Sparse BLIP: Compressed Sensing with Blind Iterative Parallel Imaging

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INTRODUCTION: In SENSE-based compressed sensing (CS) methods for parallel imaging such as SparseSENSE (1) and CS-SENSE (2), coil sensitivities are usually obtained from low resolution images or through a separate scan, where accuracy cannot be guaranteed. Inaccuracy in coil sensitivities may lead to serious image artifacts at high acceleration factors. GRAPPA-based CS methods such as L_1-SPIRiT (3) avoid explicit use of coil sensitivities, but the channel-by-channel reconstruction is computationally intensive and may also cause non-uniform intensity. Motivated by the success of JSENSE (4,5) in improving coil sensitivities estimation, we propose a new approach to blind compressed sensing in the context of parallel imaging where the sensing matrix is not known exactly and needs to be reconstructed. We name the method Sparse BLIP (compressed sensing with Blind Iterative Parallel imaging). The proposed method effectively incorporates the sparseness of both the desired image and coil sensitivities in reconstruction. The proposed method is compared with SparseSENSE and L_1-SPIRiT and demonstrates a significant improvement in image quality at high reduction factors.

THEORY AND METHOD: The proposed blind CS approach enforces the prior knowledge on both the sensing matrix and signal subject to the data consistent constraint. The data consistent term of the proposed method comes from the JSENSE framework (4), where the unknown coil sensitivities **a** and the desired image **f** are found by solving a least-squares solution $\arg\min_{\{\mathbf{a},\mathbf{f}\}} \frac{1}{2}\left\|\mathbf{d}-\mathbf{E}(\mathbf{a})\mathbf{f}\right\|^2$ [1]. Instead of the parametric models used in (6), a general pixel-based model is used for the sensitivities **a** here. To incorporate the concept of CS, the k-space data is acquired with incoherent sampling and the reconstruction enforces sparseness constraints on functionals of both image and sensitivities. For incoherence sampling, we use a 1-D random undersampling pattern with variable density in Cartesian grid as in (6). For the sparseness constraints, the total-variation (TV) of both image and coil sensitivities in spatial domain is minimized. The objective function is: $E(\mathbf{f},\mathbf{s}_l)=\sum_{l=1}^{L}\|F_D(\mathbf{f}\cdot\mathbf{s}_l)-\mathbf{d}_l\|^2+\alpha\mathrm{TV}(\mathbf{f})+\beta\sum_{l=1}^{L}\mathrm{TV}(\mathbf{s}_l)$ [2], where $\mathbf{s}_l$ is the pixel-based sensitivity function, F_D is the Fourier transform with decimation, and · denotes pixel-wise product. The positive constants α and β are adjusted to control the tradeoff between data consistency and the two sparseness priors. When the sensitivity functions are given, Eq. [2] is equivalent to SparseSENSE. When both **f** and $\mathbf{s}_l$ are unknowns, the joint optimization problem in Eq. [2] is beyond the conventional CS framework and is no longer convex. We regarded such a problem as blind CS where the sensing matrix is not given. Under Eq. [2], the energy function E is still convex with respect to **f** if $\mathbf{s}_l$ is given, and similarly, E is also convex with respect to $\mathbf{s}_l$ if **f** is given. We therefore minimize the energy function by alternating between minimizing over **f** and minimizing over $\mathbf{s}_l$ as done in (4) until the objective function stops decreasing. Nonlinear conjugate gradient (NLCG) algorithm with line search is used to solve each alternating optimization problem. Because convergence to a global minimum is not guaranteed in such a greedy approach, an accurate initial estimate for the unknown coil sensitivities is important for high quality reconstructions and is obtained using either a pre-scan or the calibration data at central *k*-space. Compared with the channel-by-channel reconstruction methods such as GRAPPA (7) and SPIRiT (3), the method is advantageous in that no root Sum of Squares (SOS) is needed. It not only saves computation when a large number of channels are involved, but also avoids the assumption that SOS of all sensitivities is spatially uniform. Because minimizing TV favors images with uniform intensity, the use of TV constraint on image potentially generate a final reconstruction that is more uniform in intensity than that given by the SOS.

RESULTS AND DISCUSSION: The proposed Sparse BLIP method was evaluated on both phantom and *in vivo* brain datasets. A T1-weighted scan was performed on a phantom using a 2-D spin echo sequence on a 3T commercial scanner (GE Healthcare, Waukesha, WI) with an eight-channel torso coil (TE/TR = 11/300 ms, FOV = 18 × 18 cm, matrix = 256 × 256, slice thickness = 1.7 mm). A 3-D MPRAGE dataset acquired with an eight-channel head coil (TE/TR = 3.45/2530 ms, TI= 1100 ms, FOV = 25.6 cm, matrix = 256 × 256, slice thickness = 1.33 mm) was obtained from http://www.nmr.mgh.harvard.edu/~fhlin/codes/mprage_8ch_slice1.mat. The reconstructions of the proposed Sparse BLIP method are compared with those of the state-of-the-art methods, SparseSENSE (1) and L_1-SPIRiT (3) in Figure 1, with a reduction factor of 5.95 (1-D undersample) for the phantom data and 16 (2-D undersample) for the brain data. It is seen that the proposed method is able to significantly suppress the aliasing artifacts in L_1-SPIRiT and SparseSENSE reconstructions without loss of resolution. In addition, Sparse BLIP reconstruction is also seen to be more uniform in intensity than the SOS reference.

CONCLUSION: We propose a novel blind CS method to reconstruct the image and coil sensitivities simultaneously from undersampled multichannel phased-array data. Phantom and *in vivo* experimental results demonstrate that the proposed Sparse BLIP method is able to accelerate parallel imaging more than the state-of-the-art CS-based methods.

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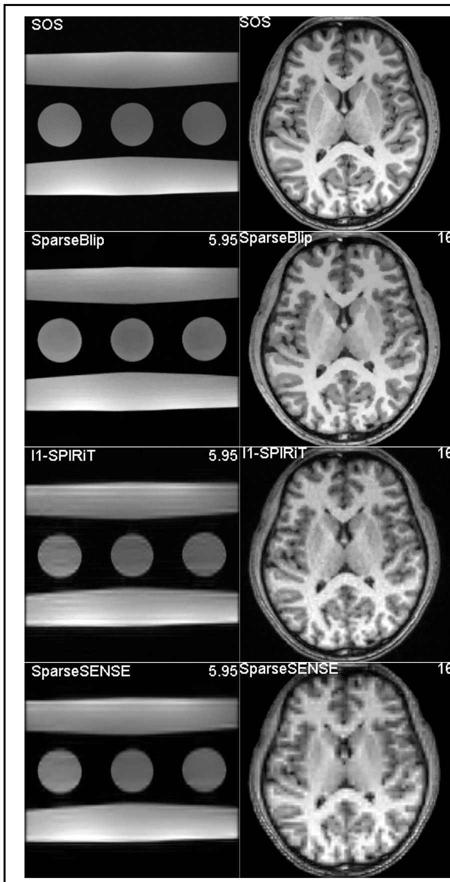

Figure 1 Reconstruction results with 2-D (left) and 3-D (right) undersampling.