Auto-Calibrated Parallel Imaging Reconstruction Using k-Space Sparse Matrices (kSPA)

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INTRODUCTION: A non-iterative parallel imaging reconstruction algorithm that utilizes **k**-space sparse matrix (kSPA) was recently introduced for arbitrary sampling patterns (1). The kSPA algorithm computes a sparse reconstruction matrix in **k**-space. This algorithm was shown to be particularly useful for a wide range of applications including 3D imaging, functional MRI (fMRI), perfusion-weighted imaging, diffusion tensor imaging (DTI) and massive parallel imaging, where a large number of images have to be reconstructed. The original algorithm requires the acquisition of low-resolution coil sensitivity maps (2). Methods for auto calibration become important in cases where sensitivity maps are difficult to obtain (3,4). Here we present an auto-calibrated kSPA algorithm for arbitrary trajectories that does not require the explicit estimation of coil sensitivities. We show that the sparse reconstruction matrix can be estimated directly from calibration data. In addition, we show that the calibration data can be located in any region of **k**-space.

METHOD: The kSPA algorithm formulates the data acquisition as a system of sparse linear equations denoted as $\mathbf{d} = \mathbf{G}\,\mathbf{m}$ (1). Here, **d** is a column vector stacked with **k**-space data acquired by all coils; **m** is also a column vector with the **k**-space value to be estimated; **G** is the coefficient matrix formed by the spectrum of coil sensitivity maps. The key feature of kSPA involves treat both **G** and its inverse $\mathbf{G}^{+}$ as sparse matrixes. Finding $\mathbf{G}^{+}$ requires the knowledge of coil sensitivity. Here, we propose to compute $\mathbf{G}^{+}$ directly from calibration data by solving the following set of linear equations:

$$\sum_{n'}\sum_{\mu_0} G^{+}_{\rho_0\mu_0,n'}\, d_{n'}(\boldsymbol{\kappa}_{\mu_0}) = d_n(\mathbf{k}_{\rho_0}) \qquad [1]$$

Here, $d_n(\mathbf{k}_{\rho_0})$ is the *n*th-coil calibration data either acquired or gridded on a small Cartesian grid, and $d_{n'}(\boldsymbol{\kappa}_{\mu_0})$ is the data gridded onto targeted sampling patterns using the calibration data. Once $G^{+}_{\rho_0\mu_0,n'}$ is computed by solving Eq. [1], it can be used to reconstruct the image for the *n*th coil.

One key result of the proposed auto-calibrated kSPA algorithm is that the reconstruction kernel for one missing point in **k**-space can be computed using calibration data acquired at any location. To accomplish that we only need to translate the surrounding sampling points to center at a set of grid points in the middle of the calibration region. We then repeat the reconstruction for each coil and perform a sum-of-squares reconstruction to form the final image similar to the GRAPPA algorithm (5).

The proposed algorithm is applied to an interleaved spiral trajectory. A Shepp-Logan phantom and an 8-channel receiving coil were used to simulate the **k**-space data *via* inverse gridding. *In vivo* brain images of a healthy volunteer were acquired using a spiral readout trajectory on a 1.5T whole-body system (GE Signa, GE Healthcare, Waukesha, WI) equipped with a maximum gradient of 50mT/m and a slew rate of 150 mT/m/s. An 8-channel head coil (MRI Devices Corporation, Pewaukee, WI) was used for image acquisition. The scan parameters were: FOV = 24cm, TR = 4s, TE = 15ms, bandwidth = 125 kHz, and matrix size = 256x256.

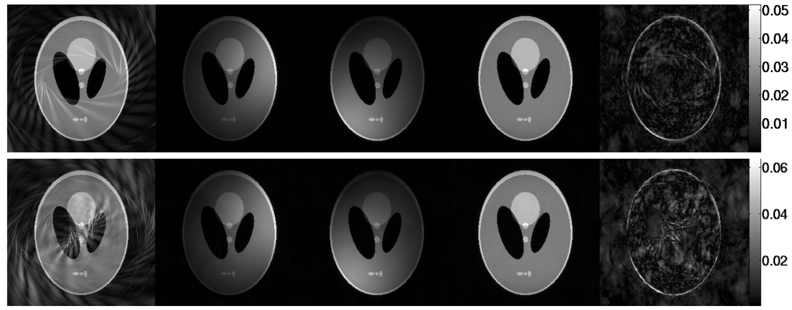

Figure 1 – Auto-calibrated kSPA reconstruction on simulated spiral data: (a) R =2; (b) R = 3. Images from left to right are: gridding recon, two examples of individual coil image by auto-kSPA, sum-of-squares, and difference between auto-kSPA and ground truth.

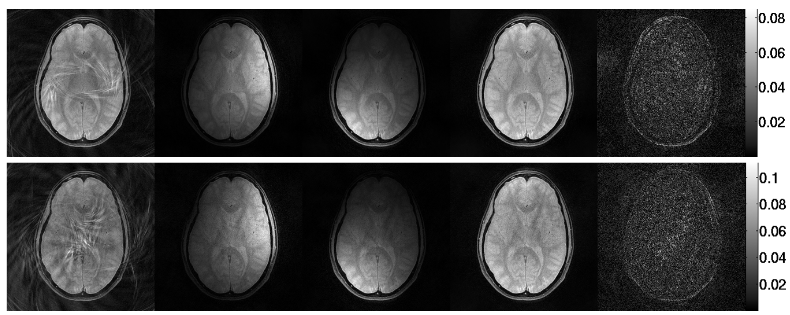

Figure 2 – *In vivo* auto-calibrated kSPA reconstruction: (a) R =2; (b) R = 3. Images from left to right are: gridding recon, two examples of individual coil image by auto-kSPA, sum-of-squares, and difference between auto-kSPA and full-sampled image.

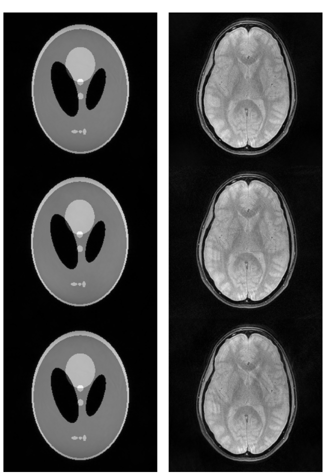

Figure 3 – Auto-kSPA (R = 3) with calibration data: (a) centered at (0, 0); (b) at (16,16); (c) at (64,64).

RESULTS: Figure 1 and 2 show images reconstructed with auto-calibrated kSPA for reduction factors 2 and 3. Both individual coil images and the sum-of-squares images exhibit excellent image quality. The averaged root-mean-square-error (RMSE) is less than 5% in call cases. All images were reconstructed with calibration data sampled on a region of 16x16 pixels. Figure 3 shows image reconstructed using calibration data centered at different regions in k-space. In all three cases, there is no residual artifact in the simulated data, while some residual artifact remains in the in vivo image when the calibration data is off-center and noisy.

DISCUSSIONS: We have demonstrated an auto-calibrated kSPA algorithm for parallel imaging reconstruction that can be applied to arbitrary **k**-space sampling trajectories. The sparse reconstruction matrix is solely determined by using the calibration data acquired on a region of 16x16 pixels. We also show that this calibration data in principle can be acquired at any region of **k**-space. For noisy data, better performance is achieved when the calibration data is acquired in the center of **k**-space where signal-to-noise ratio (SNR) is generally higher. Compared to the original kSPA technique, the proposed technique reconstructs each coil image separately and it does not require the explicit information of coil sensitivities. In cases where accurate sensitivity is difficult to obtain, auto-calibrated kSPA is more convenient.

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