A Plug-and-Play Approach to Multiparametric Quantitative MRI: Image Reconstruction using Pre-Trained Deep Denoisers

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Introduction

- Magnetic Resonance Fingerprinting (MRF) [1] based Quantitative MRI (QMRI) can acquire multiple Quantitative Maps (QMaps), of T1 and T2 relaxation times, and Proton Density (PD). However, due to aggressive subsampling required for short scan times, the MRF Time-Series of Magnetisation Images (TSMIs), and consequently the Qmaps, contain artefacts.
- Current deep learning methods produce excellent results for artefact removal, but what if the acquisition process is unknown during training time or changes during testing time.
- MRF's compressive acquisition model is $y = Ax + w$, where y = k-space measurements, A = an acquisition process incorporating a subsampling pattern, x = TSMIs, w = noise.
- The ill-posed inverse problem can be formed as the optimisation $\arg\min_x \|y - Ax\|_2^2 + \phi(x)$.
- This optimisation problem can be solved using Plug-and-Play Alternating Direction Method of Multipliers (PnP-ADMM) [2, 3, 4], which is an iterative optimisation method.

Method

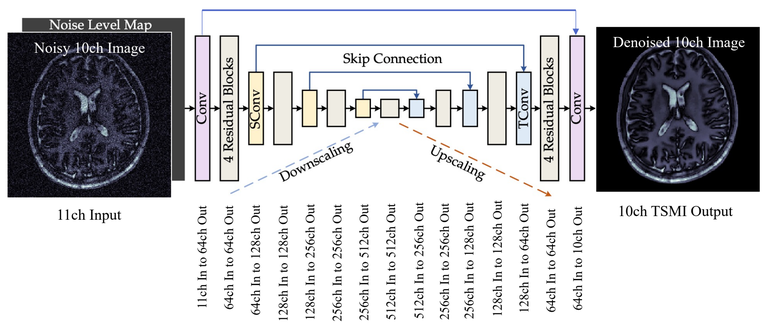
- The TSMI dataset was simulated and real-valued. It was acquired using an accelerated MRF-FISP [5] protocol which was PCA dimension-reduced from 200 timeframes to 10 timeframes [6].
- Spiral and EPI subsampling patterns were tested following [7] and [8], with acceleration = 65.
- We follow the PnP-ADMM iterations as presented by Ahmad et al. [4] below.

$$
\begin{aligned}
x_k &= h\left(v_{k-1} - u_{k-1}\right) \\
v_k &= f\left(x_k + u_{k-1}\right) \\
u_k &= u_{k-1} + \left(x_k - v_k\right)
\end{aligned}
$$

where $h(z) = \arg\min_x \|y - Ax\|_2^2 + \gamma\|x - z\|_2^2$

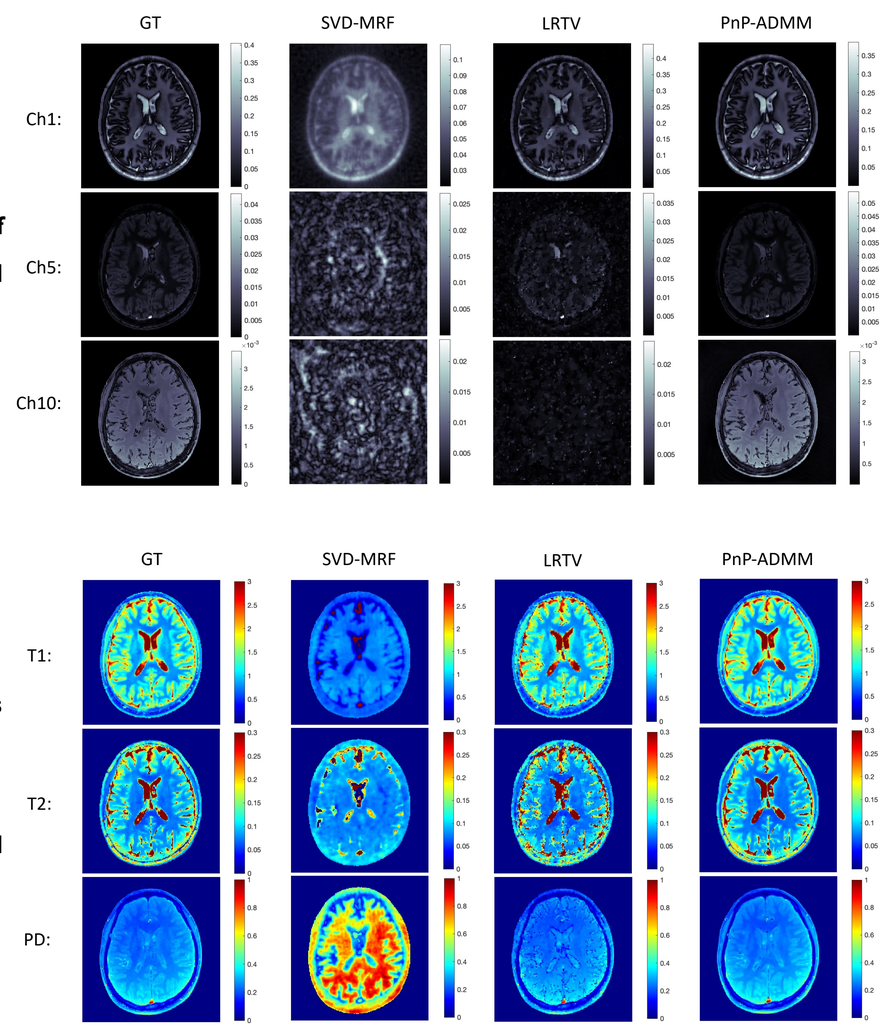
x = reconstructed 10 channel TSMIs
v = spatiotemporal priors
f = plugged in CNN denoiser
u = update variable
γ = convergence parameter, fixed at 0.05

- The PnP-ADMM algorithm was initialised with v_0 = SVD-MRF [6] given by $\hat{x} = A^H y$ and $u_0 = 0$.
- Dictionary matching was then performed on the reconstructed TSMIs to infer QMaps [1].
- For f, we used a DRUNet image-patch denoiser as presented by Zhang et al. below [9].
- We first trained a multi-level denoiser on Gaussian noise to find the optimum denoising value. This was then used to train a single-level denoiser, which was used to generate our results.

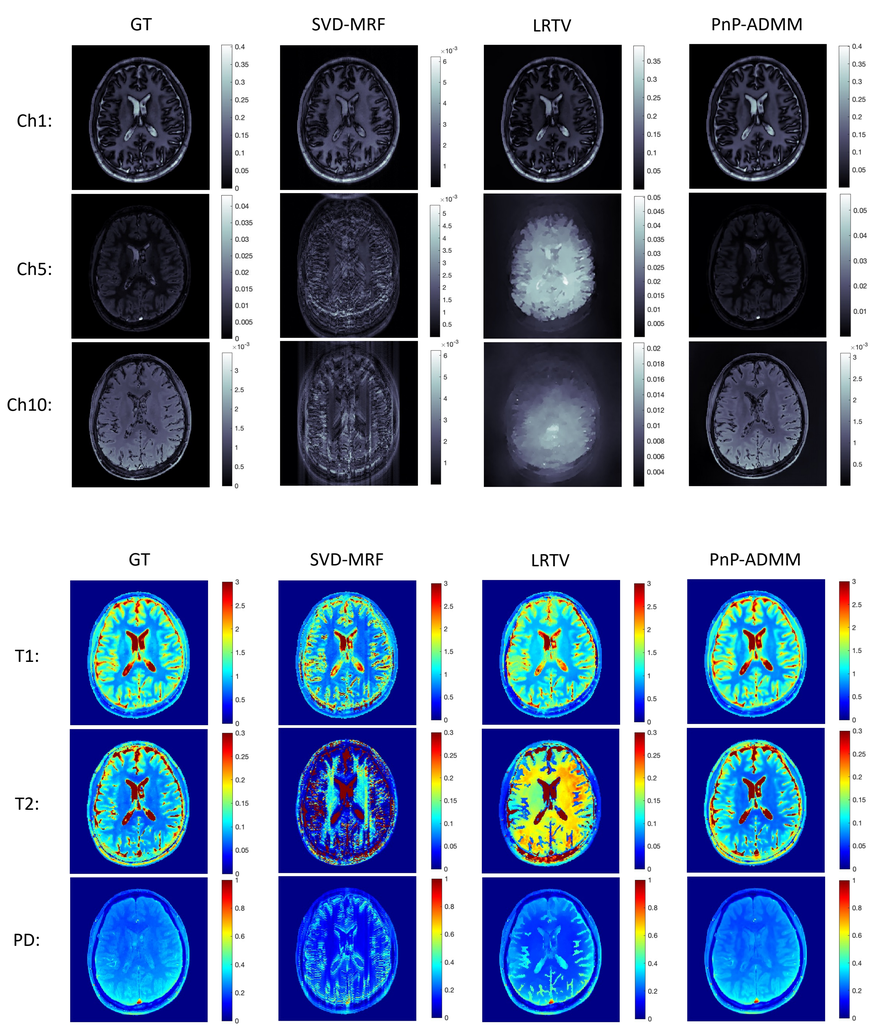


Original image by Zhang et al. [9]. This image was modified for this work and includes additional information.

Results



Reconstructions of Spiral Subsampled TSMIs



Reconstructions of EPI Subsampled TSMIs

Quantitative Maps Inferred from Reconstructed Spiral Subsampled TSMIs

Quantitative Maps Inferred from Reconstructed EPI Subsampled TSMIs

Discussion

- PnP-ADMM with a single pre-trained denoiser can be used to reconstruct TSMIs with artefacts characteristic of two different subsampling patterns (See SVD-MRF TSMI results for artefacts).
- PnP-ADMM outperforms SVD-MRF [6] and LRTV [10] relative to the Ground Truth (GT) for TSMI reconstruction and QMap inference for both subsampling patterns (see paper for more results)

Conclusion

- A proof of concept is presented for a Plug-and-Play ADMM approach using a single pre-trained deep denoiser for Magnetic Resonance Fingerprinting based Quantitative MRI, which is adaptive to different compressed measurement acquisition processes.
- Future work will include a variety of measurement acquisition settings, the use of non-gridded sampling trajectories and prospective complex-valued in-vivo scans.

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Preprint: https://arxiv.org/abs/2202.05269
Software: https://github.com/ketanfatania/QMRI-PnP-Recon-POC