CS-Dixon: Compressed Sensing for Water-Fat Dixon Reconstruction

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Introduction: Water-fat separation is of interest in several MRI applications including fat suppression and fat quantification. Chemical shift imaging allows robust water-fat separation [1, 2], however the acquisition of multiple images results in prolonged scan time. Accelerated water-fat separation using compressed sensing (CS) was partly addressed in [3] by considering the separation as a spectroscopic problem and exploiting the spectral sparsity in the reconstruction. However, this approach requires data acquisition at multiple echo times (significantly more than 3), prolonging the scan time and limiting the effective acceleration factor. In this work we consider the commonly used three point Dixon approach for water-fat separation. Dixon reconstruction already assumes signal sparsity in the spectral dimension by modeling the signal by a two point spectrum at fixed frequencies. An integrated CS-Dixon algorithm is proposed, which applies a sparsity constraint on the water and fat images and jointly estimates water, fat and field map images. The method allows scan time reduction of above 3 in 3D MRI, fully compensating for the additional time necessary to acquire the chemical shift encoded data.

Theory: Compressed sensing [4, 5, 6] is a promising method for scan time reduction by exploiting signal sparsity. Incoherent sampling, signal sparsity and a nonlinear, sparsity promoting reconstruction are the key ingredients of CS. In chemical shift imaging additional subsampling in the chemical shift dimension could be employed resulting in undersampling a higher dimensional k-ω space, and thus, improved incoherence. Applying a sparsity constraint in the water and fat images effectively exploits that additional subsampling dimension. It can also be assumed that water and fat images are usually sparser than combined images.

In chemical shift imaging data are acquired at several different echo times. Denoting the k-space data acquired at echo time t_l with y_l, the measurement vector can be written as $\mathbf{y} = [y_1, y_2, \ldots y_L]$ with typically L = 3. The signal model is given by: $y_l = \mathcal{F}\{(\rho_w + \rho_f e^{2\pi i \Delta f t_l})e^{2\pi i \Delta\varphi t_l}\}$, where $\mathcal{F}$ is the Fourier transform, ρ_w and ρ_f are the complex water and fat images, Δf is the chemical shift and $\Delta\varphi$ is the field map. The goal is to find the vector $\mathbf{x} = [\rho_w, \rho_f, \Delta\varphi]$ from the undersampled measurement data according to the model $\mathbf{y} = f(\mathbf{x})$. The proposed method solves the problem jointly for all voxels, simultaneously updating the water, fat and field map estimates. The CS-Dixon reconstruction problem can be formulated as:

$$\underset{\mathbf{x}}{\operatorname{argmin}} \left\|f(\mathbf{x}) - \mathbf{y}\right\|_2^2 + \lambda_1\left\|\Psi\mathbf{x}\right\|_1 + \lambda_2\left\|\Phi\mathbf{x}\right\|_2^2 \qquad (1),$$

where the first term accounts for data fidelity, the second term applies a sparsity constraint on the water and fat images and the last is a smoothness constraint on the field map. Different transforms can be used for water and fat (e.g. wavelets for water and TV for fat) to account for the different structure in the images. Solving the problem jointly for all voxels and applying a smoothness constraint on the field map is advantageous in reducing the ambiguity between water and fat present in pixel-wise reconstruction methods [7, 8]. However, Eq.(1) still poses a high dimensional, non-linear, non-convex optimization problem, and a good initialization of $\Delta\varphi$ is important. A low resolution field map obtained from the fully sampled central part of k-space is used here to initialize the algorithm. The map is obtained by analytically finding all possible solutions for $\Delta\varphi$ within one period and choosing the value for each pixel under smoothness constraint from the set of possible field map values within a given range (several periods). The optimization problem (1) is iteratively solved using a regularized Gauss-Newton method.

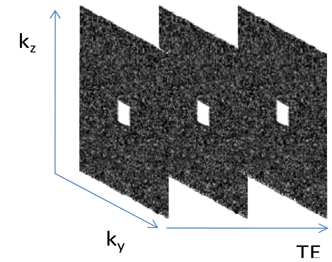

Fig. 1 3D CS-Dixon k-space sampling pattern. *Phase encoding lines are chosen at random in the* $\{\boldsymbol{k_y}, \boldsymbol{k_z}, \boldsymbol{\omega}\}$ *domain. A small portion around the k-space origin is fully sampled.*

Methods: 3D multi gradient echo measurements [9] were performed in the abdomen with the following parameters: TE1 = 1.8ms ΔTE = 1.66ms, TR = 6.9ms, FOV = 400x320x216mm, 240x192x54 matrix, flip angle 10° on a 1.5T clinical scanner (Philips Healthcare, Best, The Netherlands). The data were retrospectively undersampled according to the sampling scheme described in Fig.1. Randomized multi-echo acquisition can be performed as described in [10]. The 3D CS-Dixon reconstruction algorithm was implemented in C. 3D images were reconstructed using finite differences as a sparsifying transform and second order finite differences as a smoothness constraint.

Results: Fig.2 shows a slice from the 3D water and fat images obtained with Nyquist sampling and with an undersampling factor of 3. Excellent image quality without any swaps is obtained with a reduction factor of 3. Good image quality can also be achieved with higher reduction factors; however, a loss of contrast and eventually residual aliasing become visible as the acceleration is increased.

Conclusion: We have shown the feasibility of the proposed integrated CS-Dixon reconstruction. CS helps to regain the extra time spent on chemical shift encoding facilitating water-fat separation just for free in total scan time equal to the time of a single scan. Further acceleration could be achieved in combination with parallel imaging. The method can be further improved employing a more efficient algorithm for solving the nonlinear problem in (1) and parallel computing.

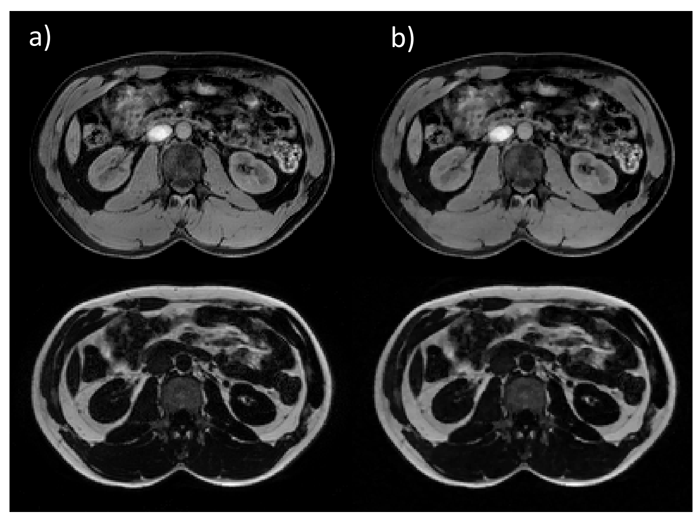

Fig. 2 CS-Dixon reconstruction. *Water / fat images reconstructed from fully sampled data a) and with reduction factor of 3 b)*

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