Accelerated MR parameter mapping using compressed sensing with model-based sparsifying transform

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Introduction: The estimation of MR parameters, such as the relaxation times T_1, T_2 and diffusion coefficients D, requires the acquisition of multiple images at different sequence parameters, which is often associated with long acquisition times. These data show a high temporal correlation, which can be described by a model facilitating accelerated image acquisition by data undersampling as shown in [1]. Recently, Compressed Sensing (CS) [2-4] was demonstrated for image reconstruction from incomplete k-space data. In this work we show that prior knowledge about the data can be used to define a model-based sparsity transform for improved CS reconstruction for MR parameter estimation.

Theory: CS relies on two premises: data compressibility and incoherent sampling. In Cartesian sampling, incoherence can be achieved by random undersampling in the phase encoding direction. An important factor for the quality of CS reconstruction is the appropriate choice of a sparsifying transform. Transforms like wavelets or finite differences can be applied to sparsify a large class of signals. In parameter estimation, there is a strong correlation of the data in the temporal dimension described by the underlying model. We use that knowledge to define a sparsifying transform by means of Principal Component Analysis (PCA). This is demonstrated here for T_2 mapping, in which the signal is described by an exponential decay. However, the method is not restricted to exponentials and could be generalized for other models.

The model-based sparsity transform is obtained as follows. Training data S are generated, based on a uniformly distributed set of T_2 times covering a broad range of values. The matrix S contains a set of exponentials corresponding to these T_2 in its columns. The matrix U, taken from the Singular Value Decomposition (SVD) of the correlation matrix $R = SS^H = U\Sigma U^H$ achieves a compact representation of the training set and also of any other exponentially decaying signal with T_2 in the given range. The reconstruction was performed by solving the unconstrained optimization problem:

$$\min \|F_u x - y\|_2^2 + \lambda_1 \|U^H x\|_1$$

Here, x is the image, y is the measured data, F_u is the undersampled Fourier operator, and λ_1 is a regularization parameter.

Methods: The proposed approach was demonstrated for multi-echo spin-echo measurements for T_2 mapping in the brain (32 echoes, 5ms echo spacing, FOV 250mm, 6mm slice thickness, 256×256 matrix, TR = 1000ms), measured on 1.5T clinical scanner (Achieva, Philips Healthcare). For each echo, different sets of 64 phase encodings (reduction factor of 4) were randomly chosen with higher sampling density near the k-space origin. The data were CS reconstructed with the PCA-based operator as a sparsifying transform in the temporal dimension, using nonlinear conjugate gradient. The training set used to determine U contained 1000 exponentials with T_2 values uniformly distributed in the range 10-300ms. CS reconstruction with wavelets (Daubechies 4) and total variation (TV) constraint [4] was performed on the same data for reference.

Results: Fig. 1 shows the images for several echo times obtained with CS reconstruction using wavelets and TV, and CS with the model-based PCA transform, obtained after 150 iterations. The model-based approach achieves better reconstruction with a normalized RMS error of 0.0529 compared to the wavelet-TV CS with an error of 0.3764. Fig. 2 shows the original and CS reconstructed signal for several pixels with different T_2 for the 32 echoes. The model-based reconstruction reduces the aliasing and results in a signal very close to the original for all T2 times. Fig. 3 shows the T_2 map, obtained from the model-based CS reconstruction, which is very similar to the full dataset map.

Conclusions: We have demonstrated a Compressed Sensing reconstruction with a new, model-based sparsifying transform that exploits the underlying model in MRI parameter estimation to efficiently reconstruct an image series for T2 mapping from reduced number of phase encoding lines. The model-based PCA sparsity transform allows improved reconstruction from reduced amount of data compared to the wavelet-TV CS reconstruction. The ability to reduce scan time could be of interest for a number of applications.

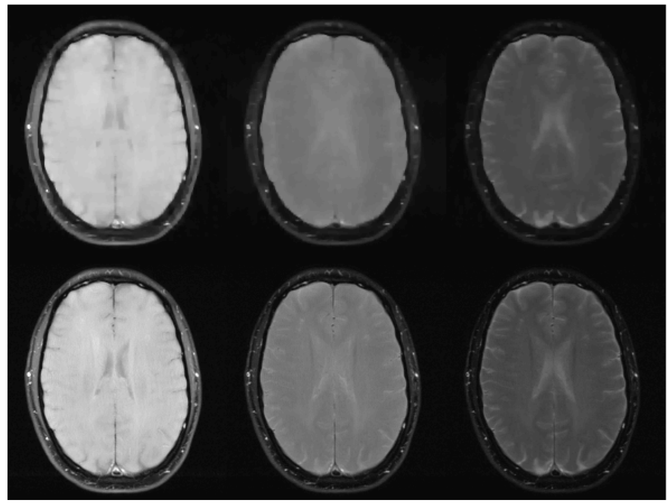

Fig. 1. Reconstruction from undersampled data with reduction factor of 4. Top: CS reconstruction with wavelets and TV constraint Bottom: CS reconstruction with model-based PCA transform

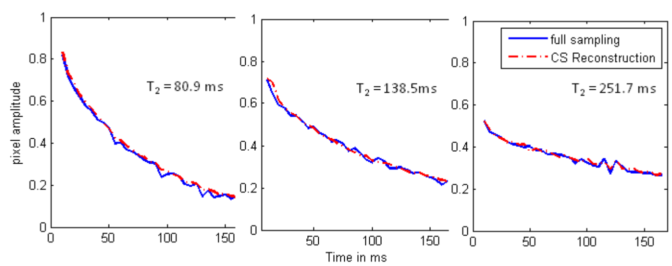

Fig. 2. Temporal signal evolution for different T_2. CS reconstruction of undersampled data with reduction factor 4 leads to very good approximation of the fully sampled data

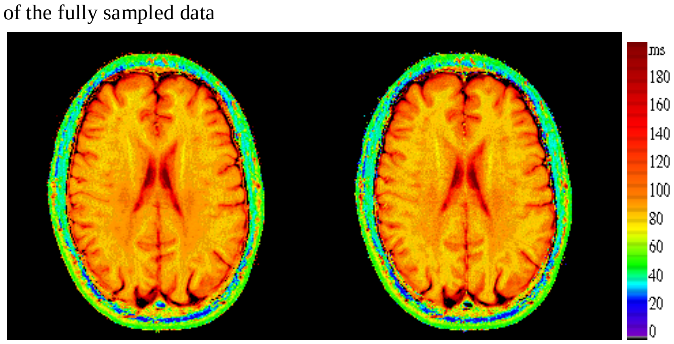

Fig. 3. T2 maps. Left is shown the map obtained from the CS reconstruction with acceleration factor 4, right is the map from the full dataset. The normalized RMS error is 0.0539

References: [1] Senegas J et al Proc ISMRM 2008 p.1394; [2] Candes E et al, IEEE Tran Info Theo 2006, 52: 489-509; [3] Donoho D, IEEE Tran Info Theo 2006, 52: 1289-1306; [4] Lustig M et al, MRM 2007, 58: 1182-1195