Deep Subspace Reconstruction with Zero-Shot Learning for Multiparametric Quantitative MRI

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Target Audience: Clinicians/researchers interested in deep-learning reconstruction algorithms and quantitative MRI.

Purpose: Low-rank subspace/shuffling methods have been powerful for reconstructing time-resolved MRI data and quantitative MRI (qMRI) since they incorporate subspace bases that are calculated from Bloch equations[1-3]. The 3D-quantification using an interleaved Look-Locker acquisition sequence with T_2 preparation pulse (3D-QALAS) has been developed and used for acquiring high-resolution T_1, T_2, and PD maps from five measurements within each repetition time (TR)[4-6]. However, when fitting the quantitative maps using a Bloch-simulated dictionary, it assumes that each k-space data is acquired instantly at the first echo of the lengthy echo train, thus neglecting T_1 relaxation during the acquisition, which might cause blurring and biases in the reconstructed maps. Thus, in this study, we propose to reconstruct QALAS time-series data using a low-rank subspace method and enable more accurate T_1 and T_2 mapping with reduced blurring compared to conventional QALAS. The overall scheme is presented in **Fig. 1**. Furthermore, we propose a novel zero-shot deep-learning subspace method (***Zero-DeepSub***), which combines a scan-specific deep-learning method[7-9] with a low-rank subspace, to further improve the fidelity of multiparametric qMRI.

Methods: We propose to use a zero-shot self-supervised learning scheme[8] for subspace reconstruction with the deep-learning-based regularization[10] as follows:

$$\min_{\mathbf{x}} \|\mathbf{y} - \mathbf{M}\boldsymbol{\mathcal{F}}\mathbf{C}\boldsymbol{\Phi}\mathbf{x}\|_2^2 + \lambda\|\mathbf{x} - \mathcal{D}(\mathbf{x};\boldsymbol{\theta})\|_2^2,$$

where $\mathbf{y}$ denotes the acquired multi-echo/multi-coil k-space data, $\mathbf{x}$ denotes the desired subspace coefficient images, and $\mathbf{A} = \mathbf{M}\boldsymbol{\mathcal{F}}\mathbf{C}\boldsymbol{\Phi} : \mathbb{C}^{N\times K} \rightarrow \mathbb{C}^{N\times C\times T}$ denotes the forward operator that has a k-space sampling matrix $\mathbf{M}$, Fourier transform $\boldsymbol{\mathcal{F}}$, coil sensitivity map $\mathbf{C}$, and subspace bases $\boldsymbol{\Phi}$, which transforms the subspace coefficients ($\mathbb{C}^{N\times K}$) into multi-echo/multi-coil k-space data ($\mathbb{C}^{N\times C\times T}$). N, K, C, and T denote the matrix size of the image, number of bases, coils, and echoes. $\mathcal{D}$ is the convolutional neural network (CNN)-based denoiser with trainable parameters $\boldsymbol{\theta}$, which can be optimized by minimizing the training loss $\mathcal{L}_{train}$:

$$\min_{\boldsymbol{\theta}} \sum_{p=1}^{P} \mathcal{L}_{train}\left(\mathbf{y}_{\Lambda_p}, \mathbf{A}_{\Lambda_p}\mathcal{H}\left(\mathbf{y}_{\Theta_p}, \mathbf{A}_{\Theta_p}; \boldsymbol{\theta}\right)\right),$$

and optimal parameters $\boldsymbol{\theta}$ can be determined by observing validation loss $\mathcal{L}_{val}$:

$$\mathcal{L}_{val}\left(\mathbf{y}_{\Gamma}, \mathbf{A}_{\Gamma}\mathcal{H}\left(\mathbf{y}_{\Omega\setminus\Gamma}, \mathbf{A}_{\Omega\setminus\Gamma}; \boldsymbol{\theta}_p\right)\right),$$

where $\mathcal{H}\left(\mathbf{y}_{(\cdot)}, \mathbf{A}_{(\cdot)}; \boldsymbol{\theta}_{(\cdot)}\right)$ is the function of the unrolled network using the k-space data $\mathbf{y}_{(\cdot)}$, forward model $\mathbf{A}_{(\cdot)}$, and trainable parameters $\boldsymbol{\theta}_{(\cdot)}$, which outputs the regularized subspace coefficients. Here, a k-space sampling strategy is used, which splits the original k-space sampling mask into three different subsets without overlap (i.e., $\Omega = \Theta \sqcup \Lambda \sqcup \Gamma$) for model training Θ, training loss Λ, and validation loss Γ in each epoch p ($p = 1, \ldots P$). The detailed architecture is presented in **Fig. 2**.

<u>Acquisition:</u> We acquired data from a volunteer using 3D-QALAS sequence on a 3T Prisma scanner with a 32ch head array. The parameters are: FOV=240x240x202mm^3, matrix size=206x206x176, BW=330Hz/pixel, echo-spacing=5.76ms, turbo factor=128, TR=4.5s, TE=2.29ms, acceleration R=2, and scan time=8m 24s. We retrospectively conducted undersampling with R=2x5 for further validation. <u>Experiments:</u> We evaluated our proposed Zero-DeepSub by comparing it with 1) conventional QALAS that fits the T_1 and T_2 maps using original five measurements, 2) subspace reconstruction without regularization, and 3) subspace reconstruction with l_1-wavelet regularization. The dictionary was generated with the following T_1, and T_2 ranges: T_1=[300–5000ms] and T_2=[10–500ms]. We used 4 bases that could generate the simulated signals within 1.25% errors. The sequence diagram of QALAS is presented in **Fig. 1b**. We used BART for estimating coil sensitivity maps and comparison subspace methods[11].

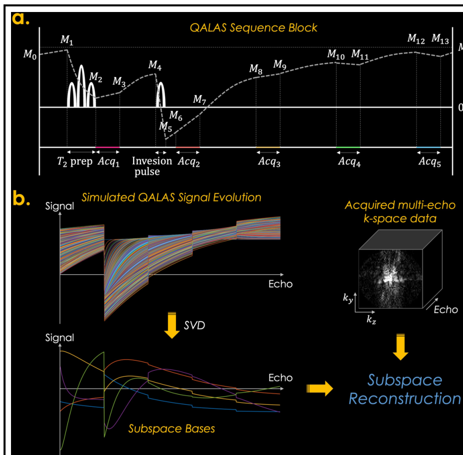

Fig. 1. (a) Sequence diagram of 3D-QALAS and (b) overall scheme of the proposed subspace reconstruction method using subspace bases.

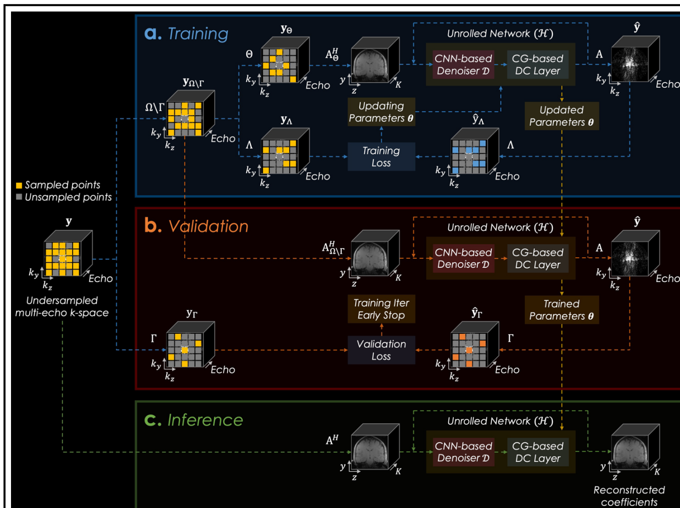

Fig. 2. Detailed architecture of the proposed Zero-DeepSub method.

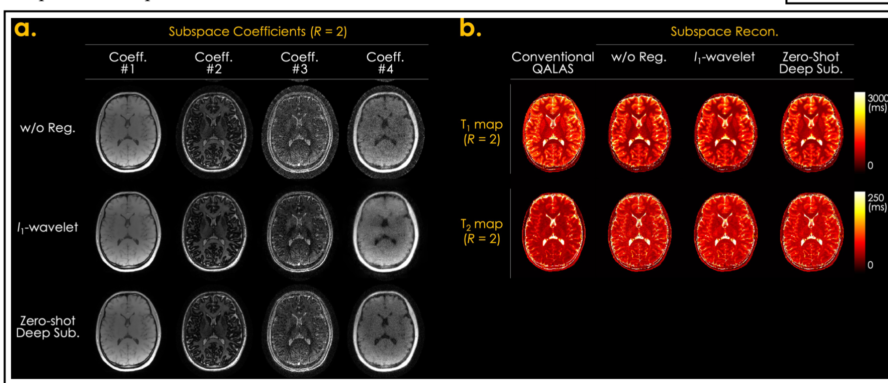

Fig. 3. *In vivo* results of reconstructed (a) subspace coefficients and (b) T_1 and T_2 maps reconstructed using three different subspace reconstruction methods.

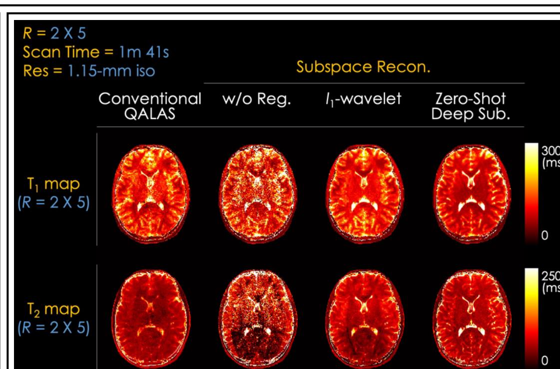

Fig. 4. Retrospectively undersampled data with R=2x5, which requires 1m 41s scan for 1.15mm isotropic resolution.

Results: **Fig. 3** presents in vivo subspace coefficients and T_1 and T_2 maps reconstructed using three different subspace methods. The proposed method shows noise-reduced and sharper coefficients, especially for the third and fourth ones, which result in better T_1 and T_2 maps. **Conclusion:** In this study, we demonstrated that accurate T_1 and T_2 maps with reduced blurring can be obtained using the proposed Zero-DeepSub, which combines scan-specific deep-learning reconstruction with low-rank subspace, from 3D-QALAS measurements.

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