Model-based Compressed Sensing reconstruction for MR parameter mapping

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Introduction: Compressed Sensing [1-4] suggests that compressible signals can be reconstructed from far less samples than required by the Nyquist-Shannon sampling theorem. Signal recovery is achieved by Basis Pursuit (BP) [2] or greedy algorithms like Orthogonal Matching Pursuit (OMP) [4]. The latter has weaker performance guarantees, but it is often faster and is thus an attractive alternative to BP. Most commonly, orthonormal bases are applied as a sparsifying transform. However, allowing the signal to be sparse with respect to an overcomplete dictionary adds a lot of flexibility with regard to the choice of the transform and could improve the transform sparsity.

MR parameter mapping measurements of relaxation times T1 and T2, diffusion coefficients, etc. require the acquisition of multiple images of the same anatomy at varying parameters, which is associated with long acquisition times. These data are described by a model with only few parameters, which could be used to design a model-based overcomplete dictionary for CS reconstruction. In this work we demonstrate this approach for the acceleration of T1 mapping data acquisition.

Methods: Inversion recovery brain data (TE = 1.9ms TR = 3.8ms, flip angle 10˚, FOV 250mm, 224x224 matrix, 40 phases) were acquired with a Look-Locker sequence on a 1.5T clinical scanner (Achieva, Philips Healthcare). The data were randomly undersampled with higher sampling density about the k-space origin (reduction factor of 4). The sampling pattern was different for each inversion time TI.

CS reconstruction was implemented based on Orthogonal Matching Pursuit (OMP) [4]. An overcomplete dictionary is a collection of discrete time signal prototypes called atoms. A signal can be represented as a sparse linear combination of these atoms. A dictionary of 100 atoms was trained using the K-SVD algorithm [5], using a set of exponentials with T1 times covering the range of expected values for training. The data were CS reconstructed with the described transform applied in the temporal dimension and T1 maps were obtained from these data applying nonlinear least squares fit and Look-Locker correction [6].

Results: The learned dictionary provides a very good signal approximation. Fig. 1 shows the temporal signal for a single pixel in the original data and its approximation restricted to 2 and 10 atoms from the dictionary. The corresponding images for selected TI are shown in Fig. 2. The approximation error is mostly related to the denoising effect of the approximation. Fig. 3 shows the T1 maps obtained from the full and the undersampled data sets as well as the difference map. The normalized RMS error is 0.0332. The number of iterations needed for the CS reconstruction was 30.

Conclusions: Learning an overcomplete signal representation from an existing model could be used to improve the transform sparsity and the performance of the CS reconstruction. This allows us to achieve a significant reduction of the required data for MR parameter mapping without compromising the quality of the maps, which is important for applications with limited scan time and contributes to increasing patient comfort.

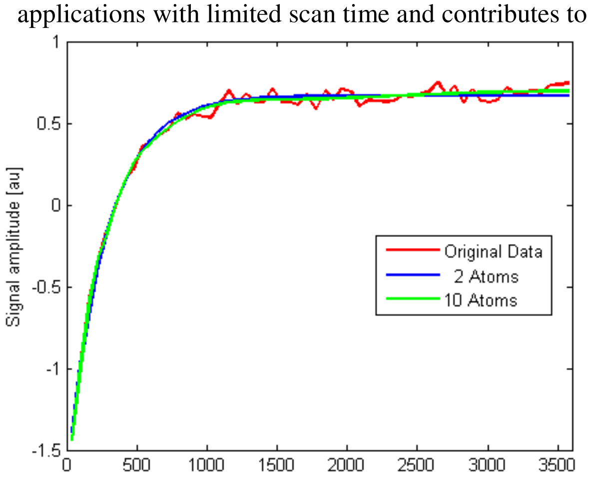
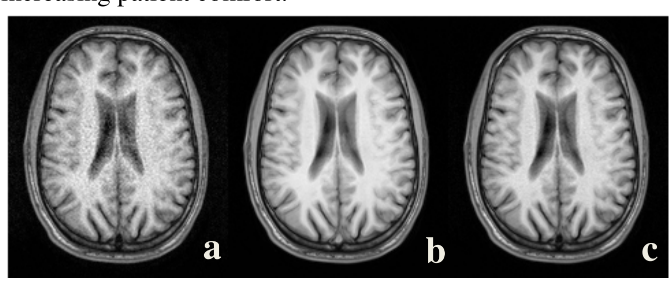


Fig. 1 Signal approximation with learned dictionary. Data given before Look-Locker correction



Original image 2 atoms 10 atoms

Fig.2 Signal approximation with overcomplete dictionary for a selected TI time (1032 ms)

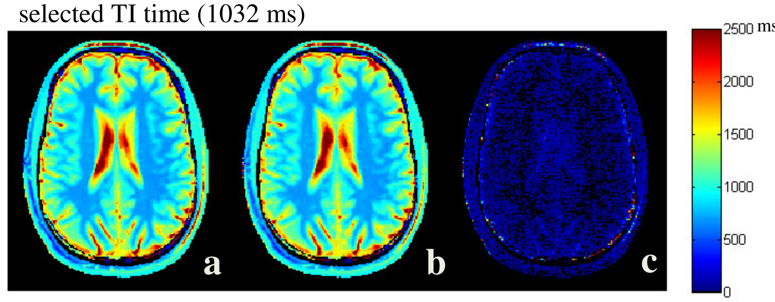


Fig.3 T1 maps obtained from a) 100% of the data b) 25% of the data; c) difference of a) and b) after Look-Locker correction

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, 58: 1182-1195
[4] Tropp J et al, IEEE Tran Info Theo 2007, 53: 4655-4666
[5] Aharon M et al, IEEE Trans Sig Proc 2006, 54: 4311-4322
[6] Look DC et al, Rev Sci Instrum 1970, 41: 250-251