

Improved spectroscopic imaging using echo-planar scans and sparse reconstruction

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INTRODUCTION

Model-based spectroscopic imaging techniques were originally proposed to reduce the number of phase encodes, and consequently the scan time [1,2]. However, in practice, these techniques can give significant artifacts for a low number of spatial encodes. This is mainly due to the assumptions embedded in the model being violated. On the other hand, it is well known that fast scan techniques can provide larger k-space coverage in the same scan time, at the cost of lower signal to noise ratio (SNR) per measurement [3]. The extended k-space coverage can drastically reduce the artifacts in model based imaging. The important question is whether the loss in the SNR can be compensated. We find that the model based framework is very effective to address this problem. This allows us to redesign the model-based MRSI schemes to the fast scan techniques so as to simultaneously achieve high resolution, low artifacts, and high signal to noise ratio.

METHOD

We use the echo-planar sequence shown in Fig 1-a. to acquire the spectroscopic imaging data. The central idea in the sequence is to shift the readout at successive acquisitions to interleave the acquisition along the time axis, to avoid temporal under-sampling.

In image reconstruction, the noisy k-space samples are processed using a model-based method. The existing image models for spectroscopic imaging are rather restrictive. Most of these techniques fail to capture lesions or details that are absent in the anatomical image. To reduce these problems, the models need to be made flexible. However, making them flexible results in reduced robustness (due to more unknown parameters). To counter this problem, we propose a data-adaptive technique.

We introduce an implicit approach to specify the basis functions using linear constraints, unlike conventional model based schemes. Specifically, we select the basis functions of the model as $\mathbf{B}\mathbf{p} = \mathbf{0}$, where \mathbf{B} is an appropriate matrix that specifies the linear constraints and \mathbf{p} is the signal. In this formulation, the basis vectors reside in the null space of \mathbf{B} . Since specifying the basis vectors reduce to an appropriate choice of \mathbf{B} , this approach is very effective for a data-adaptive basis selection. We start with a full rank \mathbf{B} and use the anatomical data to relax some of its constraints, thus obtaining a SLIM-like model. We then estimate the additional points at which they have to be relaxed from the CSI data itself. Since a large number of relaxed constraints lead to a higher dimensional reconstruction space and consequently less robust reconstructions, we penalize the number of points at which the constraints are violated. We then use the sparse reconstruction theory to formulate the problem as a convex minimization problem [4] and solve it using successive conjugate gradients optimization. Some of the constraints are derived from the anatomical data, while the others are estimated from the MRSI data itself, thus making this scheme data-adaptive.

RESULTS

A 128x128x200 numerical phantom with simulated NAA, Creatine and fat peaks was generated to test the approach. We considered 5 regions (gray matter, white matter, c.s.f, lipid and a lesion region) to generate the CSI data, but only 4 regions (except the lesion) were assumed in the reconstructions. The reconstructions were performed from the data simulated, assuming (a) 64x64 encodes at a low SNR (2 dB) and (b) 8x8 encodes acquired in the same scan duration at a high SNR (20 dB). The results are displayed in Fig 2.

Experimental MRSI data (TE/TR=100/2000ms), 15 mm thick slice, FOV=192 mm, resolution 64x64x3 were acquired on a 3T Siemens Alterra system. A mild Gaussian apodization filter was applied along the spectral direction. We also acquired anatomical slice and B0 field in-homogeneity measurements at 256x256x5 resolution for the same region. The time taken for the acquisitions is 6 minutes.

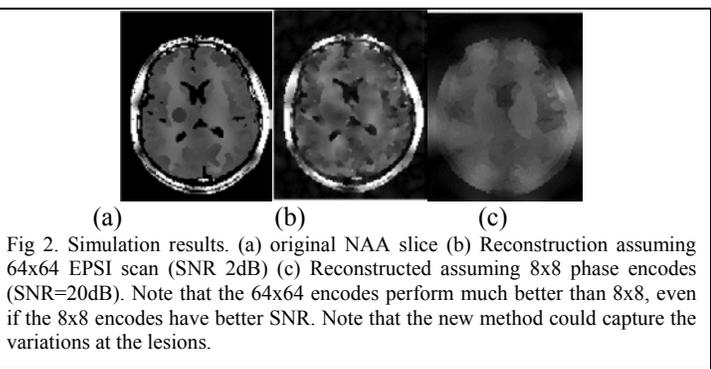


Fig 2. Simulation results. (a) original NAA slice (b) Reconstruction assuming 64x64 EPSI scan (SNR 2dB) (c) Reconstructed assuming 8x8 phase encodes (SNR=20dB). Note that the 64x64 encodes perform much better than 8x8, even if the 8x8 encodes have better SNR. Note that the new method could capture the variations at the lesions.

CONCLUSION

We observed that the model based spectroscopic imaging techniques, originally proposed for reduced encoding, are more appropriate for fast scan spectroscopic imaging. We implemented an echo-planar spectroscopic imaging sequence to make use of this property. We also introduced a data-adaptive basis function selection procedure to derive a model that can adapt to natural signal variations, while being robust.

REFERENCES:

- [1] X. Hu et al., MRM, pp 132-137, 1988.
- [2] Z-P.Liang and Lauterbur, IEEE Trans. Med. Imaging, 10, pp. 132-137, 1991.
- [3] Adalsteinsson et. al., MRM, pp 314-23, 1999.
- [4] Donoho and M. Elad, Proc. Nat. Academy of Sciences, pp. 2197-2202, March 2003.

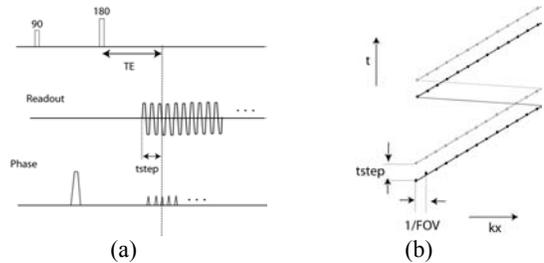


Fig 1. Echo-planar sequence used for the acquisition. (a) The readout is shifted about TE at successive acquisitions to interleave the scan along the time axis. The corresponding kx-t trajectory is shown in (b).

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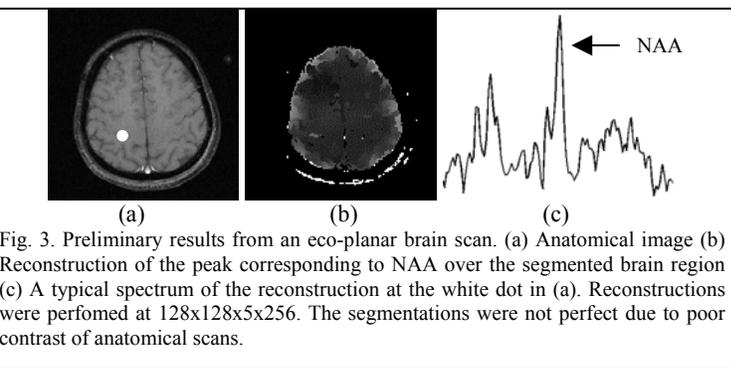


Fig 3. Preliminary results from an eco-planar brain scan. (a) Anatomical image (b) Reconstruction of the peak corresponding to NAA over the segmented brain region (c) A typical spectrum of the reconstruction at the white dot in (a). Reconstructions were performed at 128x128x5x256. The segmentations were not perfect due to poor contrast of anatomical scans.