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57: Artifacts and pitfalls in Parallel Imaging

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Artifacts and Pitfalls in parallel Imaging

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The advent of multi-coil arrays has offered the possibility to significantly increase the intrinsic SNR in an image. However, this increase is at the expense of non-uniform SNR in the final images (1). However, both the increased sensitivity and the encoding capability of modern multi-coil arrays allowed for significant scan time reductions in many clinical applications by means of parallel MRI (pMRI). In standard Cartesian pMRI scan time reduction is achieved by regularly undersampling the k-space by the reduction factor R. The most prominent pMRI reconstruction methods are SENSE (2), SMASH (3) and GRAPPA (4). Today these methods are broadly available and implemented in modern MR scanners. Any pMRI reconstruction method is associated with an often non-uniform increase of noise compared to the non-accelerated image. In general, the SNR after parallel imaging reconstruction is decreased by the square root of the reduction factor R as well as by an additional factor, the geometry factor g. The g-factor usually results in a spatially-variant noise enhancement that strongly depends on the reduction factor the sampling strategy used and finally the encoding capability of the receiver array. Analytical approaches for determining this geometry factor for SENSE (2), SMASH (5), PARS (6) and GRAPPA (7) have been published in the literature.

In the following, a brief review of the quantitative estimation of the g-factor noise enhancement in SENSE and GRAPPA reconstructions is given.

g-factor noise in SENSE reconstructions

In Fig 1 a schematic description of the SENSE reconstruction procedure is given. In the case of R-fold acceleration, the aliased signal p_k received in the coil k is given by signals originating from R equidistant pixel locations γ in the full FOV of the true object ρ weighted by their individual coil sensitivities $C_{k\gamma}$ at these locations γ and an additive noise term n_k.

$$p_k = \sum_{\gamma=1}^{R} C_{k\gamma}\rho_\gamma + n_k \qquad [1]$$

In matrix form this equation can be expressed as

$$\mathbf{p} = \mathbf{C}\boldsymbol{\rho} + \mathbf{n} \qquad [2]$$

Vector $\mathbf{p}$ contains the folded signals of all coils at a certain location in the reduced FOV and the matrix $\mathbf{C}$ all the sensitivities involved in the aliasing process.

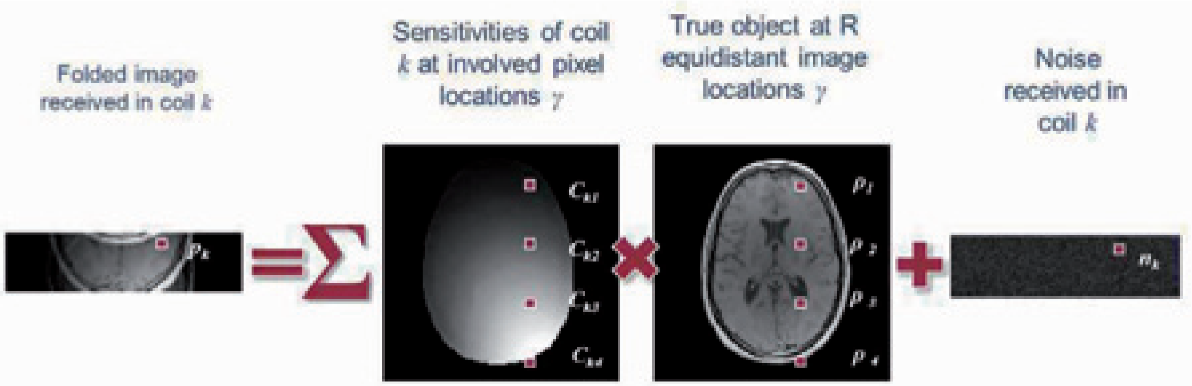

Figure 1: Regular undersampling (here R=4) results in aliased images. The pixel intensity at a particular location received in coil k is given by the signal intensities originating from the R involved equidistant pixel locations in the full FOV of the true object ρ weighted with the sensitivities $C_{k\gamma}$ at the corresponding locations γ of the receiver coil and an additive noise term. SENSE seeks to unfold the aliasing in the presence of noise to arrive at an optimal approximation of the true pixel intensities.

For each folded image pixel the SENSE method seeks for a reconstruction matrix $\mathbf{X}$, applied to $\mathbf{p}$ yielding the optimal approximation of the true object $\boldsymbol{\rho}$ at the involved pixel locations.

$$\tilde{\boldsymbol{\rho}} = \mathbf{Xp} = \mathbf{XC}\boldsymbol{\rho} + \mathbf{Xn} \qquad [3]$$

This can be achieved by e.g. by explicitly demanding Identity for $\mathbf{XC}=\mathbf{I}$. In the presence of noise the statistically normalized Moore Penrose Inversion (Eq. 4) provides both Identity for $\mathbf{XC}$ and simultaneously minimized noise variance.

$$\mathbf{X} = (\mathbf{C}^H \boldsymbol{\Sigma}^{-1} \mathbf{C})^{-1} \mathbf{C}^H \boldsymbol{\Sigma}^{-1} \qquad [4]$$

$\boldsymbol{\Sigma}$ is the so-called noise covariance matrix. The diagonal elements contain information about the noise variances of the individual coils and the off-diagonal elements characterize the correlations between two respective coils.

Thus, by explicit knowledge of the coil sensitivities $\mathbf{C}$ application of the reconstruction matrix $\mathbf{X}$ to the folded image pixels p on a pixel by pixel basis allows to effectively unfold the folded image to arrive at an aliasing-free image. In order to determine the SNR loss after SENSE reconstruction at the spatial location γ in the full FOV the ratio of the noise variance in the accelerated to the fully encoded case is taken as described in more detail in the original SENSE paper (2).

$$g_\gamma = \frac{SNR_\gamma^{full}}{\sqrt{R} \cdot SNR_\gamma^{acc}} = \sqrt{(\mathbf{C}^H \boldsymbol{\Sigma}^{-1} \mathbf{C})^{-1}{}_{\gamma\gamma} (\mathbf{C}^H \boldsymbol{\Sigma}^{-1} \mathbf{C})_{\gamma\gamma}}$$

[5]

In Fig. 2 an R=4 SENSE reconstruction and the corresponding g-factor noise enhancement is shown.

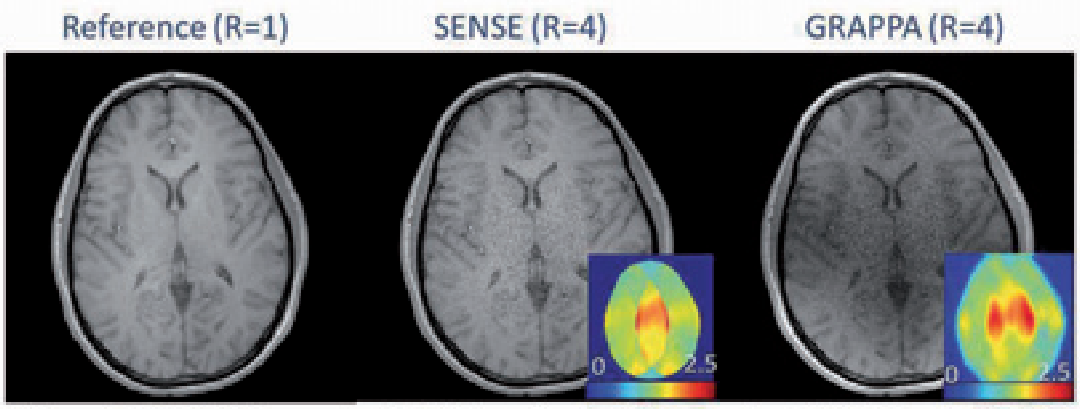

Figure 2: R=1 Reference and R=4 accelerated image after SENSE and GRAPPA reconstruction. In addition the corresponding g-factors are given characterizing the non-uniform noise enhancement in the images. For the SENSE reconstruction and g-factor calculation an explicit estimate of the coil sensitivities have been employed. For the GRAPPA image the reconstruction weights have been derived from 24 ACS lines, which were also used for the estimation of the GRAPPA g-factor for combined GRAPPA images.

g-factor noise in GRAPPA reconstructions:

In the original GRAPPA reconstruction procedure missing k-space points are calculated from a weighted linear combination of the acquired k-space points. These weights are known as GRAPPA weights. In contrast to SENSE, GRAPPA does not require explicit knowledge about the coil sensitivities. However, in order to derive the GRAPPA reconstruction weights, similar to SENSE, some additionally acquired k-space lines in the center of k-space are also required (Note: GRAPPA and SENSE require about the same amount of extra data for calibration). These auto calibration signals (ACS) can be acquired within an extra scan or within the actual accelerated experiment. In Fig 3 a schematic of the determination process of the GRAPPA weights from these ACS is shown.

While the SENSE reconstruction directly yields a composite image with uniform sensitivity, the GRAPPA reconstruction results in the individual uncombined single coil images which need to be combined in a final reconstruction step. The GRAPPA reconstruction procedure has been originally described in k-space as a convolution of the GRAPPA weights with the undersampled k-space data. However, it has been shown that by exploiting the Fourier Convolution Theorem, GRAPPA can also be reinterpreted in image space and thus formulated as a pixel-by-pixel matrix multiplication of the GRAPPA weights W in the image space with the folded (undersampled) multi-coil images (8,9,10). Image domain GRAPPA has been shown to significantly speed up the reconstruction time. In addition image domain GRAPPA has been found useful when analyzing the noise propagation into the final GRAPPA reconstruction (7). Similar to SENSE it is essential to take potential noise correlations into account when investigating the noise propagation after GRAPPA reconstructions.

Eq. 6 describes the GRAPPA reconstruction in the image domain at an arbitrary pixel location in the FOV with a noise term added. The GRAPPA reconstruction weights $\mathbf{W}$ in image space have dimension N_c x N_c and are directly derived by Fourier Transformation of the GRAPPA convolution kernel in k-space as dictated by the Fourier Convolution Theorem. This procedure is displayed in greater detail in Fig. 3.

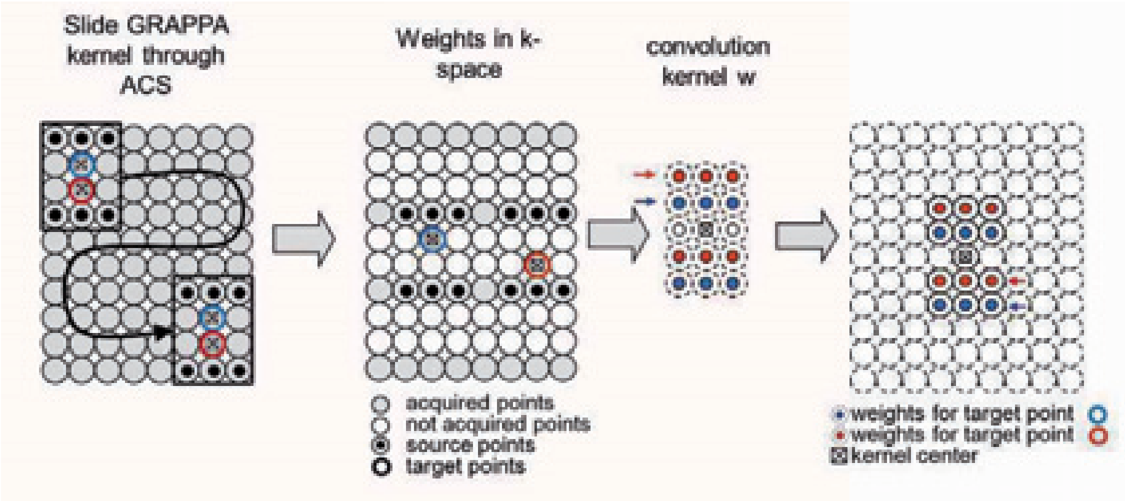

Figure 3: The GRAPPA weights in k-space are derived by sliding the GRAPPA kernel through the ACS and fitting the source points in all coils in the kernel region to a single missing point within the kernel region. The GRAPPA weights in image space are derived by reordering of the k-space GRAPPA weights to build a convolution kernel in k-space with mutual kernel center. The convolution kernel in k-space is flipped in both dimensions (indicated by arrows) and zeropadded to the full image size. Finally, after inverse 2D Fourier Transformation the GRAPPA weights in image space are derived for each pixel location.

By linearly combining the folded signals from all the coils of the undersampled image data set p_l^{red} with the appropriate GRAPPA weights W_{kl} the accelerated unfolded signal p_k^{acc} in each individual coil k can be reconstructed. The additive noise term n_k^{acc} characterizes the noise in the coil k after application of the GRAPPA weights to the noise received in all the channels.

$$p_k^{acc} + n_k^{acc} = \sum_{l=1}^{N_c} W_{kl} \cdot (p_l^{red} + n_l^{red}) \qquad [6]$$

With this formulation the noise propagation after GRAPPA reconstruction can be calculated:

$$\sigma^2(n_k^{acc}) = \sigma^2\left(\sum_{l=1}^{N} W_{kl} \cdot n_l^{red}\right) = \left|\mathbf{W} \cdot \mathbf{\Sigma} \cdot \mathbf{W}^{\mathbf{H}}\right|_{kk} \qquad [7]$$

The variance σ^2 in the GRAPPA reconstructed pixel location in the coils is given by the diagonal elements of the matrix multiplication given in Eq. 7. The Variance σ^2 in the fully encoded coil image k is simply given by the diagonal elements of the covariance matrix $\mathbf{\Sigma}$ and reduced by a factor R (reduction factor) compared to the accelerated case:

$$\sigma^2\left(n_k^{full}\right) = \frac{1}{R} \cdot \sigma_{kk}^2 = \frac{1}{R} \cdot |\mathbf{\Sigma}|_{kk} \qquad [8]$$

Similar to the SENSE g-factor we can now derive the noise enhancement in GRAPPA reconstructions. However, since GRAPPA is a coil by coil reconstruction method, we arrive in a g-factor for each individual coil.

$$g_k = \frac{SNR_k^{full}}{SNR_k^{acc} \cdot \sqrt{R}} = \frac{\sigma\left(n_k^{acc}\right)}{\sigma\left(n_k^{full}\right) \cdot \sqrt{R}} = \frac{\sqrt{\left|\mathbf{W} \cdot \mathbf{\Sigma} \cdot \mathbf{W}^H\right|_{kk}}}{\sqrt{\left|\mathbf{\Sigma}\right|_{kk}}} \qquad [9]$$

A g-factor for combined GRAPPA reconstructions can also be derived by taking knowledge about the coil combination coefficients into account. These coefficients can easily be derived from the ACS data and included into the calculation yielding:

$$g_{comb} = \frac{SNR_{comb}^{full}}{SNR_{comb}^{acc} \cdot \sqrt{R}} = \frac{\sqrt{\left|\left(\mathbf{a}^T \cdot \mathbf{W}\right) \cdot \mathbf{\Sigma} \cdot \left(\mathbf{a}^T \cdot \mathbf{W}\right)^H\right|}}{\sqrt{\left|\left(\mathbf{a}^T \cdot \mathbf{1}\right) \cdot \mathbf{\Sigma} \cdot \left(\mathbf{a}^T \cdot \mathbf{1}\right)^H\right|}} \qquad [10]$$

An R=4 GRAPPA reconstruction after adaptive coil combination (11) is given in Fig 2. In addition the GRAPPA g-factor is given calculated according to Eq. 10.

Artifacts in pMRI:

Besides g-factor noise amplifications, residual aliasing artifacts may be observed in the image in cases of misregistration or miscalibration. In SENSE reconstructions a crucial factor for a successful artifact-free image is the accurate estimation of the sensitivity maps. In image scenarios where the coils sensitivities are difficult to obtain e.g. in the lungs or in the presence of motion, residual aliasing artifacts will appear in the reconstructed images and significantly degrade the image quality. In GRAPPA, a sufficient number of ACS lines should be chosen for accurate weights determination. Here a balance between the kernel size used and the number of ACS lines is of importance. The number of ACS lines required depend strongly on the number of coils available the reduction factor and may also change from application to application. Erroneous weights will similar to SENSE result in residual artifacts in the final GRAPPA image (see Fig. 4). In addition, the sampling strategy, such as e.g. the choice of the phase encoding direction may have significant impact on the image quality and strongly depend on the coil configuration of the receiver array. Other sources of artifacts will be discussed in more detail in the presentation.

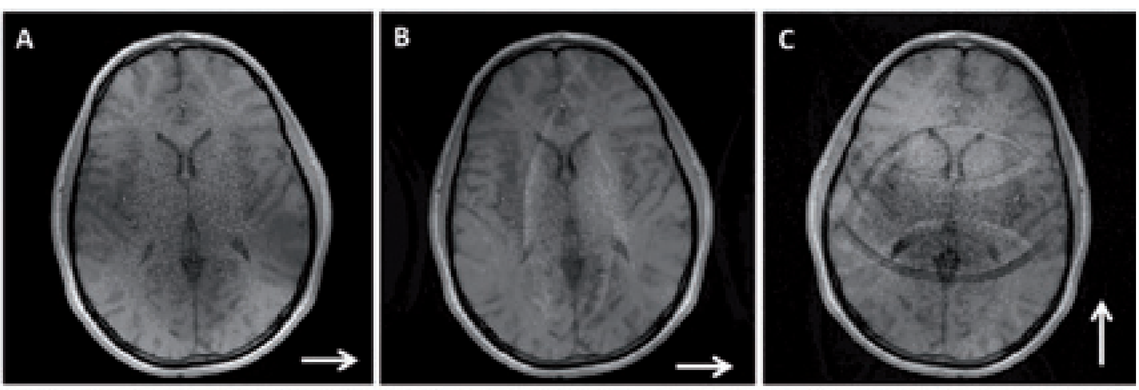

Figure 4: R=4 GRAPPA reconstructions, 32 Coils. (A) Successful Weights calibration (Nacs = 32) with g.factor noise enhancement. (B) Additional residual aliasing due to an insufficient number of ACS lines (Nacs =8) used for calibration. (C) Residual aliasing due to misregistration between ACS and undersampled data (e.g. motion). Please note that the residual aliasing artifacts appear always in the direction of undersampling (phase encoding direction) indicated by the arrows.

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