## LIST OF SUPPLEMENTARY FIGURES

- Figure S1: The true and approximate WMSE validation curves for DESIGN for data set #1 (a) and data set #2 (b) are compared against WSURE repeated for various  $\varepsilon$ 's spanning several orders of magnitude. The curves (just a single trial for each point) are nearly identical, and they all provide decent approximations of the true and approximate WMSE's for both T<sub>1</sub>-weighted data sets.
- Figure S2: The true and approximate WMSE validation curves for L<sub>1</sub>-SPIRiT for data set #1 (a) and data set #2 (b) are compared against WSURE repeated for various  $\varepsilon$ 's spanning several orders of magnitude. The curves (just a single trial for each point) are nearly identical, and they all provide decent approximations of the true and approximate WMSE's for both T<sub>1</sub>-weighted data sets.
- Figure S3: The sparsity-promoting DESIGN method yields similarly lower WMSE (a) for both WMSEoptimal and WSURE-optimized choices of  $\gamma$ , relative to the un-regularized GRAPPA reconstruction, for the second data set. The WMSE of the DESIGN reconstruction using the WSURE-optimized choice is within 0.047 dB of the true WMSE-optimal DESIGN reconstruction. This behavior is consistent with the WMSE-optimal and WSURE-optimized choices for the DESIGN regularization parameter  $\gamma$  (b) being nearly the same for this example. The L-curve-style method, however, appears to overestimate  $\gamma$ , yielding images with slightly higher WMSE, and in the high-SNR case, again worse than performing unregularized GRAPPA. The non-monotonic behavior of the L-curve estimates of  $\gamma$  confirm the difficulty of estimating the maximum curvature.
- Figure S4: The sparsity-regularized L<sub>1</sub>-SPIRiT reconstruction for data set #1 yields similarly lower WMSE (a) for both the WMSE-optimal and WSURE-optimized choices of  $\gamma$ , relative to the un-regularized SPIRiT reconstruction. The L<sub>1</sub>-SPIRiT reconstruction using the WSUREoptimized choice is within 0.057 dB of the true WMSE-optimal L<sub>1</sub>-SPIRiT reconstruction. The WMSE-optimal and WSURE-optimized choices for the L<sub>1</sub>-SPIRiT regularization parameter  $\gamma$  (b) tend to decrease slowly as the undersampling factor increases. The larger values of  $\gamma$  from the L-curve-like method increase the WMSE, but not as substantially as for DESIGN. The plotted values of *R* account for the central k-space calibration region.

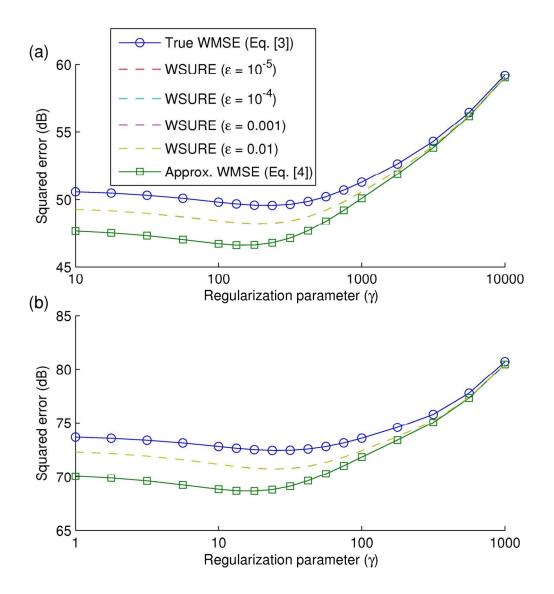


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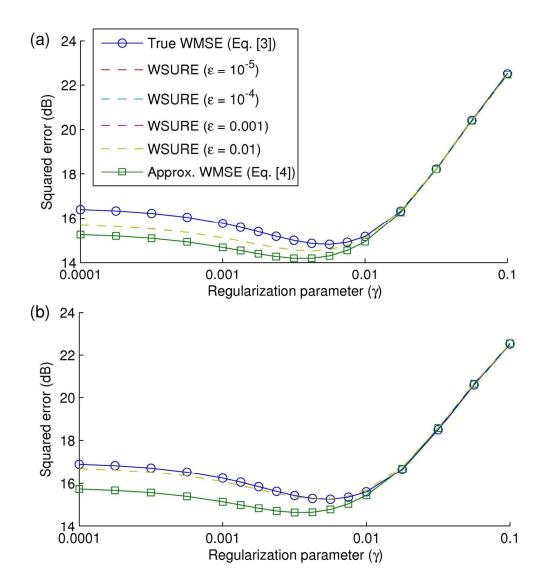


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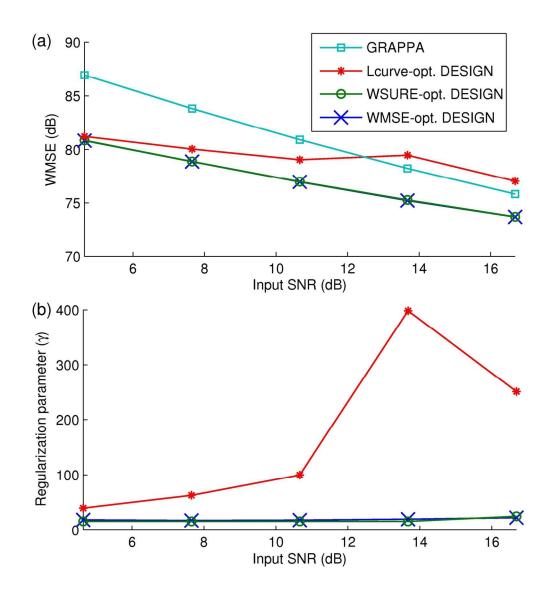


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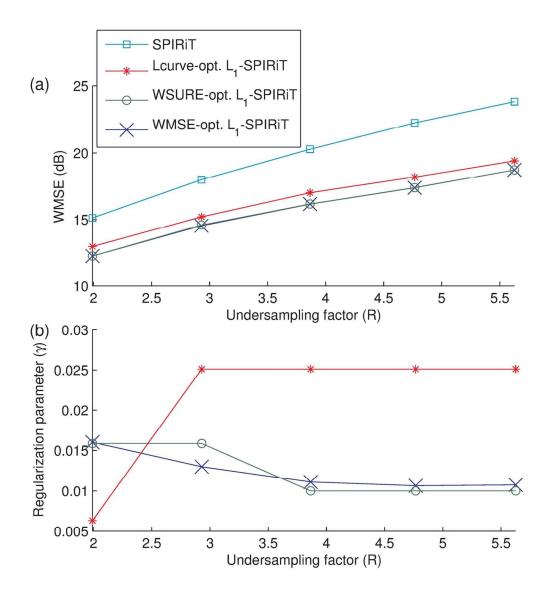


Figure S4: The sparsity-regularized L<sub>1</sub>-SPIRiT reconstruction for data set #1 yields similarly lower WMSE (a) for both the WMSE-optimal and WSURE-optimized choices of  $\gamma$ , relative to the un-regularized SPIRiT reconstruction. The L<sub>1</sub>-SPIRiT reconstruction using the WSURE-optimized choice is within 0.057 dB of the true WMSE-optimal L<sub>1</sub>-SPIRiT reconstruction. The WMSE-optimal and WSURE-optimized choices for the L<sub>1</sub>-SPIRiT regularization parameter  $\gamma$  (b) tend to decrease slowly as the undersampling factor increases. The larger values of  $\gamma$  from the L-curve-like method increase the WMSE, but not as substantially as for DESIGN. The plotted values of R account for the central k-space calibration region. 139x153mm (300 x 300 DPI)