Estimation of Compartmental Signals from Limited Fourier Samples

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INTRODUCTION

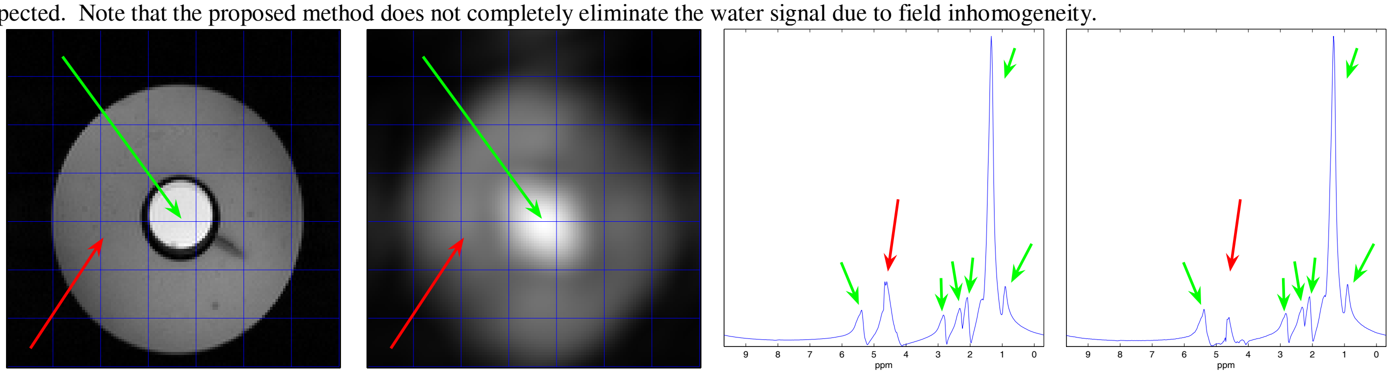
Resolution is a key factor for quantitative analysis of MR images, and is of particular relevance in experiments such as MR spectroscopic imaging (MRSI), dynamic imaging, diffusion tensor imaging, and functional imaging. In these experiments, noise and data acquisition time can severely limit the achievable spatial resolution for standard Fourier-based image reconstruction. In practice, quantitative imaging experiments are analyzed in two steps: 1) An image is reconstructed from the data, and 2) regions of interest (ROIs) are identified, and the image is averaged over these ROIs to generate summary statistics. This standard approach is insufficient in low-resolution experiments, due to signal leakage. To address this problem, a number of methods similar to [1,2] have been developed, which make strong modeling assumptions regarding local tissues. The proposed method is more powerful than existing ones in that it optimizes spatial response functions (SRFs) [3] and can incorporate a variety of different modeling constraints without modification of the imaging experiment. The optimality criterion proposed for this method also enables effective comparison of different experimental procedures for signal localization accuracy.

THEORY

The imaging equation in most MR experiments can be modeled as $d[m] = \int \rho(\mathbf{x}) \exp(-i2\pi\mathbf{k}_m\cdot\mathbf{x})\, d\mathbf{x} + \eta[m]$, where $d[m]$ is the measured data, $\rho(\mathbf{x})$ is the image function, and $\eta[m]$ are samples of a white Gaussian noise process. Many ROI estimates come from a linear combination of this data: $\rho_{\mathrm{ROI}} = \Sigma\, g_m\, d[m]$. This can be rewritten in the form $\rho_{\mathrm{ROI}} = \int \rho(\mathbf{x})\, h(\mathbf{x})\ d\mathbf{x} + \Sigma\, g_m\, \eta[m]$, where $h(\mathbf{x}) = \Sigma\, g_m \exp(-i2\pi\mathbf{k}_m\cdot\mathbf{x})$ is the SRF that describes precisely how ρ_{ROI} relates to the desired ROI estimate. With finite sampling, it is not possible for $h(\mathbf{x})$ to match its ideal version. However, it is possible to create an $h(\mathbf{x})$ that is close to its ideal version according to some optimality criterion, while simultaneously suppressing noise. The criterion we apply requires knowledge of high-resolution anatomical structure of the image we are estimating, and uses this knowledge to tailor the ROI reconstructions. We use bounds on the largest magnitude of the image in different regions to minimize estimation bias, by suppressing signal from regions that are expected to generate strong signal leakage. It is also possible to introduce constraints like the strong homogeneity assumptions of [1,2]; with these constraints in place, the estimate can be unbiased when the strong modeling assumptions apply, but still well-behaved when they do not. However, unlike [1,2], these homogeneity constraints can be applied selectively to only those regions of the image for which they are presumed valid.

RESULTS

Figure 1 shows the results of applying the proposed technique to a real MRSI experiment. The data was acquired with 7x7 *k*-space coverage from a phantom with two compartments, one filled with water and the other filled with vegetable oil. Fig. 1(a) shows a high resolution anatomical image, with the 7x7 voxel grid overlaid. In all images, green arrows point to the oil signal, and red arrows point to the water signal. Fig. 1(b) shows the zero-padded Fourier image reconstructed from the 7x7 data, which has severe signal leakage between the two compartments. ROI estimation was performed for the central compartment, and the estimated spectra from the traditional averaging approach and the proposed method are shown in Figs. 1(c) and (d), respectively. The proposed technique shows significantly reduced contamination from the water signal outside the ROI as expected. Note that the proposed method does not completely eliminate the water signal due to field inhomogeneity.



(a) (b) (c) (d)

Figure 1

CONCLUSION

We have introduced a new method for estimating the average signal from ROIs in limited-data MR experiments. The proposed technique is designed to minimize the worst-case mean-squared estimation error over the class of linear estimators. In contrast to previous methods that incorporate prior information through a restrictive image model [1,2], the proposed method is significantly more robust in the presence of modeling error and noise, and will be useful for improving ROI estimates in any experiments where high-resolution data is unavailable.

REFERENCES

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