# In Vivo MRSI Reconstruction by Low-rank Component Analysis Using 3-D High-resolution Field Inhomogeneity Mapping

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**Background:**

The supplementary spatial information provided by magnetic resonance spectroscopic imaging (MRSI) has long been coveted by the clinical and research communities, yet has thus far remained only partially realizable due to a number of practical restrictions. One stems from the traditionally long measurement process, and hence typically only the central phase encodes are acquired in order to minimize both the total scan time, and the reconstruction error following inverse Fourier transform. This effectuates a broadening of the concomitant spatial pointspread function (PSF), resulting in spectral 'leakage' between spatially distal regions. A further hindrance is the low signal-to-noise ratio (SNR) of metabolites of interest, especially in the absence of signal averaging. Therefore, in 2D MRSI, large voxel sizes along the slice direction are common, provoking additional partial volume effects. Though some limitations of Fourier-based reconstructions can be circumvented through model-based approaches, many such methods [e.g., 1,2] assume explicit signal representations - often derived directly from high-resolution structural images - which can bias reconstructions when discrepancies exist between the spatial distribution of water and that of other resonances of interest. In this work, we extend our previous inception of component-based MRSI reconstruction [3], whereby a bilinear signal model is iteratively estimated from the raw MRSI measurements, to *in vivo* scenarios. We further model the effect of partial voluming within a 2D MRSI slice by exploiting a 3D $B_0$ static field inhomogeneity map acquired along the slice thickness.

**Methods:**

We place the reconstruction procedure within a variational framework, minimizing the energy of an associated cost function, formulated as: $\min_{U,V} \mathcal{J} = \left\| \Omega\left\{\mathcal{F}\{\mathfrak{D}\{\boldsymbol{UV}\}\}\right\} - \boldsymbol{S}\right\|_F^2 + \mu TGV_\alpha^2\{\boldsymbol{U}\}$. In the first right-hand side term, $\Omega$ is a downsampling operator that retains the measured phase encodes, and $\mathcal{F}$ represents integration of the signal along the slice direction, followed by spatial Fourier transform. $\mathfrak{D}$ denotes spatial phase information derived from a high-resolution 3D static field inhomogeneity map, $\boldsymbol{S}$ are the low-resolution MRSI measurements, and $\|\cdot\|_F$ is the Frobenius norm. The product, $\boldsymbol{UV}$, constitutes a bilinear decomposition of the unknown spatio-spectral distribution into $K$ spatial and spectral components, respectively, where $K$ is smaller than the dimensionality of the acquired measurements. Thus, $K$ can be considered as a hard implementation of a low-rank penalty. The second term represents regularization on the spatial components, based on the total generalized variation of an image [4], with regularization parameter $\mu$. We solve this minimization problem using an Augmented Lagrangian framework [5], whereby the primary minimization is split into a series of sub-problems that minimize over a set of surrogate variables. To better pose the reconstruction, we additionally require that $\boldsymbol{U}$ remain static in the temporal dimension, real-valued and non-negative, and that $\boldsymbol{V}$ be constrained in Frobenius norm. These penalties are enforced via projected gradient methods within the sub-iterations. It should be emphasized that the spatial maps are estimated at the same resolution as the input static field map, i.e. at high-resolution and in three dimensions.

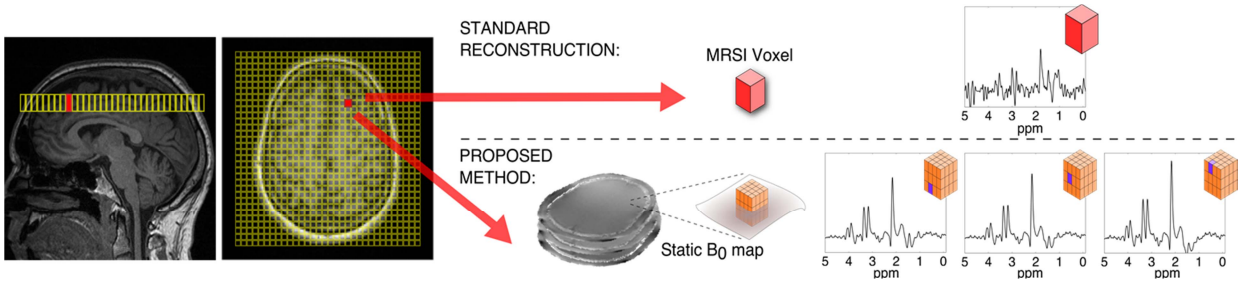


*Figure 1: Reconstruction of [1]H in vivo MRSI data by standard inverse Fourier transform (top row, right – nominal voxel size: 6.25 x 6.25 x 10 mm), versus the proposed method (bottom, right – nominal voxel size: 1.56 x 1.56 x 3 mm) for the indicated voxel.*

**Data Acquisition:**

[1]H Chemical shift imaging (CSI) data were acquired using a semi-LASER sequence from a healthy volunteer on a 3.0 Tesla Siemens Trio (Siemens Healthcare, Erlangen, Germany) scanner. A 10 mm slab was positioned in the cortex above the ventricles (CSI parameters: FOV 200 x 200 mm, TR 1700 ms, TE 288 ms, grid size 32 x 32, bandwidth 1.2 kHz, #FID sampled points 1024). No in-plane slab selection or outer spatial saturation bands were used to suppress sub-cutaneous lipids. Three 3 mm thick slices of a static $B_0$ map (grid size 128 x 128) across the CSI slice thickness using the same in-plane FOV were also acquired during the same session using two spoiled gradient echo sequences, with $\Delta$TE chosen such that water and fat were in phase. Prior to reconstruction, the residual water signal was removed using the HSVD algorithm, followed by a 10 Hz Gaussian line broadening applied along the temporal frequency dimension. For the component-based reconstruction, we found that $K = 30$ offered a good compromise between data fidelity and model over-fitting.

**Results and Discussion:**

This work follows in the wake of promising MRSI phantom experiments, whereby a number of advantages furnished by our method, such as improved spatial localization, exposure of the latent signal, and correction of static $B_0$ effects can be verified *in vivo*, as demonstrated in ***Figure 1***. When compared against the standard Fourier reconstruction, the NAA, Cr, and Cho peaks estimated by the proposed method have been clearly separated from the noise subspace, and are located at their natural resonance positions. Furthermore, some distributional information has been obtained along the slice direction, afforded through the 3D information provided by the static $B_0$ map. Nonetheless, residual contamination due to the unsuppressed lipid signal can still be observed in the reconstructed spectra. Possible explanations may include the low SNR of the acquired measurements, or an incomplete forward measurement model due to the presence of additional experimental confounds such as residual eddy currents, flow phenomena, or other such dynamic phase perturbations.

**Conclusion:**

We have demonstrated the potential of component-based MRSI reconstruction on [1]H *in vivo* data as a means for exploring the underlying spatio-spectral distribution of a given sample. Our method simultaneously addresses a number of concerns with both standard Fourier and model-based reconstructions by avoiding the most prohibitive tenets of each. In future work, we plan to explore the efficacy of our reconstruction routine in short TE acquisitions, and to further improve reconstruction quality by incorporating dynamic field effects into the basic model.

**References:**

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