Noise-facilitated GRAPPA reconstruction for fMRI

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Introduction Parallel imaging[1,2] has been widely used in MRI for scan time reduction and spatial resolution improvement. Concomitant with these advantages is the potential for higher noise and artifact levels. Various regularization techniques have been proposed to mitigate this problem[3-4]. In this work, a new regularization method, namely adding noise to GRAPPA auto-calibration signal (ACS) data, and its application to fMRI are examined.

Theory GRAPPA algorithm uses the least square fitting to calculate the weights w from the equation $T_{ACS} = S_{ACS} w$, where T_{ACS} and S_{ACS} denote the target and source matrix in the ACS area. The weights w can be solved via singular value decomposition (SVD) of the matrix S_{ACS}. When the condition number of S_{ACS} is high, the noise in the acquired data can be significantly amplified due to the Pseudo-inverse. Conventionally, truncated SVD or Tikhonov regularization is used to reduce the condition number. An alternative approach is to add noises to the ACS data. The additive noise can increase the smallest singular value while having a negligible effect on the largest singular value, resulting in a lower condition number for the equation. The goal of this work is to investigate the relationship between the additive ACS noise level and the resulting temporal SNR for fMRI signals.

Methods A gel phantom and a human subject (at rest with eyes closed) were scanned on a Siemens TIM trio scanner using a 32-channel head coil (Siemens Medical Solutions, Erlangen, Germany). EPI sequence was run for 100 repetitions. FOV = 220 mm, TR/TE = 2000/54, matrix = 128×128, one slice for the phantom scan and three slices for the human scan. Raw data were saved for off-line reconstruction. The first time frame was used as the reference scan for GRAPPA. GRAPPA reconstruction of acceleration factor (AF) 2, 3, and 4 with 48 and 124 ACS lines were simulated. Twelve neighbors were selected in computing the GRAPPA weights, and complex Gaussian noise was added to the ACS lines to lower the condition number of S_{ACS}. Then the weights were applied to the manually under-sampled k-space data of subsequent time frames to reconstruct the full k-space. Various levels of noise with an increment of half of the scanner noise calculated from the phantom data were tried in the simulation to fully investigate the effect of additive noise. The root mean square error (RMSE) between the reconstructed k-space and true k-space was approximated as the error between the acquired full k-space and the reconstructed full k-space. The temporal noise is computed for each voxel as the standard deviation of its time series after quadratic detrending. Temporal noise for the human subject is only computed on the middle slice after motion correction performed in SPM5 (Wellcome Department of Cognitive Neurology, London, UK).

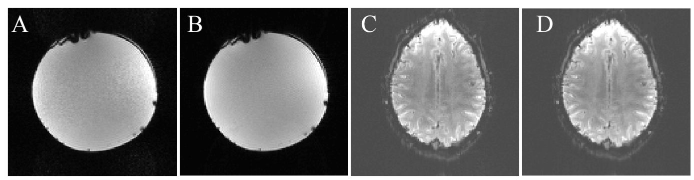

Fig. 1. Images reconstructed with additive noise level 0 and 6 for a phantom (A and B) and human brain (C and D) with AF 2 and 48 ACS lines.

Results Fig. 1 presents images of the phantom and human brain for AF 2 and 48 ACS lines, with different noise level in the computation of the GRAPPA weights. It can be seen that the images reconstructed with noise level 0 are noisier than the images reconstructed with noise level 6. Fig. 2 plots the simulation results of RMSE and mean temporal noise at different additive noise level from the phantom data. In general, RMSE is minimized at a certain additive ACS noise level while the temporal noise continues to drop with more additive ACS noise. In addition, the effect of additive ACS noise is affected by number of ACS lines. There is almost no gain for RMSE if the number of ACS lines is close to the matrix size of phase encoding because the least square error is already minimized for the ACS lines. The gain in SNR is also diminished for 124 ACS lines although the trend remains the same as for 48 ACS lines. Fig. 3 shows the results from the human subject. Since physiological noise may serve as the additive noise, RMSE is near its minimal at noise level 0. Adding Gaussian noise still helps to improve the temporal SNR, but the increase is much less than that in the phantom. This is because, on one hand, the physiological noise already helps to lower the condition number of the source matrix, and on the other hand, the GRAPPA weights only affect the scanner noise.

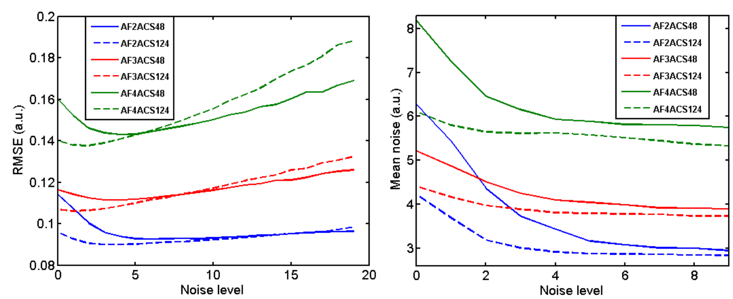

Fig. 2. RMSE (A) and mean noise (B) for GRAPPA images of the phantom with different acceleration factor and number of ACS lines.

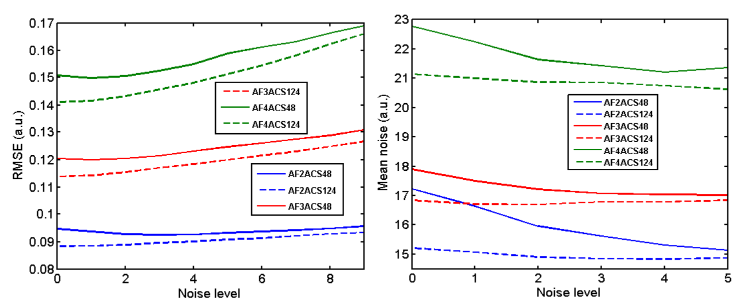

Fig. 3. RMSE (A) and mean noise (B) for GRAPPA images of a human brain with different acceleration factor and number of ACS lines.

Discussion We have demonstrated that adding noise to the ACS lines can potentially reduce image artifacts and g-factor in GRAPPA images. Furthermore, by adding more noise, it is possible to pursue higher SNR at the cost of image fidelity, and therefore may be useful for GRAPPA in fMRI. The effect of this facilitation may depend on the SNR of the image, the acceleration factor, and the number of ACS lines.

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References

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