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MODEL-BASED RECONSTRUCTION FOR MULTI-FIELD T_1 QUANTIFICATION

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Abstract

The recent introduction of in-vivo field cycling MRI systems enables the exploration of new contrast mechanics at different field strength. The present work explores changes in T_1 for main magnetic field from 200 mT down to 2 mT. The problem of inherent low SNR with such low fields is overcome by using a joint regularization approach in space and exploiting shared information between different parameter maps. This strategy enables preservation of fine details while effectively suppressing noise in the reconstructed T_1 maps. Especially in-vivo data showed huge improvements of visual quality compared to reference methods.

Keywords *fast field-cycling, MRI, multi-field T_1 quantification, ultra-low field imaging*

Introduction

Fast field cycling (FFC) MRI is a technique that allows the modulation of the main magnetic field during an imaging experiment and thus gives access to new, unexploited contrast mechanisms [1]. Recent work on MR hardware enabled the construction of the first whole-body FFC system with fields ranging from 50 µT to 200 mT [2]. The ramping of the main magnetic field can be utilized to explore the field dependency of the longitudinal (T_1) and transverse relaxation (T_2) times, also referred to as Nuclear Magnetic Relaxation Dispersion (NMRD) [3]. The controlled change of the main field allows to quantify these relaxation time constants at various field strengths. Especially T_1 shows promising potential for imaging with novel contrast in region affected by a stroke [2]. However, the small fields lead to a decreased SNR [4] which complicates evaluation and quantification of the results.

In the context of quantitative MRI in high field applications, model-based reconstruction was proven to improve SNR in the final parameter maps while simultaneously preserving quantitative accuracy [5,6,7]. Dedicated regularization functionals can exploit spatial similarity between neighboring pixels to stabilize the fitting procedure. Further, features in individual parameter maps, such as tissue boundaries, can be assumed to correlate well throughout all unknown parameter maps. To this end, we propose to incorporate the T_1 quantification process for multi-field FFC imaging in a model-based reconstruction framework [8]. Specifically, the redundancies between T_1 maps from multiple fields will be exploited by means of a total generalized variation (TGV) functional [9] in conjunction with a Frobenius norm. This type of regularization promotes spatially smooth structures but also allows for discontinuities, i.e., edges between tissue, leading to an overall improved image impression and avoids the known stair casing artifacts from total variation. The proposed approach is compared to standard non-linear fitting techniques on simulated numerical data and in-vivo stroke patients.

Theory

The MRI signal for an inversion-recovery FFC sequence [10] can be described by

$$M_z\left(t^{evo}\right)=\left[-\alpha\, M_0 - M_0^E\right] e^{\frac{-t^{evo}}{T_1^E}} + M_0^E, \qquad (1)$$

with $M_z\left(t^{evo}\right)$ being the signal after an evolution time t^{evo}. M_0 refers to the equilibrium magnetization for the detection field and M_0^E refers to the magnetization at the evolution field. α accounts for imperfections of the inversion pulse, incomplete polarization, and field ramping effects [11]. A schematic sequence diagram is given in Fig. 1.

Introducing a proportionality constant C to relate evolution B_0 field and detection field B_0^E with the corresponding magnetization, one ends up with

$$S(u) = \mathcal{F}\left\{ C\left[-\alpha\, B_0\, e^{\frac{-t^{evo}}{T_1^E}} + B_0^E\left(1 - e^{\frac{-t^{evo}}{T_1^E}}\right)\right]\right\}. \qquad (2)$$

This equation is valid for one evolution time and field strength and incorporates the sampling and Fourier transformation operator $\mathcal{F}$. The signal equation resembles the well known behavior of the

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inversion recovery sequence but relaxation takes place at the evolution field B_0^E. The unknowns u consist of C, α^E, and T_1^E and are identified from measurement data d using a regularized non-linear least squares problem given by

$$\min_{u,v} \quad \frac{1}{2}\|S(u)-d\|_2^2 + \gamma(\beta_0\|\nabla u - v\|_{1,2,F} + \beta_1\|\|\mathcal{E}v\|_{1,2,F}) \tag{3}$$

The regularization parameter γ is used to balance between data and a prior knowledge. The terms in bracket after the regularization parameter reflect the TGV Frobenius functional, with v being an auxiliary variable, enabling a weighting between first and higher order derivatives. The ratio of parameters β_0/β_1 balances the optimization costs between first and second derivatives, respectively, and is chosen as $1/2$. The derivatives a realized via finite differences for the gradient ∇ and symmetrized gradient $\mathcal{E}$. The optimization itself is carried using PyQMRI, a recently proposed Python toolbox for quantitative MRI [8]. Regularization parameter γ is chosen based on visual inspection of the results.

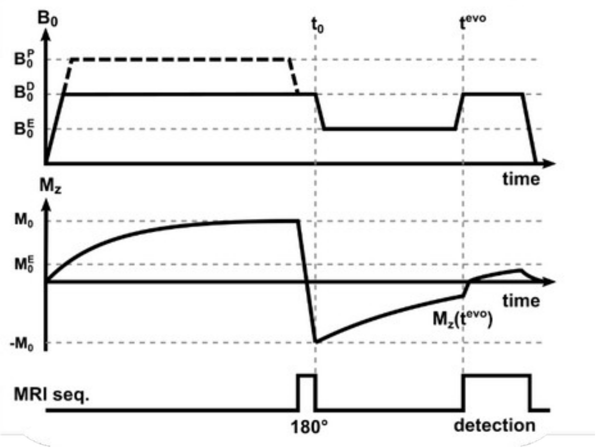

Figure 1: Exemplary sequence diagram for an inversion recovery FFC acquisition. After the inversion pulse, the main magnetic field is ramped to the evolution field where relaxation takes place. Prior to data acquisition the field is ramped back.

Methods

Numerical brain phantoms were simulated using eq. (2) and three simulated field strengths. Simulated evolution times and T_1 values were chosen similar to expected in-vivo values. Image resolution was chosen as 128x128 pixels, similar to the resolution of the acquired stroke images. To account for in-vivo SNR levels, complex Gaussian noise was added to the simulated data to achieve an SNR of 8.3 in white matter and 16.7 in gray matter, directly after inversion. The simulated ground truth is given in the top of Fig. 2.

Acquired stroke images are part of an ongoing study at University of Aberdeen and were acquired using an inversion-recovery spin-echo FFC sequence with a 128x128 matrix and at 3 field strengths. The proposed method is applied to an exemplary data set of this study to show its applicability for in-vivo applications.

The reference methods consisted of non-linear fitting for each field separate with Tikhonov regularization, a field-combined approach with Tikhonov regularization and a field-combined method using H1 regularization, i.e., penalizing the 2-norm of the gradient of the parameter maps [12].

Results

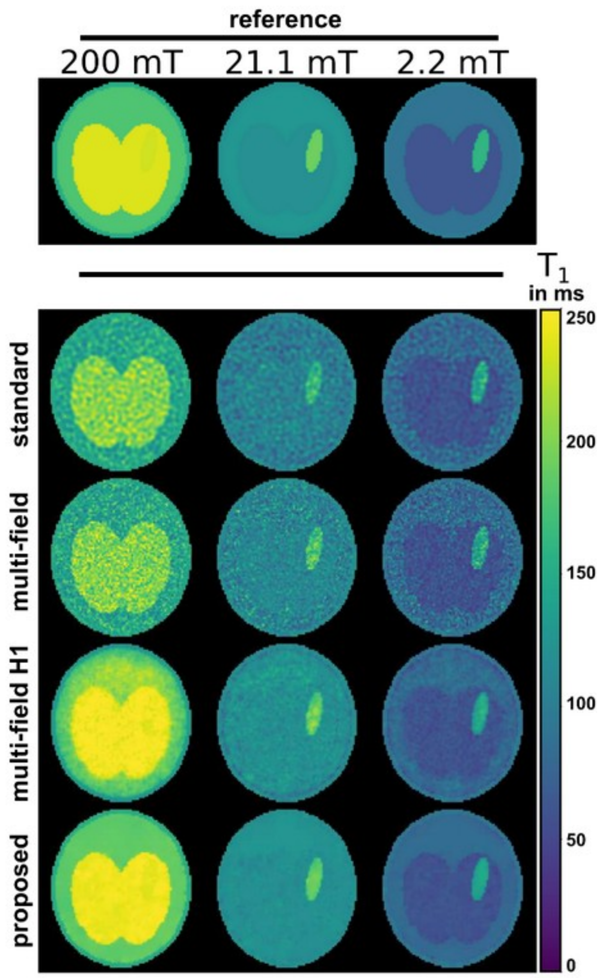

Figure 2: Ground truth phantom T_1 maps and reconstruction results using different fitting algorithms. The proposed method is visually closest to the reference.

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Numerical simulations, given in Fig. 2, show the reduced noise using spatial regularization compared to Tikhonov based methods. Further, edges are best preserved using the proposed approach. Quantitative evaluation (Fig. 3) shows good accordance to the ground truth values. The proposed method shows least residual noise and best relative absolute difference for low field strength. At 200 mT a small bias to the ground truth can be observed.

Application to in-vivo measurements show a similar picture (Fig. 4). Standard methods without spatial regularization show poor SNR which might even hide the lesion. Both spatially regularized approaches are able to recover high quality T1 maps, enabling a clear delineation of the stroke. The proposed approach shows the best suppression of noise while maintaining sharp edges between different tissue.

Discussion

This work demonstrates that spatial regularization in combination with fitting all data in a combined fashion can hugely improve the quality of T_1 maps obtained from multiple fields using FFC imaging techniques. The best results could be achieved using the proposed TGV-Frobenius prior, preserving sharp edges and effectively suppressing noise.

The improved noise suppression could be achieved by leveraging spatial information in combination with redundant information at different field strength. A limitation of such an approach might be the possibility of cross contamination from one map to the other. Although such an effect is theoretically possible, it could not be observed in practice [13, 14]. Still, care should be taken when choosing the regularization parameters as too much regularization might introduce such effects.

As the proposed method is posed as reconstruction problem from k-space, it could further be leveraged to reduce the acquisition time of the measurement, enabling either faster scanning or the acquisition of multiple additional fields in the same scan time.

Especially in-vivo applications benefit from the proposed fitting approach, showing a vast improvement in image quality. This improvement of image quality enables the exploration of the underlying contrast mechanics and is subject of an ongoing study at the University of Aberdeen. The proposed method is freely available at: https://github.com/IMTtugraz/PyQMRI

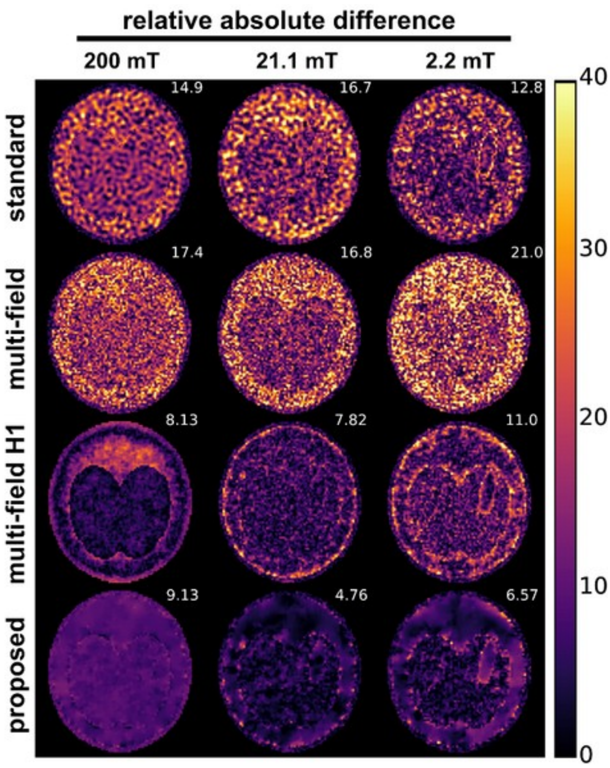

Figure 3: Relative absolute difference to the ground truth for the used fitting algorithms. Mean difference within the object is given in the top right corner of each map. The proposed method shows improved edge preservation and noise suppression, especially for maps at lower field strength.

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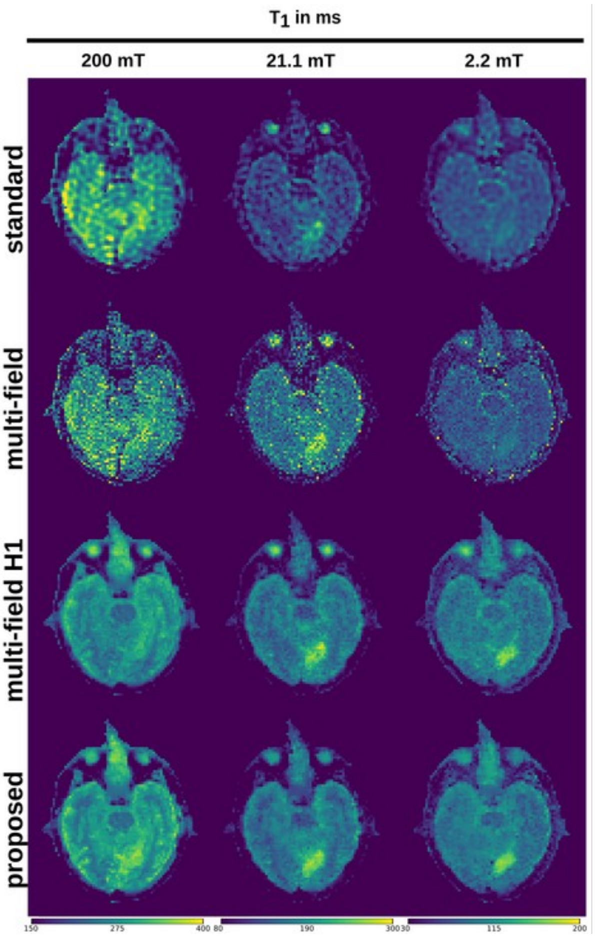

Figure 4: Exemplary in-vivo results for a patient suffering from a stroke. The stroke area can be clearly delineated in T_1 maps from lower fields and in approaches using spatial regularization and all fields combined for fitting. Results using the proposed method show the least residual noise in the T_1 maps.

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