## Iterative Reconstruction for R2 Mapping Based on Radial Fast Spin-Echo MRI

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Introduction: In fast spin-echo (FSE) imaging a train of spin echoes with an increasing T2 weighting is acquired after a preceding RF excitation. When combined with the radial encoding scheme each of the spin echoes coincides with the k-space center and, thus, all spokes carry an equal amount of low spatial frequency information. Therefore, the image contrast represents an average of the varying T2 weightings if a conventional reconstruction method like regridding is used. On the other hand, due to the oversampling of the k-space center, a single radial FSE data set implicitly contains information about the relaxation process. Here, a novel idea is presented to extract this temporal information using a numerical optimization procedure.

Theory: In a previous development for undersampled radial acquisitions with multiple coils [1] reconstruction is achieved by iteratively estimating an image that, on the one hand, is consistent with the data measured by all coils and, on the other hand, complies with prior knowledge about the object. For multi-echo data from a FSE sequence this strategy is not appropriate because it is impossible to find a single image that matches the different contrasts at the same time. Therefore, it is necessary to include the relaxation process into the signal modeling used to compare the estimate to the actual observations. As the T2 relaxation time is a locally varying quantity, this requires that the estimate comprises a spin-density and a relaxation component instead of just an intensity component. The objective of the extended approach, therefore, is to find a spin-density map and a relaxivity map such that snapshots, calculated for each echo time from these maps, best match the measured spokes at these echo times.

Estimation of the maps requires a cost function that quantifies the accuracy of the match to the measured data

$$\Phi(\vec{\rho}, \vec{r}) = \frac{1}{2} \sum_{t} \sum_{c} \left\| \vec{F}(\vec{\rho}, \vec{r}, t, c) - \vec{y}_{t, c} \right\|_{2}^{2} + \sum_{i} \lambda_{i} P_{i}(\vec{\rho}, \vec{r})$$

where  $\rho$  is a vector containing the values of the spin-density map and r is a vector containing values of the relaxivity map. Further,  $v_{re}$  is a vector containing the raw data from channel c of all spokes measured at echo time t, where c runs from 1 to the total number of channels and t runs over all echo times.  $P_i$  are penalty functions, weighted by  $\lambda_i$ , which allow to introduce additional prior knowledge. Finally, F is a vector function which calculates a snapshot from the given spin-density and relaxivity map at echo time t and translates it to k-space using a Fourier transformation and subsequent evaluation of the spokes acquired at time t. It can be seen as the forward operation of the reconstruction problem and comprises a model of the received MRI signal. The jth entry of this vector function, i.e. the jth sample of the synthesized data with k-space position  $k_j$  at echo time t, is given by

$$F_i(\vec{\rho}, \vec{r}, t, c) = \sum \rho(\vec{x}) \cdot e^{-r(\vec{x}) \cdot t} \cdot C_c(\vec{x}) \cdot e^{-i \vec{x} \cdot k_j}$$

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Methods: All experiments were conducted at 2.9 T using a Siemens Magnetom TIM Trio system with a receive-only 12-channel head coil. Images were acquired with a base resolution of 224 pixels covering a FOV of 208 mm (bandwidth 438 Hz/pixel). A train of 16 spin echoes with an echo spacing of 10 ms was recorded during each repetition (section thickness 3 mm). 32 repetitions were performed with a long repetition time of 7000 ms to avoid saturation effects of the CSF, yielding a total number of 512 spokes per slice.

All data processing was done offline using an in-house software package written in C/C++ and in part parallelized using the OpenMP interface. Coil sensitivity profiles were estimated from the data set in a preceding step using the procedure described in [1]. The proposed algorithm was run for a fixed number of 100 iterations which took about a minute per slice on a system equipped with two quad core processors.

Results: Figure 1 shows the reconstruction of a human brain in vivo using direct regridding. The image presents with a mixed contrast due to overlapping of differently weighted spokes in the center of k-space. Figure 2 shows the proton density (PD) and relaxivity map (R2) obtained from the same data set using the proposed method. Both maps are not affected by any streaking artifacts although the k-space data available for the individual echo times is clearly undersampled (32 spokes each).

Conclusion: This work presents a new idea for iterative reconstruction from radial multi-echo data with a main focus on fast spin-echo acquisitions. The method employs a signal model to account for the time dependency of the data and directly estimates a spin-density and relaxivity map from the measured data without calculating intermediate images. Because the approach involves a numerical optimization for finding a solution, it makes optimal use of all data sampled and allows for an efficient T2 quantification from a single radial data set which can be acquired in a relatively short time.

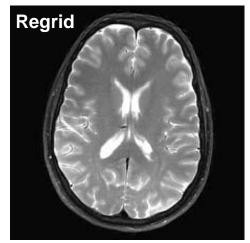


Fig. 1: Regridding reconstruction of the human brain data set (radial FSE sequence).

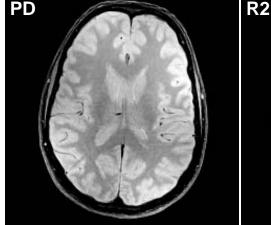


Fig. 2: Proton density (PD) and relaxivity map (R2) obtained from the human brain data set with the proposed iterative method.

1. Block, K.T. et al., MRM, 57(6):1086-1098, 2007.

2. Hager, W. et al, SIAM J Opt;16:170-192,2005.