POCS-based Compressive Slice Encoding for Metal Artifact Correction

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Introduction: Slice Encoding for Metal Artifact Correction (SEMAC) [1] fully corrects metal-induced artifacts in MR images by employing additional z-phase encoding to resolve distorted excitation profiles. The spins displaced due to metal-induced susceptibility are repositioned to their actual locations, and the signals from all excited slices are combined to reconstruct the 3D volume. There are two main problems of SEMAC technique (or another similar MAVRIC technique [2]), namely long scan times associated with the additional z-phase encoding and low signal-to-noise ratio (SNR) due to the inclusion of noise in the combination of SEMAC-encoded slices [1]. Acceleration techniques such as parallel imaging reduce the scan times of SEMAC at the cost of further loss in SNR [3]. In this work, we address the two problems of SEMAC with an alternate sampling and reconstruction procedure to exploit the correlation and sparsity in SEMAC-encoded slices.

Theory: The scan times of SEMAC acquisition are reduced by performing down-sampling in $ky-kz$ plane with a center-filled Poisson sampling disk (Fig. 1). Each down-sampled SEMAC-encoded slice is reconstructed via a projection over convex sets (POCS) algorithm, which iterates between (1) in-plane parallel imaging (PI) reconstruction at each kz location and (2) noise suppression by exploiting sparsity in 3D image domain.

For the parallel imaging reconstruction, the central filled k-space lines at each kz location are used for the calibration of the corresponding in-plane kernels. The missing k-space samples are synthesized by convolving the in-plane kernels across the coils [4]. The PI reconstruction results in the amplification of noise in the reconstructed images. Nevertheless, the noise in SEMAC-encoded slices is made incoherent with the Poisson random sampling pattern [5], and is suppressed by exploiting the sparsity in 3D image domain.

A 3D Fourier transform serves as through-plane sparsifying transform, since distorted excitation profiles are mostly sparse along the slice-select z axis. To promote in-plane sparsity, a wavelet transform is applied to sparsify the signals in the $x-y$ plane. Furthermore, the distorted excitation profiles are jointly sparse across coils: the same distorted excitation profile is modulated by different coil sensitivities. The joint sparsity across coils can be leveraged by a sum-of-squares combination of the sparsified coefficients. The noise suppression can be formulated as the following constrained optimization problem:

$$\min_{w} \sum_{c=1}^{n} \left|\left|\Psi S_c w\right|\right|_2^2$$
$$\text{subject to } F_\Omega S_c w = d_c, \forall c = 1, \cdots, n \qquad (1)$$

where Ψ represents the sparsifying transform of the distorted excitation profile w in 3D image domain, and w is modulated with the coil sensitivity S_c for n coils. The data consistency is enforced for the acquired k-space samples d_c over the sampling support F_Ω. This optimization algorithm can be easily solved by soft-thresholding, while the potential loss of details due to the soft-thresholding is mitigated by reinforcing the data consistency constraint and the PI reconstruction.

Method and Results: The knee of a subject who has several stainless steel screws in his tibia was imaged at 1.5 T using an 8-channel extremity coil. This study involves 16 additional z-phase encoding steps. The fully-sampled SEMAC-encoded slices were retrospectively under-sampled by a factor of 3 with a Poisson sampling disk. The under-sampled SEMAC-encoded slices are reconstructed and combined to correct metal artifacts. Figures 2 and 3 show the comparison of one sample SEMAC-encoded slice and SEMAC-corrected result obtained from full-sampled and under-sampled data, respectively. It can be seen that the proposed reconstruction algorithm results in significant SNR improvement despite a 3-fold acceleration. It is important to note that the constrained optimization in Eq.(1) is complementary to the parallel imaging by exploiting the inherent sparsity in SEMAC data to dramatically improve the SNR of combined images.

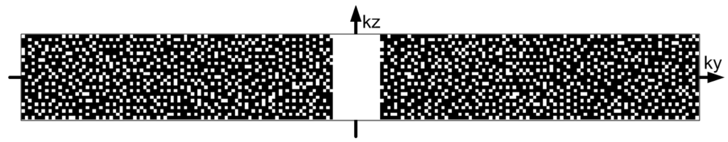

Fig. 1: Center-filled Poisson disk for under-sampling in ky-kz plane.

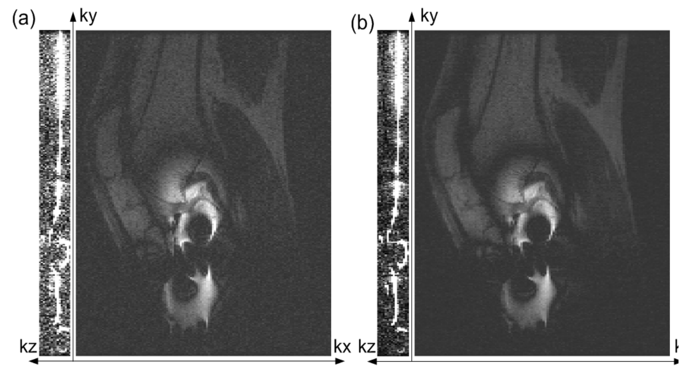

Fig. 2: Comparison of one sample SEMAC-encoded slice obtained from (a) the reconstruction of full-sampled SEMAC data and (b) the proposed reconstruction of under-sampled SEMAC data obt with Poisson disk sampling. Their reformats are shown on the left-hand.

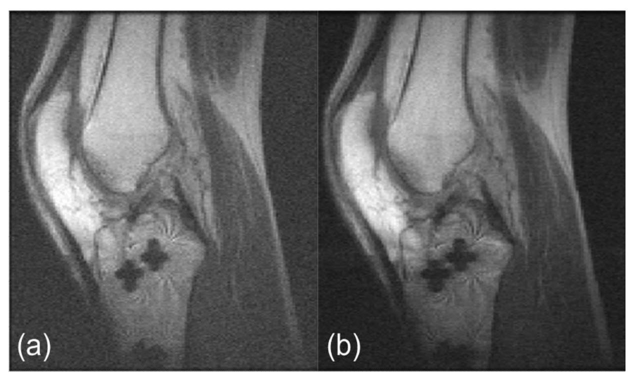

Fig. 3: Comparison of one sample SEMAC-corrected result from (a) full-sampled SEMAC reconstruction and (b) 3x accelerated POCS-based compressive SEMAC.

Conclusion: By exploiting sparsity to suppress noise buildup during the PI reconstruction and the combination of SEMAC-encoded slices, the new POCS-based compressive SEMAC not only greatly reduces scan times incurred to fully correct metal-induced artifacts but also leads to the improved SNR of SEMAC corrected result.

References: [1] Lu W. et al MRM, 2009; 62:66-76. [2] Koch K. et al MRM, 2009; 61:381-90 [3] Hargreaves BA. et al JMRI 2010;32:987-96. [4] Lustig M. et al MRM, 2010; 64: 457-71. [5] Lustig M. et al MRM, 2007; 58: 1182-95.