Whole-Brain Multi-Parameter mapping using Dictionary learning

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Targeted Audience: Researchers and Clinicians interested in using quantitative relaxation measures to the study the effect of physiological and metabolic changes including those associated with neurological and psychiatric disorders on tissue parameters.

Purpose: Quantification of multiple tissue parameters is emerging as a powerful tool in diagnosing various neurological and psychiatric diseases. However the major bottleneck in its routine clinical use is the long acquisition times needed to acquire multiple contrast weighted images. In addition, long acquisition times are likely to result in motion induced artifacts. In this work, we propose a dictionary learning based scheme to simultaneously recover $T_1\rho$ and T_2 maps. Although, $T_1\ \rho$ is sensitive to a number of tissue properties of interest, it is not specific. Acquiring additional parameters (e.g. $T_2\rho$ and T_2) can improve the specificity of $T_1\rho$. The proposed method models the data as a weighted linear combination of basis functions from a dictionary, which is learned from the measured data.

Methods: The reconstruction from under-sampled data is posed as a constrained optimization problem given by:

$$[U^*, V^*] = argmin_{U,V} \|A(UV) - b\|_F^2 + \lambda_1 \|U\|_1;\ \|V\|_F^2 < 1,$$

where b=under-sampled data, U=sparse coefficient matrix, V=learned dictionary, and A considers coil sensitivity encoding along with Fourier encoding. A sparsity-promoting l1 norm prior is enforced on U, while the Frobenius norm of the dictionary V is constrained. This approach jointly estimates the sparse coefficients U and the dictionary basis functions V from the measured undersampled k-space data b.

We evaluated the utility of the proposed algorithm using both retrospective undersampling and prospective undersampled acquisitions. A fully sampled 2D dataset was acquired using a TSE sequence combined with $T_1\rho$ and T_2 preparatory pulses[5,6] (Turbo factor=8; FOV=22x22cm^2, TR=2.5s, spin lock freq=330Hz). $T_1\rho$ and T_2 weighted images were acquired by changing the duration of the $T_1\rho$ preparation pulse spin lock time (TSL) and T_2 preparation pulse echo time (TE). The data was collected for 12 equispaced TSLs and TEs each ranging from 10ms to 120ms resulting in a scan time of 16min. The 2D data was retrospectively undersampled using a variable density sampling pattern at acceleration R=6,8,10,12.

The 3D prospective dataset with R=8 was acquired using a segmented 3D GRE sequence based on the 3D MAPSS[1] approach (TR=5.6ms, Res=1.7mm^3 isotropic, FOV=22x22x22cm^3). Ten $T_1\rho$ spin-lock images and ten T_2 TE images were acquired (10ms - 100ms) resulting in a scan time of 20min. Both the datasets were reconstructed using the proposed scheme and the results were compared with kt-PCA[2] and CS[3] based schemes. The proposed scheme was solved using two algorithms: Algorithm 1- without variable splitting[4] and Algorithm 2 – with variable splitting. The parameters were estimated using a single exponential model given by $M(p) = S0 \exp\left(-\frac{TE(c)}{T_2}\right) \exp\left(-\frac{TSL(c)}{T_1\rho}\right)$.

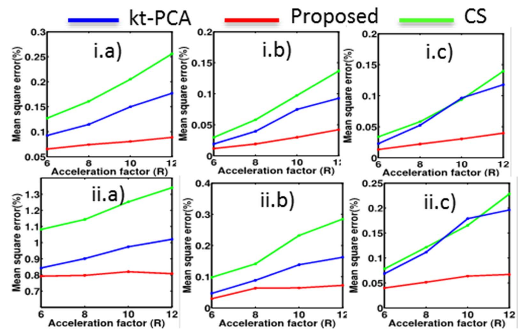

Figure 1: Comparison of the proposed method with CS and kt-PCA (i) without motion and (ii) with motion. The plots corresponding to a) Reconstruction error, b) $T_1\rho$ map error and c) T_2 map error are shown. It is observed that proposed scheme gives better performance than CS and kt-PCA.

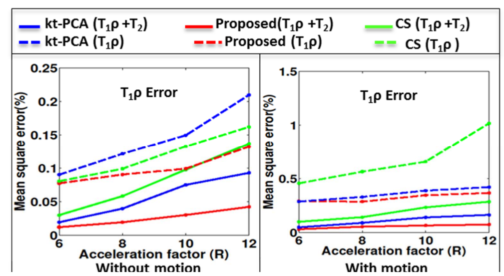

Figure 2: Plots for $T_1\rho$ map error obtained from reconstructions for combined $T_1\rho$+T_2 dataset and the $T_1\rho$ only dataset. We observe that combining the datasets yields superior reconstructions which translates to lower MSE in parameter estimation

Results: From Fig. 1, we observe that the proposed scheme performs better than the CS and kt-PCA scheme in both cases with and without motion because the dictionary is subject-specific and the sparsity constraint allows implicit model order selection. Since, the dictionary in CS scheme is estimated from a model (formed using second equation), it does not account for subject motion. As the model order is fixed *a priori* in kt-PCA scheme, it tends to model noise leading to nosier reconstructions. To study the benefit of multi-parameter mapping from the technical perspective, comparisons of $T_1\rho$ maps obtained from reconstructions of the combined ($T_1\rho$ +T_2) dataset and from just the $T_1\rho$ dataset itself are shown in Fig 2. Since the changes in parameters due to physiological changes is very small (~1-2%), accurate estimation of parameters plays an important role. We observe that combining the two datasets yields more accurate parameter estimation and thus improves the specificity of parameters in shorter acquisition times. The 3D dataset was reconstructed slice-by-slice using both Algorithms 1 and 2 to compare their results and reconstructions times. From Fig. 3, we observe that both the algorithms yield similar results but Algorithm 2 takes 5.2 hours to reconstruct the entire 3D dataset whereas Algorithm 1 takes >50 hours.

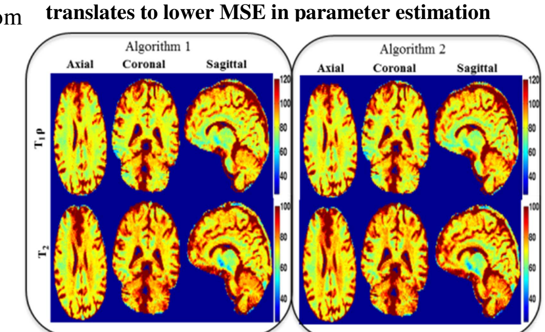

Figure 3: Axial, Coronal and Sagittal views of the $T1\rho$ (top row) and T_2 (bottom row) parameter maps using Algorithm 1 (left) and Algorithm2 (right). Algorithm 2 yields similar results as Algorithm 1 but reduces the reconstruction time by ~10 fold

Conclusion: In this work we propose a novel dictionary learning scheme to accelerate whole-brain multi-parameter mapping. The proposed scheme yields reasonable parameter estimates at high accelerations as compared to other schemes. The robustness of the proposed scheme to motion makes it well-suited for multi-parameter mapping applications.

References:[1] Li *et al*, MRM-08 [2] Petzschner *et al*, MRM'11 [3] Doneva *et al*, MRM'10 [4] Ramani *et al*, TMI'11 [5] Charagundla *et al* JMRI'03 [6] Brittain *et al*, MRM'95.