Improved Spatial Homogeneity and Sensitivity Estimation for Multi-coil Image Reconstruction

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Introduction: Receiver coil arrays have been used in MRI for improving SNR and accelerating the acquisitions. Since arrays are usually composed of small surface coils, the overall sensitivity depends on the individual coil sensitivities, the relative placement of the elements, and the image combination method. If the sensitivity profiles are known, then an optimal linear combination can be used to reconstruct an image with homogenous coverage over the spatial extent of the array [1]. However, for most applications, the sensitivity profiles are not precisely known. With phased-arrays, a sum-of-squares (SOS) reconstruction has been typically employed

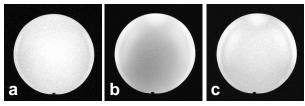


Figure 1. a: Phantom image acquired with a quadrature coil. 8-channel array data reconstructed as b: P_{sos} and c: P_{norm} .

because it generally yields a near-optimal SNR. Nonetheless, this combination can lead to intensity modulations across the FOV due to the inhomogeneity of the overall sensitivity. We propose an improved method to significantly increase the signal homogeneity and to estimate coil sensitivities. The improved estimates are further shown to enhance self-calibrating parallel imaging reconstructions.

Methods: For an array of N elements, the signal \mathbf{S}_i from the ith coil at a given pixel is $\mathbf{S}_i = \mathbf{M}\mathbf{C}_i$, where \mathbf{M} is the tissue-based MR signal, \mathbf{C}_i is the sensitivity profile of the coil, and noise is omitted for simplicity. The SOS image, $\mathbf{P}_{sos} = (\sum |\mathbf{S}_i|^2)^{(1/2)} = |\mathbf{M}|(\sum |\mathbf{C}_i|^2)^{(1/2)}$, has intensity modulations apart from tissue contrast since $(\sum |\mathbf{C}_i|^2) \neq$ 'constant' for most arrays. Another approach is to optimally combine the data after image-based estimation of the coil sensitivities [2]. The optimal linear combination is $\mathbf{P}_{opt} = \sum \mathbf{S}_i \mathbf{b}_i$, where $\mathbf{b}_i = \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{j=1}^{n} \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{j=1}^{n} \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{j=1}^{n} \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{j=1}^{n} \sum_{i=1}^{n} \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{i=1}^{n} \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{i=1}^{n} \sum_{i=1$

 $C_i^*/(\sum |C_i|^2)$. Normally, the sensitivities are estimated as: $\hat{C}_i = \langle S_i \rangle /(\sum |\langle S_i \rangle|^2)^{(1/2)}$, where $\langle \rangle$ denotes a low-frequency image reconstructed from central k-space data. Here, the denominator is assumed to represent tissue-based contrast and to be relatively free of coil-based intensity modulations. In fact, it contains profile-based spatial variations because it employs an SOS combination, and the reconstruction mistakes these variations to be part of the tissue contrast.

We propose a generalized pth-norm combination, $\mathbf{P}_{norm} = (\sum |\mathbf{S}_i|^p)^{(1/p)}$, which increases the signal homogeneity because $(\sum |\mathbf{C}_i|^p)^{(1/p)}$ has a flatter profile than $(\sum |\mathbf{C}_i|^2)^{(1/2)}$ for p<2. Furthermore, this combination can be used to obtain improved sensitivity estimates, $\hat{\mathbf{C}}_i = \langle \mathbf{S}_i \rangle / (\sum |\langle \mathbf{S}_i \rangle|^p)^{(1/p)}$, resulting in a more truthful depiction of the tissue contrast in the final image. If \mathbf{P}_{norm} by itself is used for combination, it increases the signal homogeneity at the expense of SNR. However, when used for sensitivity estimation as in \mathbf{P}_{opt} , the final image SNR is minimally degraded.

The value of p yielding the flattest profile for a given array can be determined with a calibration scan of a uniform phantom. Images of a uniform spherical phantom acquired with a quadrature coil and an 8-channel head coil are shown in Fig.1. For $p \sim 0.5$, P_{norm} achieves the uniformity of the quadrature coil image. Although coil loading changes the sensitivities, the combination is tolerant to deviations from the optimal value of p. A range of p values, 0.2 to 0.8, can be safely used while only allowing for 20% of the mean-squared error between the P_{norm} (for optimal p) and the SOS images.

If the central portion of k-space is sampled densely enough, improved coil sensitivity estimates can be obtained with the proposed method without the need for separate calibration scans [3]. These estimates can be used to perform a SENSE [4] reconstruction on an accelerated acquisition.

Results: Figure 2 displays T1-weighted brain images acquired with an 8-channel head coil at 1.5 T. The SOS image and the P_{opt} combination for p = 2 have high SNR; however, the central part of the image is dimmer due to the array profile. The P_{norm} image achieves a flatter profile and gray/white matter signal is more uniform across the brain, but the image has reduced SNR. The P_{opt} image for p = 0.5 achieves a flat overall profile in addition to near-optimal SNR.

The reconstructions for a 2X accelerated acquisition using the sensitivities estimated with p = 2 and p = 0.5 are shown in Fig.3. Improved flatness of the profile (p = 0.5) results in a more accurate depiction of the image contrast as predicted.

References:

- 1. Roemer PB, et al. MRM 16:192-225, 1990.
- **2**. Bydder M, *et al*. MRM 47:539-48, 2002.
- **3**. McKenzie CA, et al. MRM 47:529-38, 2002.
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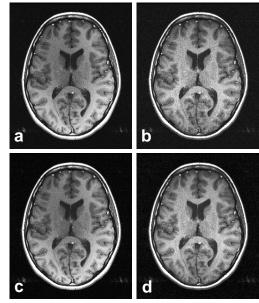


Figure 2. Spin-echo brain images acquired with an 8-channel head coil with the following parameters: α = 30°, TR = 300 ms, 24 cm FOV, 0.7x0.7x4 mm³, ±15.63 kHz BW, 10 s per slice. **a:** P_{sos}, **b:** P_{norm}, **c:** P_{opt} (**p** = 2), **d:** P_{opt} (**p** = 0.5).

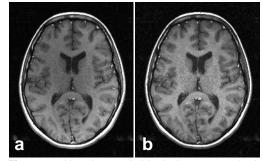


Figure 3. 2X undersampled brain images acquired with the same parameters except for 1 mm in-plane resolution. Central $1/16^{th}$ portion of k-space was fully sampled for calibration purposes. SENSE reconstruction for **a**: **p** = **2**, **b**: **p** = **0.5**.