# Superresolution Parallel Magnetic Resonance Imaging

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**INTRODUCTION.**

Parallel MRI has been introduced has a method to accelerate the encoding process by sub-sampling k-space while maintaining the total extent [1-2]. The rationale for this sub-encoding scheme is that the coil sensitivity maps are very smooth and retrieve k-space information only from the neighborhood of the actual gradient-encoding point. New array coil designs with a large number of small elements [3-4] provide strong variation of the coil sensitivities which may result in residual aliasing artifacts in parallel MRI due to sensitivity variation within the image voxel [5]. In this work, a novel parallel MRI method known as superresolution SENSE (SURE-SENSE) is proposed as an alternative to standard SENSE using coils with strongly varying coil sensitivities. Acceleration is performed by acquiring the low spatial resolution representation of the object being imaged and the coil sensitivity maps are acquired with much higher target spatial resolution. The increase in spatial resolution will be determined by the degree of coil sensitivity variation within the low resolution voxel and the SNR in the low resolution object image. We show feasibility of the method for human brain imaging using receiver arrays with 32 and 96 RF elements.

**THEORY AND METHODS.**

The forward model $\mathbf{y}=\mathbf{E}\mathbf{s}$ for SURE-SENSE is constructed assuming that $\mathbf{y}$ is the multi-coil low spatial resolution representation of $\mathbf{s}$. A conjugate gradient algorithm [6] is used to solve the computationally intensive inverse problem. The encoding matrix $\mathbf{E}$ for SURE-SENSE is poorly conditioned since the variation of the coil sensitivities within the acquired voxel is lower than across larger distances which is case for sub-sampled acquisitions. Pre-conditioning [7] is employed to regularize the conjugate gradient solution by solving the transformed system $\mathbf{M}^{-1}\mathbf{E}^{H}\mathbf{E}\mathbf{s}=\mathbf{M}^{-1}\mathbf{E}^{H}\mathbf{y}$, where $\mathbf{M}$ is a matrix that approximates $\mathbf{E}^{H}\mathbf{E}$, but it is easier to invert. For $\mathbf{M}$ we used the matrix $\mathbf{E}^{H}\mathbf{E}$ for the case of fully-encoding where we have a diagonal matrix with entries given by the sum of coil sensitivity squares. The transformation results in inverting a well-conditioned encoding matrix with all the singular values clustered around a single point. Pre-conditioning will enforce low values of g-factor at the expense of attenuating high spatial frequencies in the solution. The maximum spatial resolution is the limited by the g-factor reduction by regularization that is consistent with acceptable SNR in the reconstructed high resolution image.

Human brain data were acquired with a 3 Tesla MR Siemens scanner using close-fitting helmet array coils with 32 [3] and 96 [4] elements. A GRE sequence was employed with a 256×256 spatial matrix and a FOV of 220×220 $mm^2$, resulting in in-plane spatial resolution of 0.86 $mm^2$. Low spatial resolution data was extracted from the central k-space region of the acquisition. Coil sensitivity maps were estimated from the fully-encoded acquisition using a $4^{th}$ order polynomial fitting optimized for the 32-channel array coil [2]. For comparison purposes, the fully-encoded and the sub-encoded data were conventionally reconstructed using FFT and sensitivity-weighted combination.

Reconstruction at lower spatial resolution, which represents higher intra-voxel sensitivity variation, was simulated to compare the performance of standard SENSE and SURE-SENSE for the same acceleration factor. Fully-encoded low resolution data was obtained from the central 64×64 k-space matrix. Standard SENSE reconstruction was applied to sub-sampled data obtained by decimating the 64×64 data with a factor R=4×4. SURE-SENSE reconstruction was applied to the central 16×16 k-space matrix. The reconstruction results were interpolated to a 256×256 matrix by using zero-filling in k-space.

**RESULTS.**

Fig. 1 shows the reconstruction of human brain MRI data. The average error with respect to the fully-encoded reconstruction was 9.6% for the 32-channel data (R=16) and 10.7% for the 96-channel data (R=64). Note that the reconstruction using the 96-channel array is recovering more spatial features as suggested by the uniformity of the error image. This highlights the advantages of the stronger variation of the coil sensitivities with this array.

Standard SENSE reconstruction with intra-voxel sensitivity variation presented residual aliasing artifacts, especially periphery where sensitivity variation is stronger (Fig. 2). Superresolution SENSE is free of residual aliasing artifacts at the expense of a small loss in the final spatial resolution. The average error for SENSE was 18.1% while for SURE-SENSE was 7.5%.

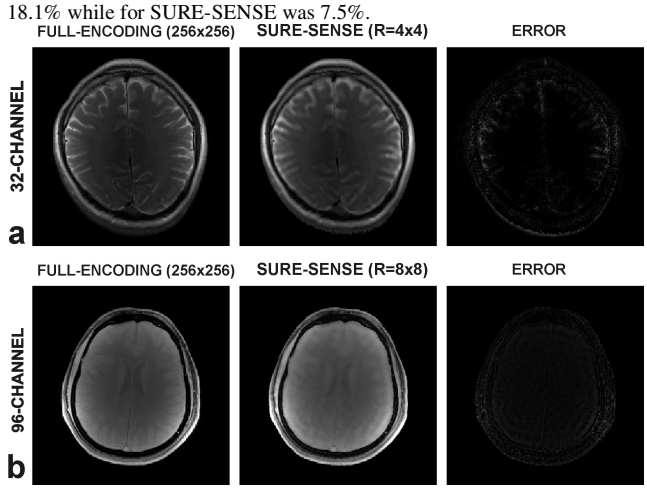


Fig. 1: Conventional reconstruction of fully-encoded data and SURE-SENSE reconstruction of sub-encoded data for a) 32-channel array with R=4x4, and b) 96-channel array with R=8x8.

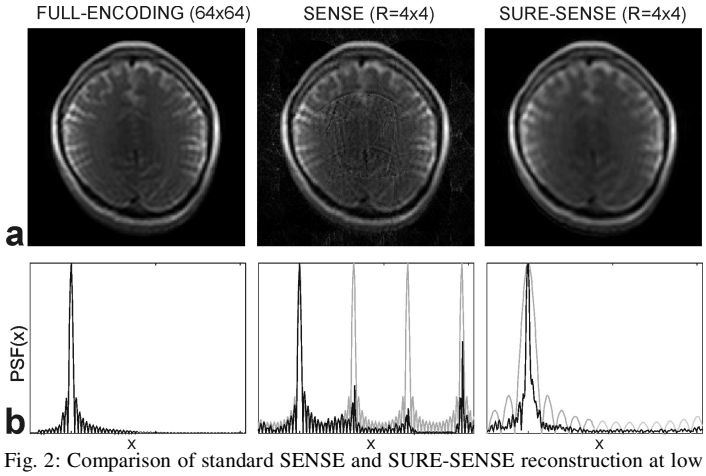


Fig. 2: Comparison of standard SENSE and SURE-SENSE reconstruction at low spatial resolution. a) Magnitude images. b) PSF along the x dimension. The PSF of the accelerated raw data is shown in gray lines while the black lines represent the PSF of the reconstructed data.

**DISCUSSION.**

Superresolution SENSE provides a powerful means of accelerating low spatial resolution parallel MRI data that compares favorably to standard SENSE for the same acquisition time. The reconstruction technique provides low g-factor at the expense of a slight spatial resolution loss in the reconstructed image. We are in the process of implementing the technique using similar arrays at 7 Tesla which will provide higher sensitivity and stronger spatial modulation of the sensitivity functions [8]. The technique is particularly applicable to intrinsically low spatial resolution modalities such as spectroscopic and functional imaging and provides flexible tradeoff between spatial and temporal resolution for accelerating scans in clinical studies.

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