Fast relaxation parameter mapping from undersampled data

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Introduction: The quantitative assessment of MR parameters like T1, T2, ADC, etc. requires the acquisition of multiple images of the same anatomy, which results in long scan times. However, these data can be described by a model with only a few parameters and in that sense they are highly compressible. Thus, Compressed Sensing (CS) could be applied to accelerate the data acquisition. In this work we introduce a model-based reconstruction from undersampled data, which performs simultaneous image reconstruction and parameter mapping and demonstrate it for the example of T1 mapping.

Theory: Compressed Sensing [1,2] suggests that a signal can be reconstructed from much less data than required by the Nyquist limit, provided that the signal is compressible and incoherent sampling is performed. Different methods to solve the CS problem include convex optimization [3] and greedy algorithms, such as orthogonal matching pursuit (OMP) [4].

Prior knowledge about the signal (like an underlying model) could be used to design a suitable sparsity transform for the given data. This work focuses on T1 mapping. Similar approaches could be used for other applications.

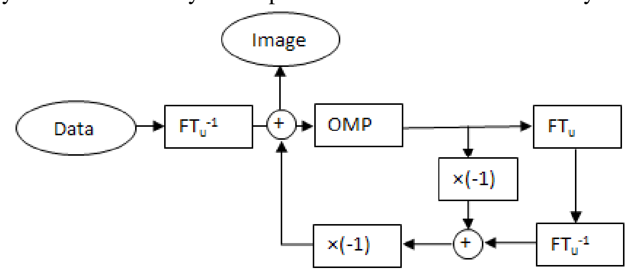
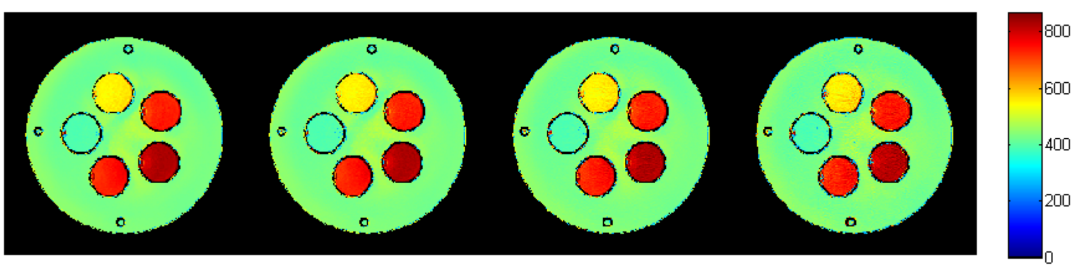


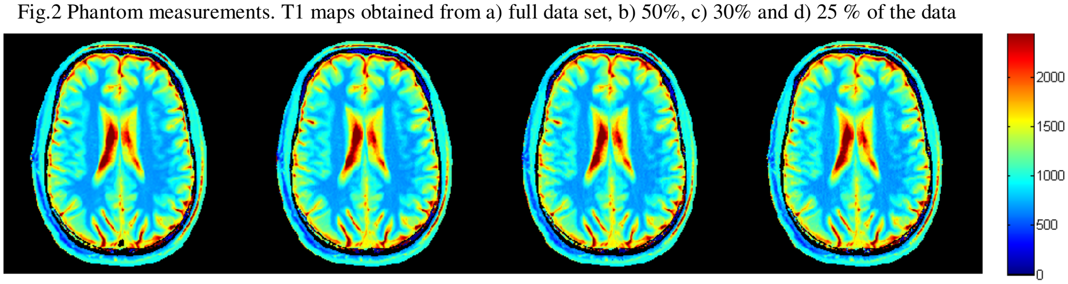
Fig.1 Reconstruction procedure: FT_u denotes an undersampled Fourier transform, ×(-1) a multiplication with -1 and OMP the orthogonal matching pursuit.

In the context of relaxation parameter mapping, the time resolved data are described by an exponential model. We designed an overcomplete dictionary of exponentials with decay constants in the range of the expected T1 values and use OMP to identify the signal representation in that dictionary. Mono- or multi-exponential models could be used by restricting the OMP to a fixed number of coefficients to be recovered. The reconstruction procedure is described in Fig1. The algorithm is initialized with the inverse Fourier transform of the undersampled k-space data, showing aliasing artifacts. Image estimation is performed by recovering a fixed number of coefficients with the OMP. The aliasing, resulting from this estimation is then subtracted from the initial image and the result is passed to the next iteration. The resulting images are already described by an exponential model and the T1 map could be obtained by matching the recovered column of the dictionary to the corresponding time constant.



a) reference b) NRMSE = 0.0675 c) NRMSE = 0.1039 d) NRMSE = 0.1526

Fig.2 Phantom measurements. T1 maps obtained from a) full data set, b) 50%, c) 30% and d) 25 % of the data



a) reference b) NRMSE =0.0131 c) NRMSE = 0.0783 d) NRMSE = 0.0874

Fig.3 In-vivo measurements.T1 maps obtained from a) full data set b) 50%, c) 30% and d) 25 % of the data

Methods: Inversion recovery data were acquired with a Look-Locker sequence [5] using a phantom comprising 6 different T1 compartments (300-800ms). Furthermore, in-vivo experiments were performed in the human brain. All measurements were performed on a 1.5T clinical scanner (Achieva, Philips Healthcare) with the following parameters: TE = 1.9ms, TR = 3.8ms, FOV = 250mm, 224x224 matrix, flip angle 10˚, 40 phases. The data for each phase are randomly undersampled with reduction factors 2, 3.3 and 4 with higher sampling density near the k-space origin. For each reduction factor the proposed algorithm was used to remove the aliasing in the images and to obtain T1 estimates. Finally, Look-Locker correction [6] was applied to obtain the T1 maps. The dictionary used in the reconstruction contained one DC component, 500 exponentials with decay parameters uniformly distributed in the interval of expected T1 values and 100 vectors containing Gaussian noise.

Results: Fig.2 and Fig.3 show examples for the T1 maps obtained from the Nyquist sampled data and the maps from undersampled data for the phantom and in-vivo measurements, respectively. The normalized RMS error with respect to the fully sampled map is given below each map. The number of iterations needed for the reconstruction was between 10 and 30. Higher accuracy of the maps could be obtained by increasing the size of the dictionary at the cost of increased computations per iteration.

Conclusion: The proposed reconstruction method allows simultaneous CS reconstruction and T1 mapping within a small number of iterations. The method allows significant reduction of the required data without compromising the quality of the parameter maps. This could be used to accelerate MR parameter mapping, which is important for applications in which scan time is limited, and further contributes to increasing patient comfort.

References: [1] Candes E et al, IEEE Tran Info Theo 2006 52: 489-509;[2] Donoho D, IEEE Tran Info Theo 2006 52: 1289-1306; [3] Lustig M et al, MRM 2007, 1182-1195; [4] Tropp J et al. IEEE Tran Info Theo 2007 53: 4655-4666; [5] Look DC and Locker DR Rev Sci Instrum 1970 41: 250-251; [6] Deichmann R et al MRM 1999 42: 206-209