Dictionary Learning for Compressive T2 Mapping with Non-Cartesian Trajectories and Parallel Imaging

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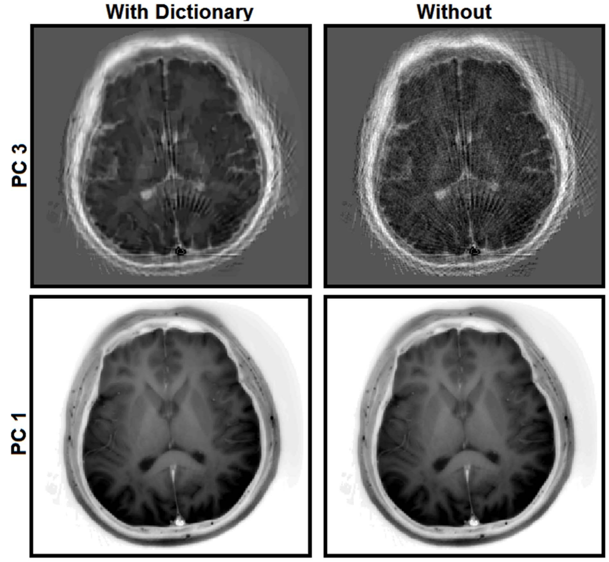
Introduction: Parameter estimation in MRI is a valuable quantitative tool for examination of soft tissue. However, long acquisition times needed to produce parameter maps using conventional methods limit their clinical utility. Recently, techniques for accelerated parameter mapping based on compressed sensing (CS) have been developed[1,2,3]. The REPCOM method[3] combines radial Fast Spin Echo[4] (radFSE) acquisition and CS reconstruction to produce accurate T2 maps from highly undersampled data. REPCOM enforces temporal sparsity through principal components (PCs) of T2 decays across the echoes and enforces spatial sparsity through Total Variation (TV) and wavelet sparsity constraints on the principal component coefficient maps. Recently, it was also shown that using linear decomposition of signals with a few atoms of a learned overcomplete dictionary (instead of a predefined orthonormal basis such as wavelets) can yield state-of-the-art results in many image processing tasks. These dictionaries do not impose that the basis vectors be orthogonal and allow increased flexibility to adapt the representation to the data. Such learned dictionaries have been applied to CS MRI[5,6,7]. Ravishankar and Bresler[6] demonstrated dictionary learning in many MRI problems, but did not consider multi-channel data. Caballero et al.[7] used dictionary learning to reconstruct images from multi-coil Cartesian cine data. In this work, we propose a CS method that uses learned dictionaries to reconstruct images from multi-channel, non-Cartesian MRI data. The proposed method is used to obtain T2 maps from highly undersampled radFSE data and compares favorably to the state-of-the art parameter mapping methods such as REPCOM.

Principal component coefficient maps Fig. 1



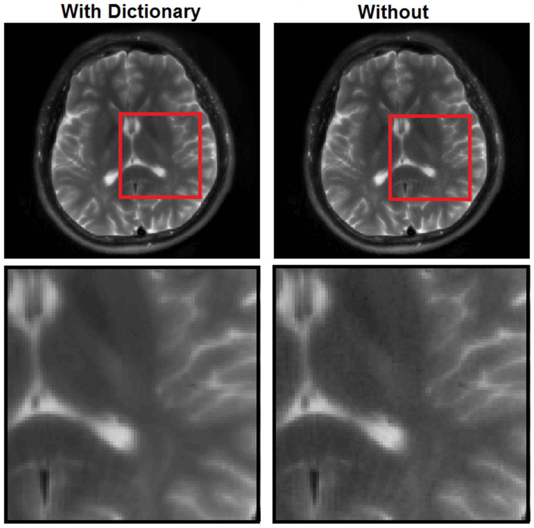
Methods: The proposed reconstruction method solves the problem

$$\widehat{M} = \underset{M,D,A}{\operatorname{argmin}} \sum_{j=1}^{ETL} \left\| F_j\left(S\left(MB_j^T\right)\right) - K_j \right\|_2^2 + \lambda_1 TV(M) + \lambda_2 \|W(M)\|_1$$
$$\text{s.t.} \ \ \|P(M) - DA\|_F < \sigma \ \text{ and } \ \|a_i\|_0 \le T_0.$$

In this equation, M denotes the PC coefficient maps, B_j denotes the precomputed truncated PC basis for T2 decay, S denotes the coil sensitivities, K_j denotes the k-space data at echo j, F_j denotes the NUFFT operator[8] for k-space points at echo j, and TV and W denote the total variation and wavelet operators, respectively. Without the additional constraints shown in the second line of the equation, this equation corresponds to the REPCOM algorithm. In the second line, the additional constraints, P denotes an operator that reformats M into patches, D denotes the dictionary, and A is the matrix of sparse representations of the patches in the dictionary D. Each representation a_i satisfies a preset sparsity level T_0, and the dictionary representation error is kept below a threshold σ. The entire problem is solved iteratively using a nonlinear conjugate gradient algorithm. At each iteration, the dictionary is updated using K-SVD[9] and the coefficients a_i are found by orthogonal matching pursuit. Then the PC coefficient maps are updated in terms of the dictionary. Once the optimal PC coefficients $\widehat{M}$ are reconstructed, the echo images I are recovered using $I_j = \widehat{M}B_j^T$, and are used to create the T2 map.

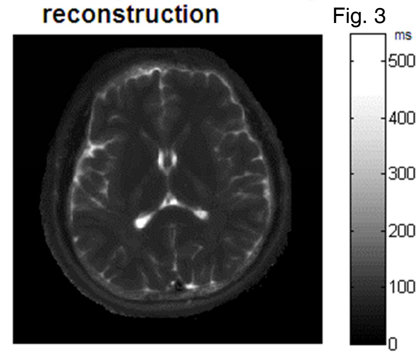
Data were acquired using the radFSE sequence on a 1.5T scanner. An 8-channel head coil was used to collect data with ETL=16, echo spacing=8.8ms, slice thickness = 5mm, BW=±31.25kHz, TR=4s, FOV=22cm, and 32 views per TE. This acquisition corresponds to roughly 12.5× acceleration with respect to a fully sampled data set. 3 PCs were used to represent T2 decays over 16 echoes. Dictionaries for 4x4 patches of each PC were initialized using an overcomplete Discrete Cosine Transform and updated independently over the iterations.

Fig. 2 Echo image 16 (ETL 16)



Results and Discussion: Fig. 1 shows the first and third PC coefficients reconstructed with and without the proposed dictionary constraint. It can be seen that the use of the dictionary constraint yields significant reduction in noise and undersampling artifacts while preserving the underlying structure of the third PC coefficient map. This reduction in noise is also clearly visible in individual echo images as shown in Fig. 2. Furthermore, the proposed dictionary constraint does not lead to over-regularization as compared to the REPCOM method when the underlying signal structure is successfully recovered by REPCOM. This is evident in Fig. 1 by comparison of the images for the first PC where no apparent differences (i.e. blurring of structures) are observed between the two methods. Finally, Fig. 3 shows the T2 map obtained by the proposed method.

T2 Map from dictionary reconstruction Fig. 3



Conclusion: We developed a CS method that uses learned dictionaries to reconstruct images from highly undersampled, multi-channel, non-Cartesian MRI data. The proposed method was used to obtain T2 maps from accelerated radFSE acquisitions. This method resulted in reduced noise and artifacts in the reconstructed images.

References: [1]Block et al. IEEE TMI. 2009. [2]Doneva et al. MRM. 2010. [3]Huang et al. MRM 2012. [4]Altbach et al. MRM 2005. [5]Bilgin et al. Proc. ISMRM. 2010. [6]Ravishankar Bresler. IEEE TMI. 2011. [7]Caballero et al. IEEE TMI. 2014. [8]Fessler. IEEE TSP. 2003. [9]Aharon et al. IEEE TSP. 2006.