

Supplementary Information for

Accelerated Diffusion Magnetic Resonance Imaging at 7 T:
Joint Reconstruction for Multi-Band Multi-Shell Shift-Encoded
Echo Planar Imaging (JETS-EPI)

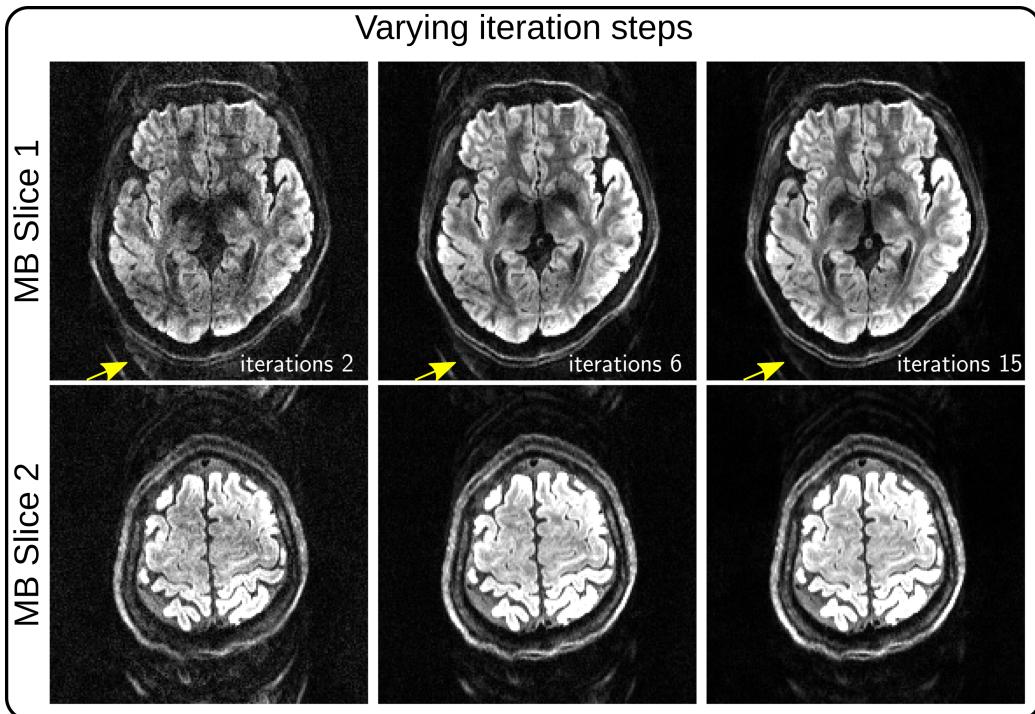
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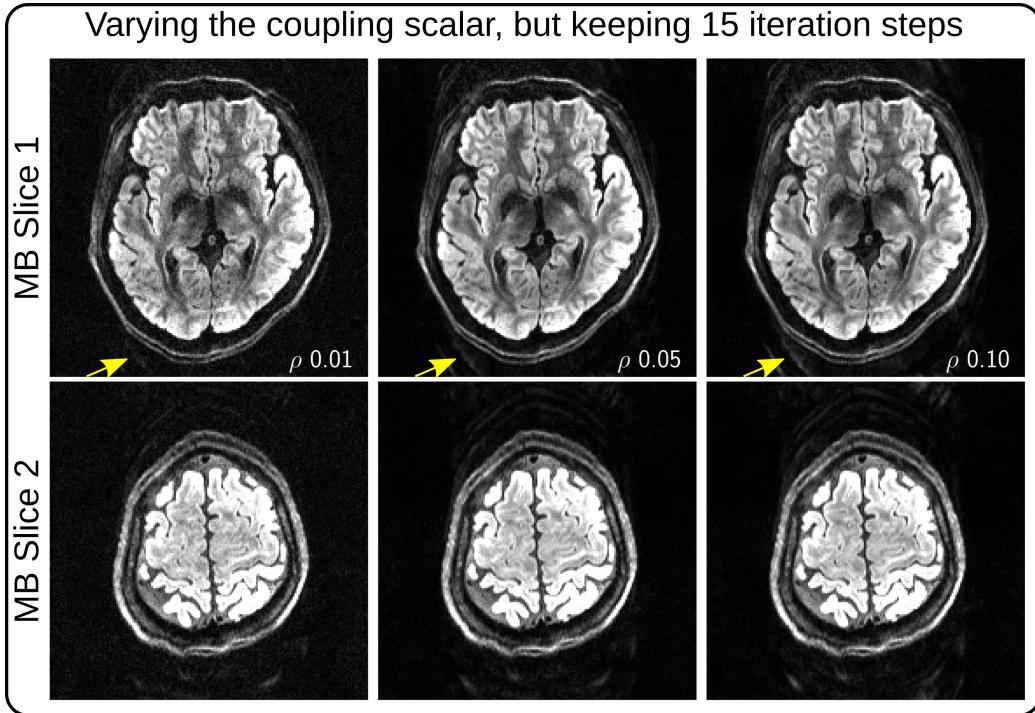
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1. Investigating Iteration Steps and ρ in ADMM

We used the data acquired with single-shell encoding and 1.2 mm isotropic resolution to demonstrate the effects of ADMM iteration steps and the coupling scalar ρ on convergence.

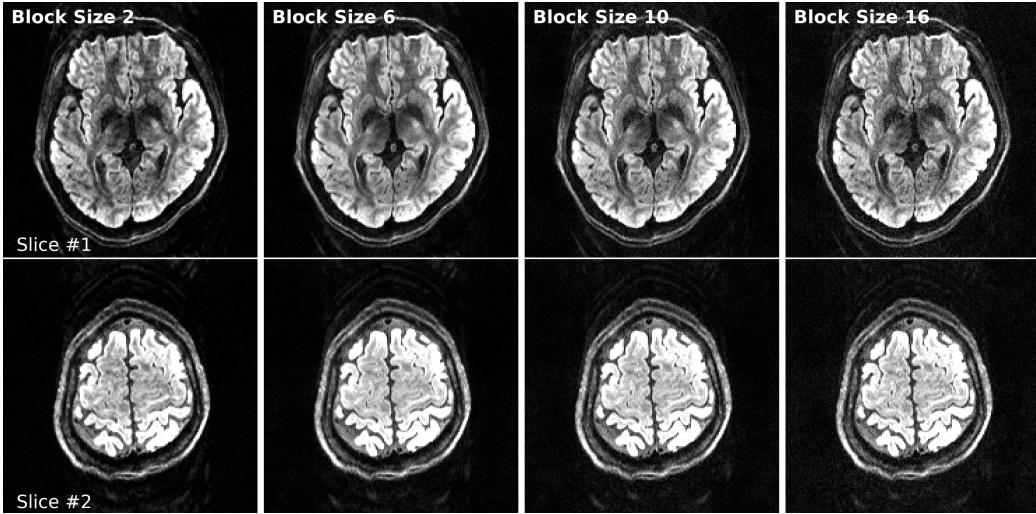


SI Figure S1: Investigation of ADMM convergence with varying iteration steps while keeping $\rho = 0.05$ and $\lambda = 0.04$. Reconstructed multi-band diffusion-weighted images at the 11th diffusion encoding with 2, 6, and 15 ADMM iterations are displayed from left to right, respectively. Inadequate iteration suffers from residual aliasing artifacts due to undersampling (indicated by yellow arrows).



SI Figure S2: Investigation of ADMM convergence with varying ρ while keeping 15 iteration steps and $\lambda = 0.04$. Reconstructed multi-band diffusion-weighted images at the 11th diffusion encoding with ρ as 0.01, 0.05, and 0.10 are displayed from left to right, respectively. As indicated by yellow arrows, smaller ρ (0.01) supplies less aliasing artifacts compared to larger ρ (0.10), but also shows more noise.

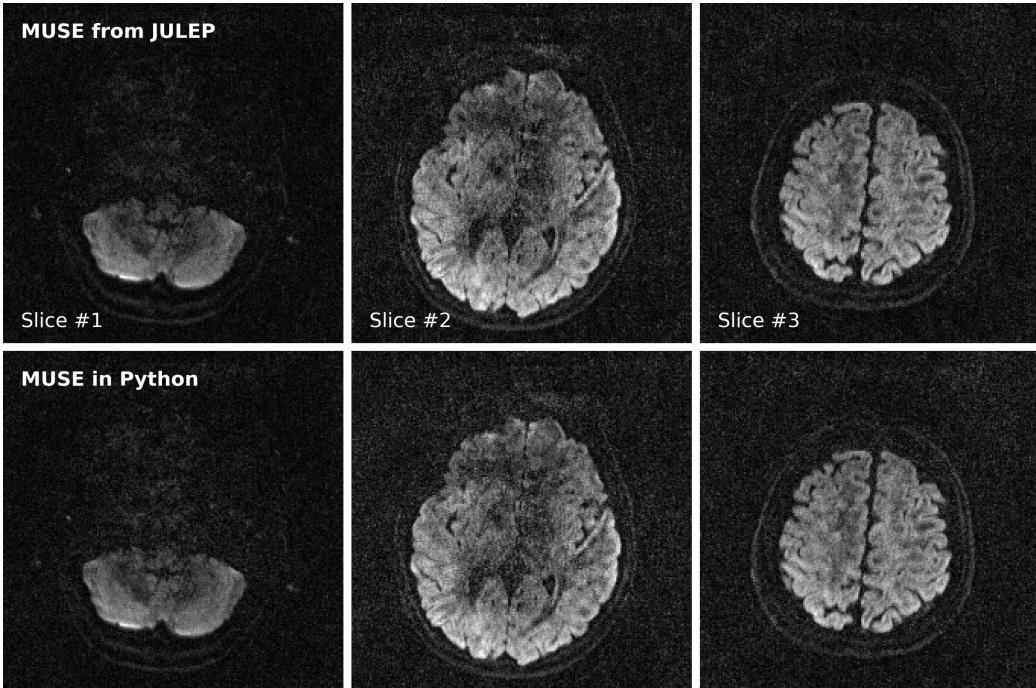
2. Investigating Block Size in LLR Regularization



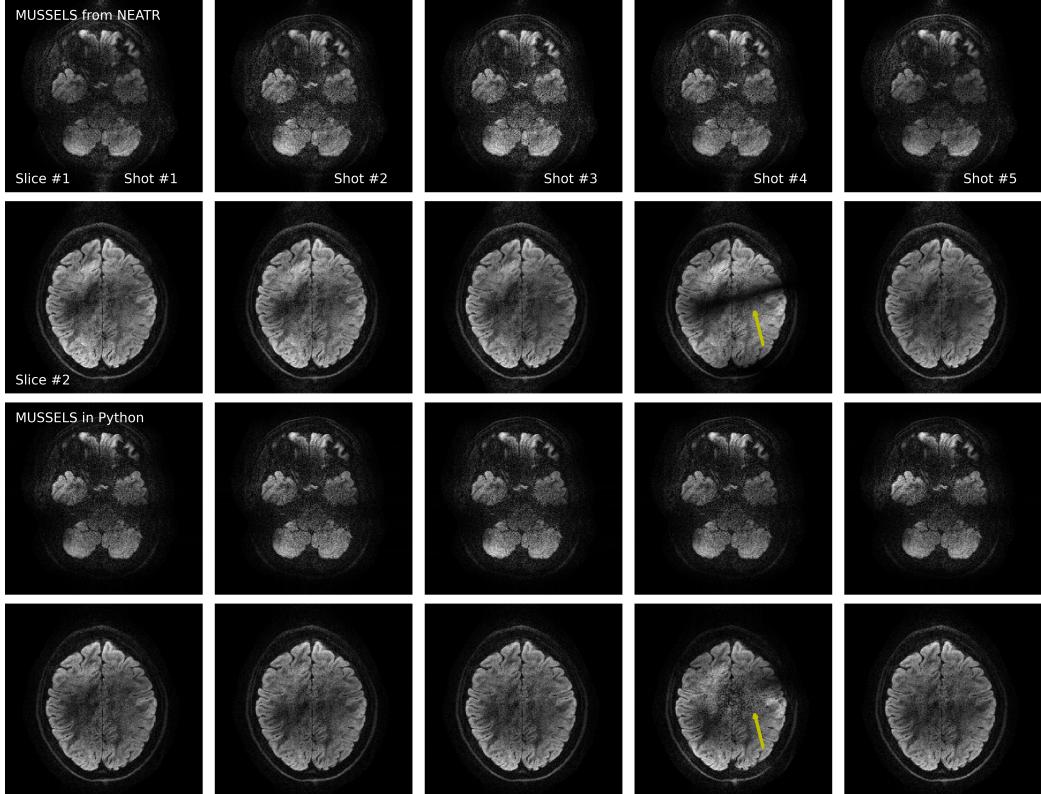
SI Figure S3: Investigation of block size in LLR regularization. Reconstructed multi-band diffusion-weighted images at the 11th diffusion encoding with block sizes as 2, 6, 10, and 16 from left to right, respectively. Small block size (i.e., 2) suffers from image blurring, whereas increasing block size gradually leads to increased noise. Therefore, block size of 6 is used in this work.

3. Reproducing MUSE and MUSSELS in Python

For the use of the state-of-the-art multi-echo EPI diffusion MRI reconstruction techniques, i.e. MUSE and MUSSELS, we firstly reproduce these techniques in Python based on open source codes and data.

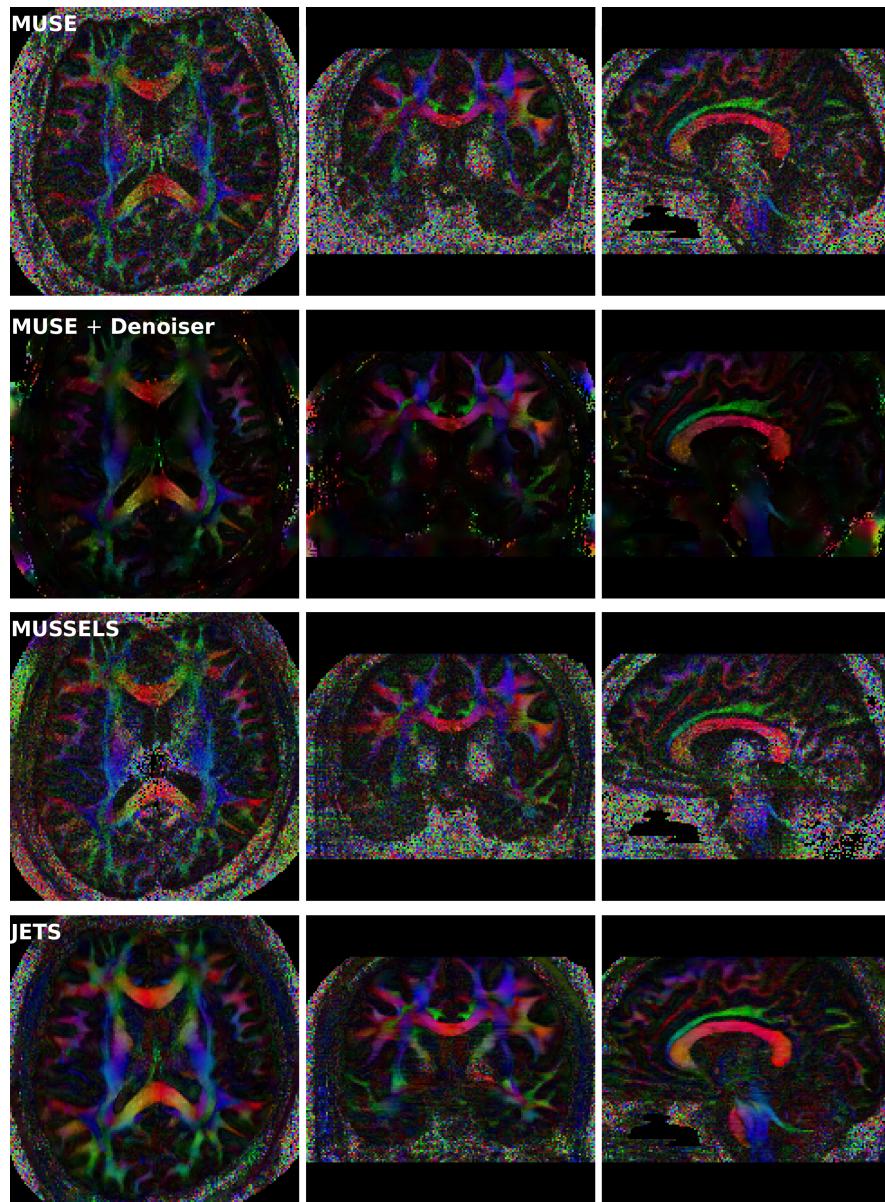


SI Figure S4: Reproduce MUSE from the source code and data from JULEP (<https://github.com/daidep/JULEP>). This data is acquired by 4-shot interleaved EPI with in-plane acceleration factor per shot being 4 and multi-band factor being 3. The top and bottom rows display the reconstruction results of MUSE from JULEP and our Python implementation, respectively. With this comparison, we validate our Python implementation, which is then served for the MUSE reconstruction of our 7T data in this work.



SI Figure S5: Reproduce MUSSELS based on the data from NEATR (<https://bit.ly/2QgBg9U>). The data is acquired by 9-shot interleaved EPI with multi-band factor being 2. 5 shots are extracted from this data for MUSSELS reconstruction. Therefore, the in-plane acceleration factor per shot is 9. The top two rows present the MUSSELS reconstruction results based on the implementation in NEATR, whereas the bottom two rows present our Python implementation. Note that the MUSSELS implementation from NEATR shows artifacts in the 4th shot image of the second slice.

4. Supporting Results from Diffusion Acquisition with Three-Shell Encoding and 1 mm Isotropic Resolution



SI Figure S6: Comparison of reconstructed color-coded FA maps based on 1 mm.