Array Compression for 3D Cartesian Sampling

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Introduction: Array compression (AC) [1,2] is a technique to reduce data size and reconstruction computation for large coil arrays. The original multi-channel data can be compressed, by a linear combination in *k*-space, into a few virtual channels, on which the reconstruction is performed. Among different AC methods, data-driven array compression [2] has the advantages of not requiring coil sensitivity measurement and having fast calculation of the compression matrix, and it has been demonstrated for fast reconstruction with 2D or multi-slice data acquisition. However, simply extending data-driven AC to 3D datasets will lead to non-optimal compression (signal loss), and is problematic with autocalibrating methods using 3D synthesis kernels, such as SPIR-iT [3] and ARC [4]. In this work, an optimal data-driven AC for 3D Cartesian sampling is proposed.

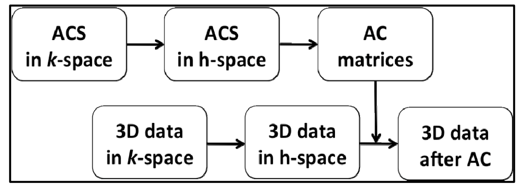

Fig.1 Flowchart of 3D SBS AC with 2D kernels: Compression matrix is calculated for each x location, and is applied to the h-space data. Both calibration and data synthesis are performed on the h-space data after SBS AC.

Methods: Coil sensitivities of large arrays vary spatially in 3D. Applying the same compression matrix for the whole 3D dataset will lead to noticeable signal loss. A spatially varying AC (slice-by-slice AC) would solve this problem.

(I) slice-by-slice (SBS) AC with 2D synthesis kernels: The flowchart is shown in Fig.1. Autocalibration signals (ACS) [5] are first acquired, followed by an inverse Fourier transform along the fully sampled readout direction. At each x location (defined as a slice), reformat the ACS from each channel in this slice into vectors, X_1, X_2, …, X_N (total N channels), and define matrix $X=(X_1, X_2, \ldots, X_N)$. Perform singular value decomposition (SVD) of X, $X=U\Sigma V^T$, where V is an NxN unitary matrix. Take the first M columns of V to form the compression matrix A. For each acquired data point (including ACS) in this slice (ky, kz), assume the original data is $Y=(y_1,y_2,\ldots y_N)$. Then the new data after AC is $Y'=YA$, which has only M channels. Autocalibrating parallel imaging (ACPI) reconstruction with 2D synthesis kernels, such as GRAPPA [5], including both the calibration and data synthesis step, can be performed on the compressed dataset.

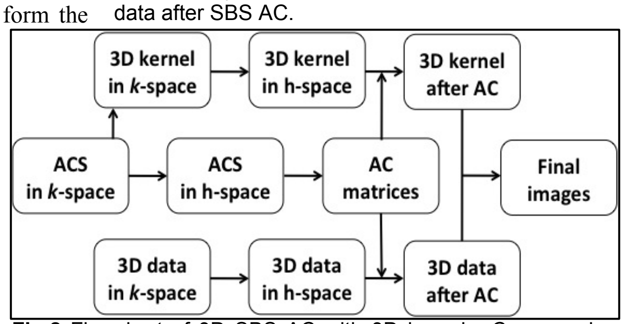

Fig.2 Flowchart of 3D SBS AC with 3D kernels. Compression matrices are applied to both the hybrid-space data and synthesis kernels correspondingly.

(II) SBS AC with 3D synthesis kernels: Better ACPI reconstruction can be achieved using 3D kernels [6]. Calibration of 3D kernels, however, can not be performed on the compressed data from (I) due to inconsistent compression along the readout direction. Instead, the original ACS is used for calibration. The 3D synthesis kernel (in h-space) is compressed slice-by-slice using the same matrix that compresses the original data. For each slice, the original synthesis kernel size is Ny x Nz x N x N, where Ny and Nz are the kernel sizes in ky and kz. Let Gij (NxN matrix) represent the kernel at the kernel point (Ny(i), Nz(j)). The new synthesis kernel Gij' can be found by $Gij'=A^TGijA$, where A is the NxM compression matrix from (I). The flowchart of method (II) is shown in Fig.2.

Results: A 3D contrast-enhanced abdominal MRA dataset (matrix size: 192x224x184) was acquired with a 32-channel coil on a 3T GE Signa Excite scanner. The results of single AC and SBS AC on the fully sampled dataset are shown in Fig.3. Figure 3 (a) and (b) are the square root of sum of squares (SSOS) images of 4 compressed coils from 32 coils using single AC and SBS AC respectively. Fig.3(c) is the SSOS image of 8 compressed coils by single AC. SBS AC had the least compression signal loss even though fewer compressed coils were used. The dataset was then 4x undersampled using variable density Poisson-disc pattern with ACS 20x20. L1SPIRiT [3] with 3D kernels (5x7x7) was used for reconstruction in Matlab. Faster reconstruction was achieved using the proposed SBS AC method (22 seconds/slice for 8 compressed coils) compared with reconstruction on the original 32 channel data (190 seconds/slice). The result is shown in Fig.4. SBS AC achieved similar image quality with an 8x improvement in reconstruction time.

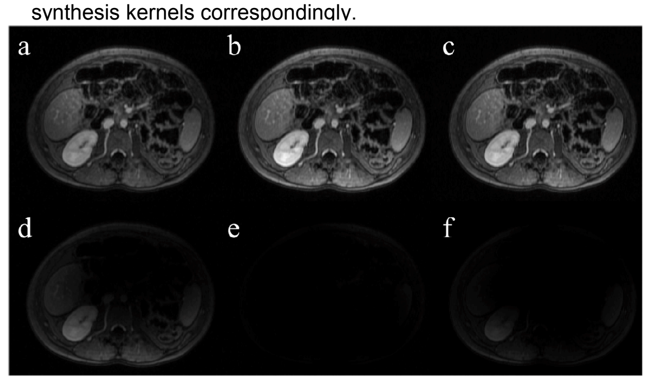

Fig.3 SSOS images of one slice of a 32 channel 3D dataset: (a) single AC, 4 compressed coils; (b) SBS AC, 4 compressed coils; (c) single AC, 8 compressed coils; (d-f) compression error of (a-c) compared to the original 32 channel SSOS image.

Conclusion: We have proposed a slice-by-slice array compression for 3D Cartesian sampling and have shown that it can achieve better data compression than direct extension of single AC. We have also designed SBS AC for autocalibrating parallel imaging with 3D synthesis kernels to achieve faster reconstruction.

References: 1. Buehrer, *et al.* Magn Reson Med 57:1131-1139, 2007; 2. Huang, *et al*. Magn Reson Imag 26: 133-141, 2008; 3. Lustig, *et al*. Magn Reson Med 64: 457-471, 2010; 4. Beatty, *et al.* Proc 15th ISMRM, p1749, 2007; 5. Griswold, *et al*. Magn Reson Med 47: 1202-1210, 2002; 6. Brau, *et al*. Magn Reson Med 59: 382-395.

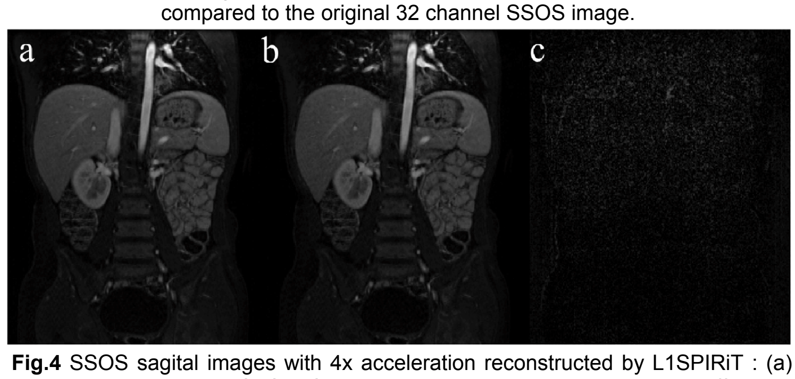

Fig.4 SSOS sagital images with 4x acceleration reconstructed by L1SPIRiT : (a) origzinal 32 coils; (b) SBS AC, 8 compressed coils used; (c) 10x difference between (a) and (b).