ESPIRIT-Based Coil Compression for Cartesian Sampling

Dara Bahri[1], Martin Uecker[1], and Michael Lustig[1]
[1]*Electrical Engineering and Computer Sciences, University of California, Berkeley, Berkeley, California, United States*

Target Audience: Engineers interested in speeding up high-channel-count parallel MRI reconstruction.

Introduction: While receiver arrays with many channels can increase parallel imaging acceleration and provide high signal-to-noise, processing the large datasets they produce is computationally demanding. Coil compression algorithms reduce, and denoise in the process, data from many coils into fewer virtual ones. Huang et al.[1] proposed using principal component analysis to globally compress multi-coil k-space data. While this scheme (SCC) is resilient to noise, it does not achieve optimal compression if there are fully-sampled dimensions. Zhang et al.[2] improved SCC for Cartesian sampling by compressing locally along fully-sampled directions, but the method (GCC) suffers in low-SNR sections of k-space. In this work we present an algorithm that compresses locally while remaining noise-robust, thereby offering the best of both worlds.

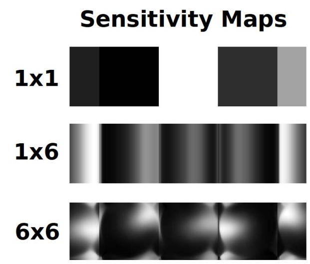

Figure 1: Maps for various kernel sizes

Theory: Data that is fully-sampled in all directions can be combined into one channel using sensitivity maps. However, this case hardly arises in practice where undersampling is used to achieve a speedup. Compression schemes like SCC employ a computation that is equivalent to combining using multiple sets of constant maps. In our method (ECC), we use ESPIRIT[3], an eigenvalue-based approach to estimating sensitivity maps from just auto-calibration lines, to produce sets of maps which are constant in sub-sampled directions and spatially varying in fully-sampled ones. We combine the data using these maps. A calibration matrix is constructed by sliding a kernel across the auto-calibration region. Extracting the kernel subspace and inverse-Fourier transforming its basis produces maps by a pixel-wise eigendecomposition in image space. By restricting the kernel to selected directions, we compute multiple sets of maps that vary only along those directions. Let y_i be coil i's k-space data, n the number of original channels, F and F^{-1} forward and inverse Fourier operators that act only on fully-sampled directions, and S_{ij} coil i's map in set j. Then data from virtual coil j is given by $F\{\sum_{i=1}^{n} F^{-1}\{y_i\}.* S_{ij}{}^{*}\}$ where .* and * represent point-wise multiplication and complex conjugation respectively.

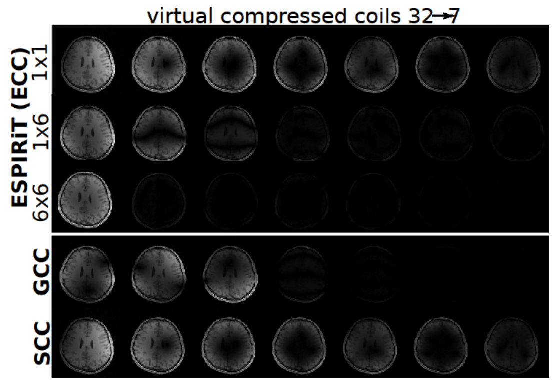

Figure 2: Images for the first 7 virtual channels for different methods and kernel sizes.

Methods and Results: Fully-sampled 2D data sets were acquired using a 32-channel head coil. Fig. 1 shows 5 of 32 maps from the first set for various kernel sizes. As expected, the 1x1 kernel gives constant maps, the 1x6 kernel gives maps which are constant in one direction and varying in the other, and the 6x6 kernel gives maps which spatially vary in both directions. Fig. 2 suggests that the 1x6 kernel and GCC both compress to 3 channel, confirming our expectation that GCC and ECC compress by the same factor. To test noise-robustness, a Monte Carlo simulation with 100 trials was conducted. Noisy datasets of different SNRs were synthesized by adding complex I.I.D. Gaussian noise to the original, noiseless dataset. Compression coefficients were computed using these noisy datasets and applied to the noiseless dataset. The mean and standard deviation of the normalized root mean squared error (nRMSE) was calculated, where $\text{nRMSE} = \frac{1}{\max(x)-\min(x)}\sqrt{\frac{1}{Np}\sum_{i=1}^{Np}(\tilde{x}(i)-x(i))^2}$, Np is the number of pixels, and $\tilde{x}$ and x are the SSOS (square root sum of squares) of the noiseless compressed channels and the SSOS of the noisy compressed channels respectively. Fig. 3 depicts these results for noisy datasets with SNR 4 - 20.

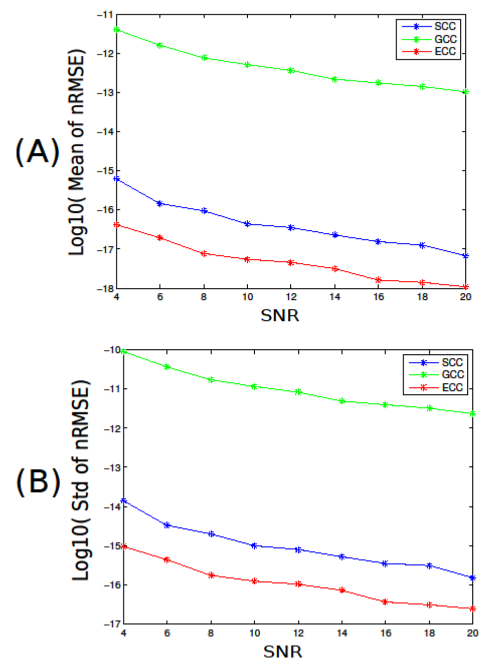

Figure 1 (in color): (A) mean and (B) standard deviation of nRMSE of combined images from compressed channels as a function of SNR.

Conclusion: We presented a coil compression technique for Cartesian sampling which utilizes fully-sampled directions and showed that it is less susceptible to noise than existing methods.

References: [1] Huang F, Vijayakumar S, Li Y, Hertel S, Duensing G. A software channel compression technique for faster reconstruction with many channels. Magn Reson Imaging 2008;26:133-141; [2] Zhang T, Pauly J, Vasanawala S, Lustig M. Coil compression for accelerated imaging with cartesian sampling. Magn Reson Imaging 2012;doi:10.1002/mrm.24267; [3] Uecker M, Lai P, Murphy M, Virtue P, Elad M, Pauly J, Vasanawala S, Lustig M. ESPIRIT – an eigenvalue approach to autocalibrating parallel MRI: where SENSE meets GRAPPA, submitted to Magn Reson Med.