Optimal SNR combinations of multi-channel coil data for GRAPPA-reconstructed and time-series EPI data

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Target audience: Clinicians/researchers using accelerated echo planar imaging, especially in high-field or high-resolution applications.

Purpose: Data acquired across multiple channels of an array coil can be combined in such a way as to maximize the SNR in the combined image.[1] This combination requires an accurate estimate of the noise covariance, and typically the thermal noise covariance matrix is used. However, in several applications the noise covariance across the coil channels differs substantially from the thermal noise covariance, including in accelerated parallel imaging reconstructions[2] or in functional MRI time-series data[3], and furthermore the true noise covariance matrix varies spatially over the image. Here we present a coil combination method that accounts for the spatially-varying noise covariance to boost SNR in the combined image. Because this matrix must be inverted to calculate the combination weights, and the rank of this matrix also varies spatially, a per-voxel regularization is required to yield SNR gains.

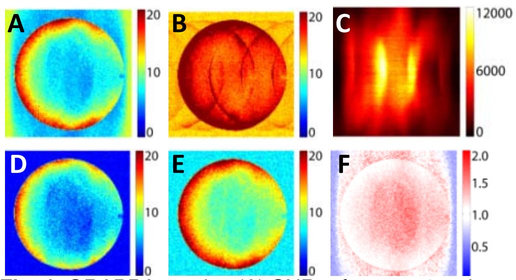

Fig. 1: GRAPPA results. (A) SNR_0 of conventional optimal SNR combination. (B) SNR_0 of direct combination using ID-NCM. (C) Condition number of ID-NCM (square root). (D) SNR_0 of weakly regularized combination. (E) SNR_0 of moderately regularized combination. (F) SNR_0 ratio: (E) over (A).

Theory: The optimal SNR combination of individual channels requires the noise covariance across channels and the sensitivity profiles of the elements. (Here we assume the uncombined images serve as an estimate of the sensitivity profiles.) Thermal noise is temporally white; however the image reconstruction can alter the noise correlation yielding a distinct image domain noise covariance matrix (*ID-NCM*) that can vary voxel-to-voxel. The ID-NCM can be estimated via Monte Carlo simulation.[4] In fMRI time-series data, physiological noise contributes to the channel correlations, and the resulting time-series noise covariance matrix (*TS-NCM*) also varies across voxels and tissue types.[3] Accounting for these correlations in the combination can potentially boost image SNR (SNR_0) or time-series SNR (tSNR), however these matrices can be poorly conditioned (see Fig. 1c). Therefore we employ a *per-voxel regularization scheme* based on the truncated SVD to invert the matrix at each voxel and form the optimal SNR_0 or tSNR combination. The regularization can be parameterized either by a target condition number for each voxel or by the number of truncated singular vectors.

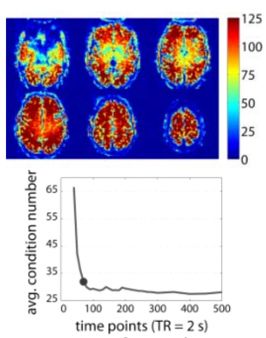

Fig. 3: (A) tSNR of regularized combination of *last* 70 TRs of data using TS-NCM calculated from *first* 70 TRs of data. (B) The condition number of the TS-NCM as a function of the number of TRs included. This suggests that the matrix stabilizes in a short time period.

Methods: Agar phantom data were acquired with a conventional spoiled gradient-echo pulse sequence with 1.5 mm in-plane voxel size, TR/TE/flip/BW/matrix = 10 ms / 3 ms / 2° / 400 Hz/pix /128×128 with a single 3-mm thick slice and 512 repetitions. Two volunteers having given informed consent were scanned with a 3 Tesla whole-body Tim TRIO MR scanner (Siemens Healthcare, Erlangen, Germany) using the vendor 32-channel receive coil. BOLD-weighted fMRI data were acquired with conventional single-shot GRE-EPI with 3.0 mm isotropic voxel size, TR/TE/flip/BW/matrix/esp = 2 s/30 ms/90°/2298 Hz/pix/128×128/0.50 ms with 33 slices and 500 repetitions.

Results: Fig. 1 shows the SNR_0 of the phantom data after 4-fold undersampling and GRAPPA reconstruction. The conventional thermal noise covariance-weighted combination[5] yields moderate SNR_0 (Fig.1a), however direct inversion of the ID-NCM in the calculation of the combination weights introduces strong edge artifacts (Fig 1b). The condition number of the ID-NCM is spatially varying (Fig. 1c), indicating that the inversion may be unstable in some locations. While weak per-voxel regularization of the matrix yields low SNR_0 (Fig. 1d) more moderate regularization (Fig 1e) provides low artifact levels and SNR gains (Fig. 1f). Fig. 2 shows the tSNR for the conventional thermal noise covariance-weighted combination and the regularized TS-NCM combination. The largest tSNR boost is seen when the TS-NCM is computed from a subset of the data (in this example a set of 70 TRs), and with a high degree of regularization (31 of 32 components truncated). tSNR gains are highest in the cortical gray matter (1.33) and lower in the white matter (0.93) and ventricular CSF (0.86). Fig. 3 addresses the generalizability of the TS-NCM estimate: the TS-NCM can be calculated from one block of data then applied to a later block while providing the same increase in tSNR.

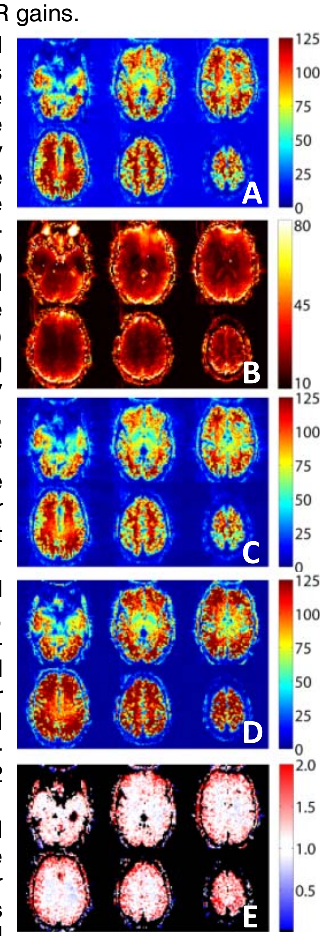

Fig. 2: (A) tSNR of conventional noise-weighted combination. (B) Condition number of TS-NCM (square root). (C) tSNR of regularized combination using TS-NCM from 500 TRs. (D) tSNR of regularized combination from TS-NCM calculated from 70 TRs. (E) tSNR ratio: (D) over (A).

Discussion: Because the GRAPPA reconstruction alters the noise covariance, pre-whitening the data prior to reconstruction will not remove the resulting spatially-varying ID-NCM. The low SNR gains seen from a TS-NCM calculated from a long range of data suggests some degree of long-range nonstationarity or slow drift in the noise coupling across channels, however the generalizeability of the matrix suggests that the covariance seen in a short period of data may accurately reflect the "instantaneous" TS-NCM. For task-driven fMRI studies, a separate resting-state pre-scan is needed to estimate the TS-NCM[5], however as few as 70 TRs may be required (Fig. 3a). In the case of the GRAPPA-reconstructed data it is possible to calculate the ID-NCM analytically[2,6], but the TS-NCM must be estimated from the data. Investigation of this approach applied to GRAPPA-reconstructed fMRI time-series data is currently underway.

Conclusion: The proposed method increases SNR by exploiting the true channel noise covariance. Tissue-specific gains in tSNR support the presence of a meaningful physiological noise covariance, and this noise exhibits sufficient local stationarity to boost tSNR.

References: [1] Roemer *et al.* (1990) *MRM* **16**:192. [2] Polimeni *et al.* (2008) *Proc ISMRM* **16**:1286. [3] Polimeni *et al.* (2012) *Proc ISMRM* **20**:2089. [4] Robson *et al.* (2008) *MRM* **60**:895. [5] Triantafyllou *et al.* (2011) *NeuroImage* **55**:597. [6] Breuer *et al.* (2009) *MRM* **62**:739.

Acknowledgements: Supported by NIBIB K01-EB011498, R00-EB012107 and R01-EB006847, and NCRR P41-RR14075.