Ultra-low-field MRI noise suppression using a data consistency constraint

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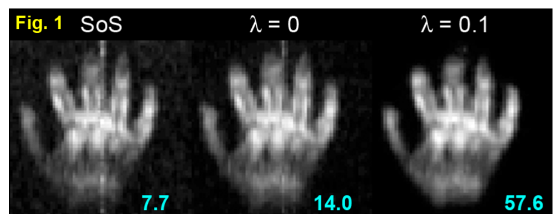
TARGET AUDIENCE Scientists and engineers interested in reducing noise in multi-channel ultra-low-field MRI.

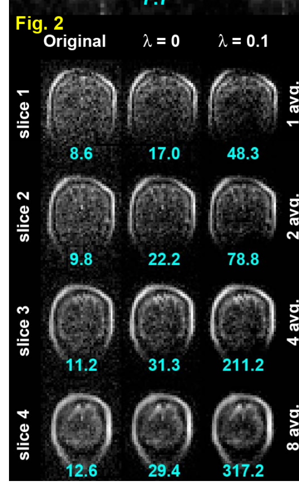
PURPOSE One significant challenge of ultra-low-field (ULF) MRI is the low SNR. This difficulty is partially addressed by 1) using separate magnets for polarization and precession fields, and 2) using superconducting quantum interference devices (SQUIDs) to detect the weak magnetic fields in ULF MRI[1]. Since a SQUID array with up to tens or hundreds of sensors can be used in a ULF-MRI system for signal detection, the collection of all spatially localized measurements from all sensors may be used to suppress noise that deteriorates theoretical data consistency (DC) across coils. Specifically, as demonstrated in accelerated high-field MRI, the *k*-space data obtained from one receiver coil can be linearly related to *k*-space data from the adjacent coils[2,3]. This DC constraint can be imposed to reduce noise by iteratively estimating the convolution kernel and reconstructing images. Here, we used empirical ULF MRI data to demonstrate that the DC constraint can improve the ULF-MRI data by suppressing noise and improving the peak SNR by a factor of approximately 2.

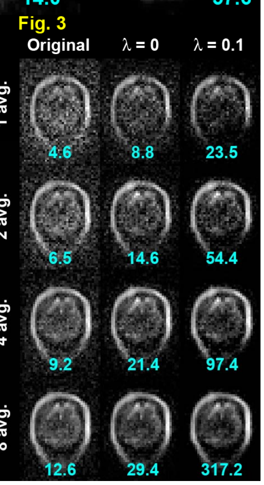
METHODS Assuming that the coil sensitivity profiles of an MRI detector array are distinct and spatially smooth, each chosen *k*-space data point of a coil can be expressed as the linear combination of the *k*-space data points from all coils in the vicinity of the chosen *k*-space data point. Mathematically, such DC relationship is described as $\mathbf{x} = \mathbf{G}\,\mathbf{x}$, where $\mathbf{x}$ denotes the concatenation of *k*-space data from all coils and $\mathbf{G}$ is a convolution kernel[3]. In practice, given the data from all coils at the i^{th} iteration, we first estimated the convolution kernel: $\mathbf{x}_i \rightarrow \mathbf{G}_i$ and then reconstructed images $\mathbf{G}\,\mathbf{x}_i \rightarrow \mathbf{x}_{i+1}$. This process was repeated until convergence $\mathbf{x}_i = \mathbf{x}_{i+1}$. Mathematically, this iteration becomes a minimization problem with the cost $|\mathbf{Gx}-\mathbf{x}|^2$. We can also include a constraint to promote image sparsity such that the cost becomes $|\mathbf{Gx}-\mathbf{x}|^2+\lambda|\mathbf{WFx}|^1$, where $\mathbf{F}$ denotes Fourier transform, $\mathbf{W}$ is the Total Variation operator, and λ is a regularization parameter.

Empirical ULF-MRI data were acquired with our system using 47 SQUID sensors distributed below the back of the head with field sensitivity of 4 fT/√Hz. A constant B_0 = 50 μT was applied for magnetization precession. We used a 3D spin-echo sequence with TE = 80 / 122 ms to generate hand and head images of 6x7.1 / 4x4 mm^2 in-plane resolution (slice thickness 10 / 6 mm), with a maximal gradient strength of 85 / 130 μT/m respectively. Before each *k*-space read-out measurement, the sample was polarized in a 22-mT field for 1 s for hand and 0.915 s for head measurements. The total imaging time was 35 and 90 minutes for hand and head measurements, respectively. Images were combined using the sum-of-squares (SoS) method or regularized SENSE reconstruction[4] with coil sensitivity profiles determined from saline phantom images. To quantify the image quality, we calculated the peak signal-to-noise ratio (pSNR) of the image as the ratio between the largest pixel value and the background noise fluctuation, which was the square root of the mean of the image pixel values outside the imaging object.

RESULTS Figure 1 shows experimental images of the right hand of a subject. Our SoS images showed five digits and the palm. Notably, there was a clear vertical strip artifact in the SoS image, potentially due to the SQUID noise at 3 kHz in our system. The background noise σ was 0.021. The data consistency constraint alone (λ = 0) reduced the vertical strip artifact and the background noise (σ = 0.012) significantly. Applying the data consistency constraint also increased the pSNR (cyan texts in the figure) from 7.7 to 14.0. Furthermore, the use of the sparsity prior (λ = 0.1) gave a reconstruction similar to the one with λ = 0. The pSNR was further improved to 57.6 because of the strong suppression of the background noise. Figure 2 shows brain images. The shapes of the skull and brain parenchyma were observed in the regularized SENSE reconstructions. We found that signals potentially from gray and white matter increased as the data consistency constraint was applied (λ = 0). The average pSNR across six images increased from 11 to 26. Furthermore, when the sparsity constraint was added, the average pSNR dramatically increased to 296. Figure 3 shows the regularized SENSE reconstruction of slice 4 using data with an average of 1, 2, 4, and 8 excitations. The pSNR increased in proportion to the square root of the number of excitations for the original data. Using the same data, reconstructions that applied the data consistency constraint with λ = 0 had a 2.2-fold pSNR improvement. Specifically, the pSNR of the reconstruction with four excitations gave similar pSNR to the reconstruction using unaveraged data with the data consistency constraint. This is similar to the 8-average data and 2-average data with the data consistency constraint. Using the sparsity constraint with λ = 0.01 further improved the pSNR by a factor of 12.







DISCUSSION Our results demonstrate that using the DC constraint to reconstruct multi-sensor ULF-MRI data can reduce the noise level and thus increase the quality of the reconstructed image. Note that our implementation did *not* discard any data point in the *k*-space for accelerated acquisitions, because SNR is the most critical limiting factor in current ULF MRI. Instead, the reconstruction algorithm preserved the same amount of the data and adjusted the dependency within the data. Our method is different from signal-space projection (SSP)[5] and signal-space separation (SSS)[6] methods in MEG processing, both of which are spatial filtering methods to separate measurements into signal and noise components and to remove the latter. The DC constraint is a unique *k*-space property in MRI, while MEG does not have similar spatial encoding. However, we expect that this DC constraint can be integrated with SSP and SSS to further suppress noise and thus to improve the quality of ULF MRI.

REFERENCES

1 McDermott R., Lee S., ten Haken B. *et al.* Microtesla MRI with a superconducting quantum interference device. Proc Natl Acad Sci U S A.2004; 101:7857-7861.

2 Griswold M. A., Jakob P. M., Heidemann R. M. *et al.* Generalized autocalibrating partially parallel acquisitions (GRAPPA). Magn Reson Med.2002; 47:1202-1210.

3 Lustig M. & Pauly J. M. SPIRiT: Iterative self-consistent parallel imaging reconstruction from arbitrary k-space. Magn Reson Med.2010; 64:457-471.

4 Lin F.-H., Kwong K., Belliveau J. *et al.* Parallel imaging reconstruction using automatic regularization. Magn Reson Med.2004; 51:559-567.

5 Uusitalo M. A. & Ilmoniemi R. J. Signal-space projection method for separating MEG or EEG into components. Med Biol Eng Comput.1997; 35:135-140.

6 Taulu S., Simola J. & Kajola M. MEG recordings of DC fields using the signal space separation method (SSS). Neurol Clin Neurophysiol.2004; 2004:35