

Array Compression for MRI with Large Coil Arrays

M. Buehrer¹, K. P. Pruessmann¹, P. Boesiger¹, and S. Kozerke¹

¹Institute for Biomedical Engineering, University and ETH Zurich, Zurich, Switzerland

Introduction:

Arrays with large numbers of independent coil elements become increasingly available [1] as they provide increased signal-to-noise ratios (SNR) and improved parallel imaging performance [2-3]. Processing of data from a large set of independent receive channels is, however, associated with an increased memory and computational load in reconstruction. This work addresses this problem by introducing coil array compression. The method allows reducing the number of data sets from independent channels by combining all or partial sets in the time-domain prior to image reconstruction.

Methods:

The purpose of coil array compression is to reduce the number of independent data streams from n coil input channels to m output channels by applying a suitable linear combination in the time-domain prior to image reconstruction. An ideal combination minimizes the noise in a given region-of-interest (ROI) of the final reconstructed image, translating array compression into an optimization problem. When using SENSE an analytical description of the average SNR in the ROI after compression can be derived and is expressed as noise minimization given unit signal response:

$$\sum_{\rho \in ROI_{folded}} Tr(X_{\rho}) = \sum_{\rho \in ROI_{folded}} Tr \left[\left(S_{\rho}^H A^H (A \Psi A^H)^{-1} A S_{\rho} \right)^{-1} \right] = \min$$

where A is the linear transformation used for compression and S_{ρ} denote the coil sensitivity matrices. Ψ represents the noise covariance matrix and the sum runs over all pixels in the folded ROI.

Solving the above equation directly is computationally very demanding. For this reason an approximation of A is found according to:

$$A = CU^H T$$

Where U is given by the singular value decomposition of the matrix:

$$P = \sum_{\rho \in ROI_{folded}} \hat{S}_{\rho} \hat{S}_{\rho}^{\dagger}$$

such that $R = UEU^H$. The transformation T decorrelates the physical coil elements by transforming the noise covariance matrix to identity and matrix C has the block form $C=(identity,0)$ with dimension $m \times n$ defining the number of virtual coil elements after combination. \hat{S}_{ρ} denote the decorrelated coil sensitivity matrices and \dagger represents the pseudo inverse.

For evaluation of the method a 2D cine short-axis view was acquired on a 1.5T Philips Intera System (Philips Medical Systems, Best, The Netherlands) using a 32 channel cardiac coil array. A steady-state free precession sequence was used with following parameters: TR = 3.4ms, TE = 1.7 ms, flip angle = 60°, scan matrix = 192x182, FOV = 320x320 mm², slice thickness = 8mm, 14 lines/segment, 30 cardiac phases.

Sensitivity maps were obtained from a SENSE reference scan and the region of the heart was roughly defined on these images. Reduced virtual coil arrays for that region were computed for a fully sampled dataset and 2-fold undersampled data with subsequent SENSE reconstruction

Results:

Reconstructions from the in vivo cine dataset are shown in Figure1. Images and noise maps obtained from all 32 physical coils are compared to images reconstructed from compressed virtual coil sets. It is shown that when using the fully sampled data the average noise in the ROI was amplified by 0.3% when compressing the number of coils to 4 corresponding to a compression factor of 8 and 13% for a compression factor of 32 resulting in just one virtual coil element. When performing 2-fold undersampling the noise amplification in the ROI was 2% for a reduction to 4 virtual coils and 10% for 2 virtual coils (Figure2). Using array compression, the raw data storage size of the fully sampled dataset could be reduced from 160MB to 20MB for 4 virtual coils and 5MB for 1 virtual coil. Accordingly, reconstruction time for the SENSE algorithm was reduced by 15% for 4 virtual coils and 30% for 1 virtual coil. The time for computing the compression matrix was approximately 0.5s on a standard PC.

Discussion:

Array compression allows significant reduction of the number of channels to be processed in image reconstruction thereby alleviating speed and memory constraints which emerge when using coil arrays with a large number of independent channels. The algorithm proposed facilitates fast and efficient computation of a linear transformation matrix which reduces the number of physical coil channels to a reduced virtual set.

References:

- [1] McDougall MP, et.al, MRM 54(2):386-392 (2005)
- [2] Wiesinger F, et.al, ISMRM2005, Abstract 672 (2005)
- [3] Zhu Y, et.al, M25RM 52(4):869-77 (2004)

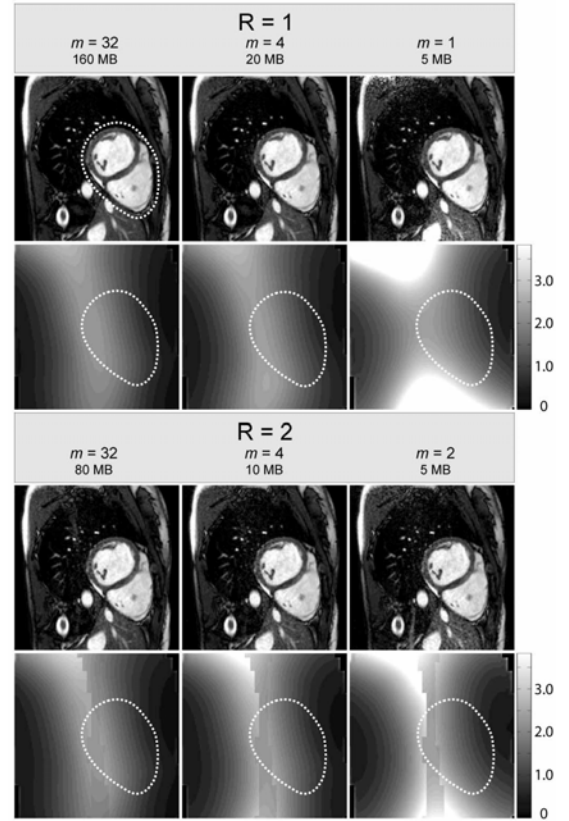


Figure1: Images of an exemplary time-frame from the cardiac cine acquisition as well as total image noise maps for the reduced virtual coil arrays consisting of different output channels m without and with 2-fold SENSE. The undersampling was performed in right-left direction. The region of interest is marked as dotted line. Note that very little noise amplification occurs in the region of interest after compression.

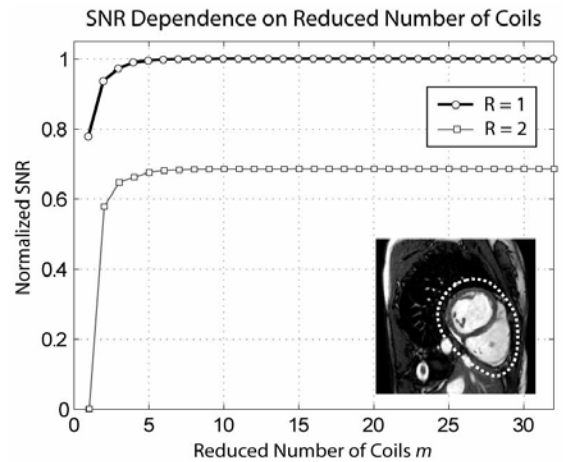


Figure2: The SNR dependence on the number of virtual coils m for the cardiac cine acquisition without and with 2-fold SENSE. Shown is the normalized averaged SNR over the ROI.