with the E2E-VarNet (5) as the representative DL model. We adjust this model to process DCE-MRI data by using spatiotemporal 2D+t convolutions. In the supervised approach, the simulated dynamic images undergo k-space undersampling with a radial pattern, after which noise is added to the undersampled k-space data to better approximate realistic acquisition conditions. To avoid inverse crime (6), coil sensitivity maps are estimated directly from the noisy, undersampled k-space data rather than relying on the already existing coil sensitivity maps which come with the DRO toolkit. For coil sensitivity map estimation, we use ESPIRiT (7) in the CS approach and a U-Net architecture in the DL approach. We split these noisy, undersampled k-space data, along with the estimated coil sensitivity maps into three subsets: training (80%), validation (10%), and testing (10%). In the self-supervised approach, we follow the SSDU approach (8) by implementing a spoke-wise split of the radial in-vivo k-space data. By this, we create subsets for data consistency and loss calculation. This spoke-wise split has shown to perform better than point-wise splitting in the NLINV-Net approach (9).Following both training strategies, DL reconstruction results on test samples are compared to CS reconstructions using temporal total variation regularization (10). For evaluation, we use quantitative metrics - PSNR and SSIM - and assess a downstream task by analyzing each reconstructed image with the pharmacokinetic model used during data generation (two-compartment exchange model (TCM) and the tissue-uptake model (TUM)). Reconstructed pharmacokinetic parameters are compared to ground truth values, and t-tests as statistical analyses are conducted to determine if DL methods provide a significant improvement over conventional approaches, or if CS methods retain an advantage in quantitative imaging tasks, like breast cancer diagnosis.

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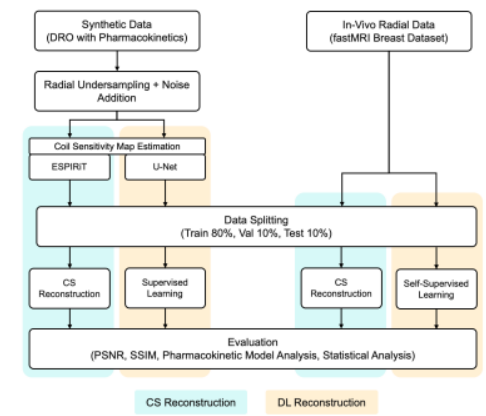
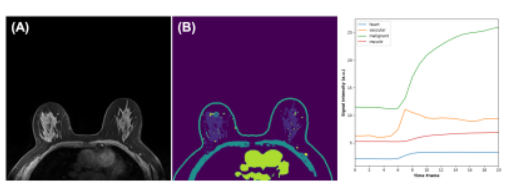
Figures



Methodology overview.



Anatomical breast image (A), tissue segmentation (B) and signal intensity enhancements in different tissues at different time frames.