

A Novel Reconstruction Approach Using Model Consistency Condition for Accelerated Quantitative MRI (MOCCA)

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INTRODUCTION: Quantitative MRI (qMRI) parameter mapping using analytical models of MR signal may offer unique information about tissue microenvironment. However, most qMRI methods are often too time-consuming because they require multiple measurements ($N > 1$) along additional (parametric) dimension (i.e., echo time in T2 mapping). Hence, undersampling the k -space data becomes an attractive choice for acceleration of qMRI. A typical qMRI procedure first reconstructs the images from k -space data and then performs pixelwise fit of a model. As both stages are decoupled, the image reconstruction fails to benefit from the knowledge of the signal behaviour in the parametric dimension; as a result, errors accumulated during image reconstruction from incomplete data (e.g., undersampling artifacts, resolution loss, and amplified noise) directly propagate into the parametric maps. One strategy is to utilize the analytical model [1] or its linearized transforms [2] to "glue" images in the parametric dimension during reconstruction. Realization of this strategy, however, faces practical problems including detrimental performance due to inaccurate modeling, partial voluming, imaging imperfections, and motion artifacts. In this work, we put forward a Model Consistency Condition for Accelerated imaging (MOCCA), and use it to derive a novel, practical method for improved reconstruction of parametric image series and quantitative maps from undersampled data.

THEORY: Model Consistency Condition: Let $\bar{\mathbf{f}} = [\mathbf{f}_1 \dots \mathbf{f}_N]^T$ be a vector containing a parametric image series, which dependence on model parameters $\bar{\mathbf{p}}$ (e.g. longitudinal or transverse and relaxation times $T1$, $T2$) is described by an analytical signal model $\bar{\mathbf{f}} = S(\bar{\mathbf{p}})$. Let $\bar{\mathbf{p}} = \tilde{S}(\bar{\mathbf{f}})$ be the inverse operator mapping back from image series to parametric maps. If $\bar{\mathbf{f}}$ is consistent with the signal model, the condition $S(\tilde{S}(\bar{\mathbf{f}})) \equiv \bar{\mathbf{f}}$ should hold. In accelerated imaging, $\bar{\mathbf{f}}$ has to be obtained from an underdetermined matrix equation $\bar{\mathbf{E}}\bar{\mathbf{f}} = \bar{\mathbf{s}}$, where $\bar{\mathbf{E}}$ is the signal encoding matrix [3] and $\bar{\mathbf{s}}$ is the measured k -space data from all datasets. To allow estimation of image series from the incomplete data, we propose to solve the constrained minimization problem, which include both the model consistency and data consistency terms:

$$\min_{\bar{\mathbf{f}}} \|S(\tilde{S}(\bar{\mathbf{f}})) - \bar{\mathbf{f}}\|_2, \text{ subject to } \|\bar{\mathbf{E}}\bar{\mathbf{f}} - \bar{\mathbf{s}}\|_2 < \varepsilon, \quad [1]$$

where $\|\cdot\|_{l/2}$ is l_1/l_2 norm, respectively, and ε is a non-negative parameter chosen according to noise level.

Linearization: The iterative solution to Eq. [1] may be computationally expensive or even infeasible to obtain because of nonlinearity of $S(\bar{\mathbf{p}})$. To circumvent the problem, we represent $\bar{\mathbf{f}}$ as a result of linear mapping from an intermediate space of linear coefficients $\bar{\mathbf{f}} = \mathbf{D}\mathbf{a}$, with inverse operator given by pseudoinverse \mathbf{D}^\dagger . If \mathbf{D} is designed such that $S(\tilde{S}(\bar{\mathbf{f}})) = \mathbf{D}\mathbf{D}^\dagger\bar{\mathbf{f}}$ for a certain range of model parameters $\bar{\mathbf{p}}$, Eq. [1] may be transformed to unconstrained form (\mathbf{I} is the identity matrix):

$$\min_{\mathbf{a}} (\|\bar{\mathbf{E}}\mathbf{D}\mathbf{a} - \bar{\mathbf{s}}\|_2 + \lambda \|\mathbf{D}\mathbf{D}^\dagger - \mathbf{I}\|_F \|\mathbf{a}\|_2), \quad [2]$$

METHODS: Application to T1 and T2 mapping: Recent works have demonstrated that the set of signals in the parametric dimension of many qMRI applications such as $T1$ and $T2$ mapping is highly compressible [1,2]. To demonstrate our new method, we utilized principal component (PC) analysis (PCA)-based compression [2], though the transform may be calculated by alternative compression techniques such as K-SVD [1]. The set of 2500 exponential decay curves was calculated in range of $T1=[0.1, 3]$ s and $T2=[0.1, 2.5]$ s, and only a few ($n_{pc}=2$ or 3) its principal components were used to build \mathbf{D} . MOCCA was compared to method of Ref. 3 (REPCOM), which directly represents image series as a linear combination of the same principal components. **Data:** For $T1$ mapping, inversion recovery data were acquired with a Look-Locker sequence (4) (single channel, 40 inversion times with $\Delta=72$ ms, $TR=3$ s, $FOV 250 \times 250$ mm, 7-mm slice, 224×224 matrix, $TE = 1.9$ ms, readout $TR = 3.8$ msec, flip 10°). For $T2$ mapping, multi-spin-echo data were collected (16 echoes, 8.4 ms echo spacing, $FOV 220 \times 220$ mm, 6-mm slice, 256×256 matrix, $TR=1.5$ s, 8 coils). All data were undersampled with variable density randomized Cartesian trajectory.

RESULTS: Figure 1 illustrates performance of MOCCA on $T1$ data (reduction factor $R=5$). The root-mean-squared (RMS) error in respect to the fully sampled data demonstrated that MOCCA provides more significant image error reduction than REPCOM for each number of PCs. The $T1$ maps (Fig. 1b) shows reduced noise level with MOCCA, which demonstrates improved regularization properties of the new method allowing efficient handling of undersampling and minimized noise amplification. Figure 2 show results of accelerated $T2$ brain mapping. SENSE [3] reconstruction was not able to provide adequate image quality at the large $R=7.2$. The test slice contains many vessels that introduce pulsatile artifacts in the image plane (observed even in fully sampled image). These inconsistent artifacts break down assumption of the exponential T2 decay in the image series, and lead to significant image artifacts in REPCOM reconstruction and corresponding $R2$ maps (white arrow). MOCCA shows much reduced level of artifacts and noise both in image and $R2$ map.

DISCUSSION: We presented a novel method to reconstruct parametric image series sampled below the Nyquist limit, which utilizes prior knowledge of a signal evolution in the parametric dimension. We found that MOCCA is resilient to data errors such as noise and poor representation of signal evolution in the parametric dimension caused by imaging imperfections such as motion artifacts. This may be explained by the fact that it avoids hard constraining to the model specified by just a few several principal components. Instead, it allows utilization of l_1 norm in the formulation for improved robustness. The proposed model consistency condition and associated formulations (Eqs. [1,2]) may be useful for a wider spectrum of problems than $T1/T2$ relaxometry. For example, in dynamic imaging, there is no analytical function describing signal evolution between time frames. Here, linear transform \mathbf{D} may be learned from low-resolution frames using same PCA analysis [5,6].

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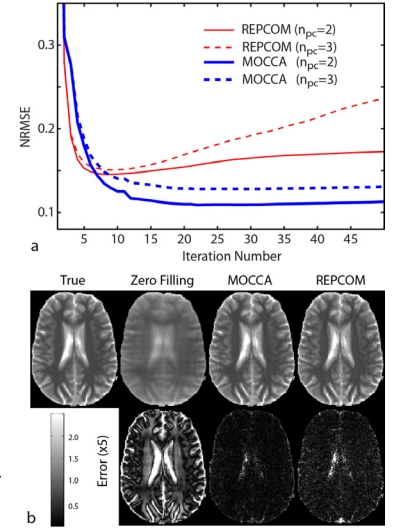


Figure 1: *In vivo* $T1$ mapping results. a) Normalized RMS image error (NRMSE) vs. iteration. b) Images reconstructed by different methods and corresponding errors ($n_{pc}=2$, 45 iterations).

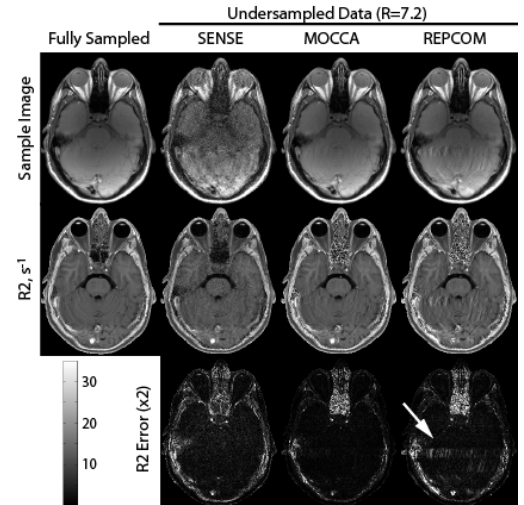


Figure 2: Performance of SENSE, MOCCA, and REPCOM for $R2=1/T2$ mapping in the presence of model-corrupting image artifacts (pulsatile motion). Note amplified pulsatile artifact in the region of interest (brain) in REPCOM.