Spatial 3D EPR Imaging with Compressed Sensing Reconstruction

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ABSTRACT

The goal of this study was to produce 3D EPR images with only a small number of projections using a compressed sensing (CS) reconstruction and to test the reconstruction on typical EPR imaging datasets. EPRI is posed as an optimization problem, which is solved using regularized least-squares with sparsity promoting penalty terms, consisting of the l_1 norms of the image itself and the Total Variation (TV) of the image. The reconstruction was compared to the traditional Filtered Back-Projection (FBP) reconstruction for simulations, phantoms, isolated rat hearts and mouse GI tracts labeled with paramagnetic probes. Improvements in SNR and accelerations of up to 16X were observed.

INTRODUCTION

Continuous wave spatial EPRI is used for preliminary studies of probe distribution and redox kinetics, especially when spectral-spatial EPRI is too slow or SNR is limited. Spatial EPRI can be posed as a form of tomography where a 3D object is recovered from projections blurred by a known point spread function (i.e., the spatially invariant electron spectrum). The image reconstruction is usually based on Filtered Back-Projection (FBP)[1], which requires a large number of projections. Alternative reconstructions include algebraic reconstruction techniques (ART), the maximum entropy method and Tikhonov regularization [2-4], which still require a relatively large number of projections to reconstruct an image. We hypothesize that a much smaller number of projections is actually required to reconstruct EPR images when the methods of Compressed Sensing are applied. While CS has been applied to particulate EPR probes with analytical lineshapes [5-7], diffuse probes with complex lineshapes are still widely used in EPR research. The goal of this study was to show the potential to accelerate static spatial 3D EPRI with diffuse probes with empirical lineshapes and a special emphasis on in vivo applications.

THEORY

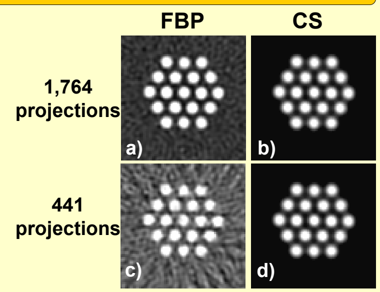
Compressed sensing [8] can recover images from very few measurements provided that 1) image is sparse in some domain, 2) the noise in the image is incoherent, and 3) a nonlinear reconstruction is used to recover the image. We propose the following model for introducing sparsity into spatial EPR images:

$$\arg\min_{x} \left\| CRx - y \right\|_2^2 + \lambda_1 \left\| x \right\|_1 + \lambda_2 \left\| \mathrm{TV}(x) \right\|_1 \qquad (1)$$

Eq (1) poses the recovery of the image (x) from noisy, blurred projection data (y). The operator R represents the 3D Radon transform, and C represents convolution with the measured electron spectrum. The second and third terms act like filters that favor images which are mostly zeros and piece-wise constant, respectively. Numerical values for λ_1 and λ_2 are chosen manually to balance sparsity and data consistency, and Eq (1) is solved using FISTA [9].

PHANTOM EXPERIMENTS

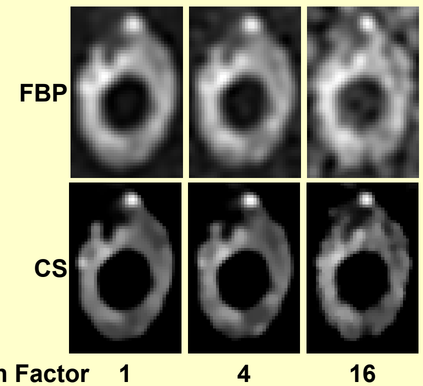
A phantom of 19 tubes with 1 mM TAM radical were scanned in a 1.2 GHz EPR imaging system with 26.7 mT/m gradient amplitude and 5 s per projection [10].



The CS reconstruction (b) has higher SNR than the Filtered Back-Projection reconstruction (a) when all the projections are used. When only 441 of the projections (25%) were used, streaking artifacts, spatial blurring, and SNR degradation appear in the FBP reconstruction (c) but not the CS reconstruction (d).

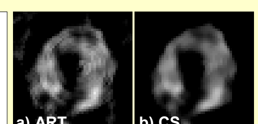
CARDIAC EXPERIMENTS

Ex vivo rat hearts were infused with a cardioplegic suspension of LiNc-BuO, and 1,024 projections were collected in 266 seconds on a 1.2 GHz EPRI scanner with 47 mT/m gradients [11].



Both CS and FBP reconstructions were applied to subsets of the acquired projections to retrospectively compare how many projections were actually necessary to reconstruct acceptable EPR images. An acceleration factor of 4 (i.e., only 256 projections) resulted in little visual change in the either reconstruction. However, an acceleration factor of 16 caused significant degradation of the FBP reconstruction.

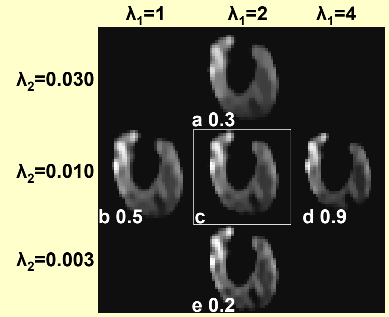
In the absence of any regularization, the reconstruction is equivalent to ART with lineshape information (a). When using both the l_1 and TV penalty terms, the image has increased SNR and decreased artifacts (b).



RESULTS

Sensitivity Analysis

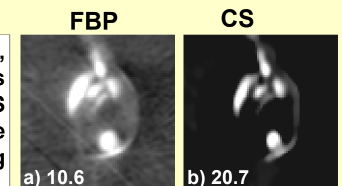
Repeating the CS reconstruction with different reconstruction weights λ_1 and λ_2 causes different effects in the resulting images.



The suggested reconstruction (c, boxed) has moderate l_1 and TV weighting. Mean-squared error with respect to (c) is indicated by the numbers in the images. A weaker l_1 weight (b) makes little visual difference to the reconstruction, whereas a strong l_1 weight (d) results in some loss of signal intensity around the heart. Increased TV weighting (a) causes some blurring or "stair step" artifacts, and decreased TV weighting (e) causes oscillations to appear in the image.

GI Tract Imaging

Mice were fed activated charcoal, and GI tract imaging was performed [12]. Use of the CS reconstruction doubled the image SNR and suppressed streaking artifacts.



DISCUSSION AND CONCLUSION

Spatial 3D EPR images appear to be sparse using a combination of minimizing the number of pixels with any signal at all and also minimizing the total variation of the image. The biases introduced by these terms allows recovery of the image from fewer projections, which can be used to shorten the acquisition or increase SNR in each projection. While we only demonstrated the static case here, the extension to dynamic EPR reconstructions (i.e., redox kinetics) is straightforward.

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