An Eigen-Vector Approach for Coil Sensitivity Estimation in the 3D Scenario

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Introduction: Parallel imaging achieves scan time reduction by utilizing the correlation among an array of receiver coils to reconstruct an image from under-sampled data. For SENSE-type reconstruction [1], explicit estimation of the coil sensitivity map (CSM) is critical in achieving good image quality. When the data is acquired using 3D Cartesian sampling, one way for estimating the coil profiles is to decouple the data along the frequency-encoding direction and then perform the estimation in a 2D manner, which, however, ignores the correlation between the calibration data in the frequency-encoding direction. In this work, we propose a 3D CSM estimation method, extending the Eigen-Vector approach that was developed for the 2D scenario. Experiments show the coil profiles are smoother with proposed approach compared to the 2D estimation method, and good image quality has been achieved.

Methods: The 2D Eigen-Vector approach [2, 3] makes use of the idea that the coil sensitivities can be computed as the Eigen-Vector of a calibration matrix in the image space corresponding to eigenvalues '1'. When the data is in 3D, one way is to estimate the coil profiles in a 2D manner along the frequency-encoding direction, and then the 3D coil profiles can be obtained by stacking the estimated 2D coil profiles. The independent estimation of the coil profiles for each slice causes discontinuity in the profile along the frequency-encoding direction. This discontinuity can be propagated into the reconstruction causing artifacts. In addition, applying the 2D Eigen-Vector approach ignores the correlation between the calibration data in the frequency-encoding direction and downgrades the effect of rank reduction in the Eigen-Vector approach which was achieved by singular value decomposition. The 3D Eigen-Vector approach overcomes these problems by utilizing all the calibration data together and estimating the coil profiles from different slices simultaneously. As shown in Fig. 1, the calibration matrix A is constructed from calibration data of size $c_x \times c_y \times c_z$ by gathering sliding blocks of kernel size $k_x \times k_y \times k_z$. The number of columns of A is $(c_x - k_x + 1) \times (c_y - k_y + 1) \times (c_z - k_z + 1)$, and the number of rows of A is $k_x k_y k_z n_c$, where n_c is the number of coils. We then compute a low rank subspace of A by singular value decomposition $A = V\Sigma U^{H}$, and set $V_{||}$ to the left singular vectors of A corresponding to the leading τ singular values. Let S^c be the coil sensitivity at coil $c \in [1,2,\dots,C]$, which are computed following the approach discussed in [3], i.e., set to the eigenvectors corresponding to the largest eigenvalues.

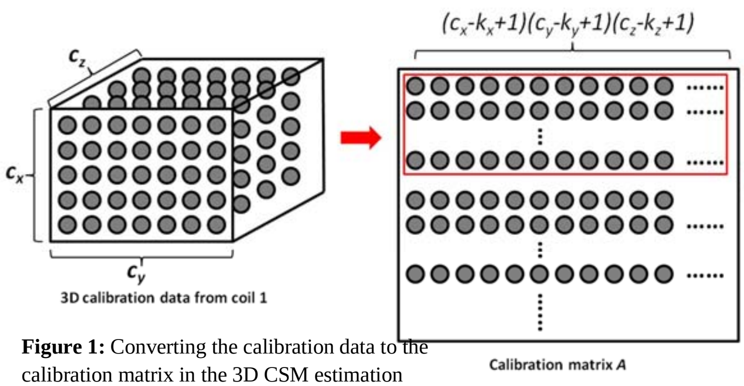

Figure 1: Converting the calibration data to the calibration matrix in the 3D CSM estimation

Results: The proposed 3D CSM estimation method is compared with the 2D method using 3D data. The data were acquired in healthy volunteer on a 1.5T clinical MR scanner (MAGNETOM Aera, Siemens Healthcare, Erlangen, Germany). Imaging parameters include field of view 320×260×96 mm^2, number of coils is 26. In the phase encoding-partition plane, a total of 2370 (out of 24960) points were acquired, and the central 24×24 block was treated as calibration data. As shown in Fig. 2 (a-f), the vertical direction is the frequency-encoding direction. The coil profiles from the 3D method are smoother than the ones from the 2D method, especially along the frequency-encoding direction. Fig. 2 (g-f) compare the central region of the reconstructed image at slice 72 along the transversal axis. The overall image using coil profiles from the 3D method is smoother than the one from the 2D method. The artifact marked by the red circle is less obvious than in the image from the 3D coil profile method.

Discussion and Conclusion: We proposed a 3D coil profile estimation method by utilizing the correlation in all three dimensions of the calibration data. The resulting coil profile from this method is smoother than the ones from the 2D method. Reconstruction with the coil profile from the 3D method gets rid of some artifacts caused by the discontinuity along the frequency-encoding direction from the 2D method. The overall image noise is lower in the 3D method due to a smoother coil profile. Efficient computation of the 3D Eigen-Vector can be achieved by utilizing the approach specified in [3] and a well-organized implementation which requires a storage cost of only $O(k_x n_y n_c^2)$.

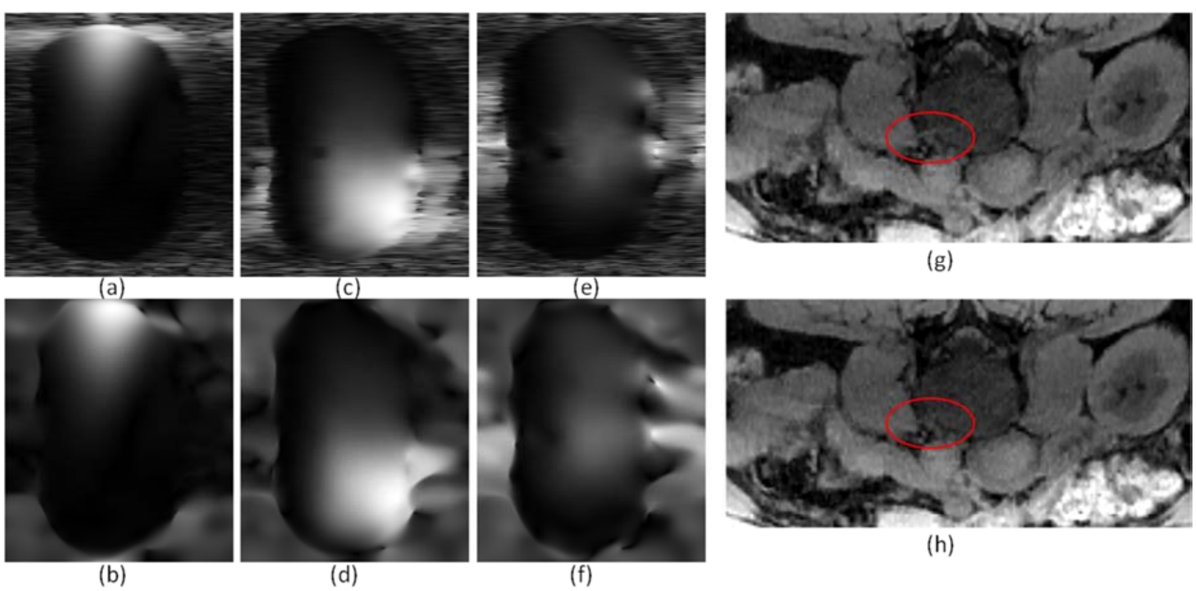

Figure 2: Comparison of the 2D Eigen-Vector approach and the 3D Eigen-Vector approach. **(a,c,e)** Coil profiles of coil #1, #5 and #10 from the 2D eigen-vector approach. **(b,d,f)** Coil profiles of coil #1, #5 and #10 from the 3D eigen-vector approach. **(g)** Central region of a reconstructed image slice using the coil profile from the 2D eigen-vector approach. **(f)** Central region of a reconstructed image slice using the coil profile from the 3D eigen-vector approach.

Disclaimer: The concepts and information presented in this paper are based on research and are not commercially available.

References: [1] K. P. Pruessmann, et al., Magn Reson Med, 42:952-962, 1999. [2] M. Lustig et al., Proc Intl Soc Mag Reson Med, #479, 2010. [3] Liu et al., technical report, 2012.