TAILORING THE IMAGE BACKGROUND PHASE BY SPATIALLY SELECTIVE EXCITATION FOR IMPROVED PARALLEL IMAGING RECONSTRUCTION PERFORMANCE

Johannes T. Schneider¹, Martin Blaimer², and Peter Ullmann¹

¹Bruker BioSpin MRI GmbH, Ettlingen, Germany, ²Research Center Magnetic Resonance Bavaria, Würzburg, Germany

Introduction & Theory: It was shown recently [1] that the image background phase in Parallel Imaging (PI) experiments has an impact on the sensitivity encoding and therefore on the reconstruction performance. The present study describes the determination of an optimal background phase and its generation by parallel spatially selective excitation (PEX) resulting in significantly improved reconstruction quality in SENSE and GRAPPA experiments.

The encoding capabilities of the background phase can be exploited by the very general approach of a "virtual coil concept" [1] that interprets conjugate symmetric k-space signals as additional signals from virtual coils as summarized briefly in the following:

For PI with N coils, the received signal S_j in coil j=1..N reads

$$S_i(\mathbf{k}) = \int \rho(\mathbf{x}) \cdot e^{i\varphi(\mathbf{x})} \cdot C_i(\mathbf{x}) \cdot e^{-i\mathbf{k}\mathbf{x}} d\mathbf{x} = \text{FT}[\rho(\mathbf{x}) \cdot D_i(\mathbf{x})]$$
 [Eq. 1]

where $\rho(\mathbf{x})$ is the signal density that is modulated by a background phase $\varphi(\mathbf{x})$, $C_j(\mathbf{x})$ are the complex coil sensitivities and \mathbf{k} is the k-space vector. This can be interpreted as the Fourier transform (FT) of ρ weighted with an effective coil sensitivity $D_j(\mathbf{x}) = e^{i\varphi(\mathbf{x})} \cdot C_j(\mathbf{x})$ that already contains the background phase. If then the conjugate signal S^* is considered at the location $-\mathbf{k}$ this can be interpreted as signal acquired by a virtual coil with the sensitivity profile $D_j^*(\mathbf{x})$:

$$S_{i}^{*}(-\mathbf{k}) = \int \rho(\mathbf{x}) \cdot e^{-i\varphi(\mathbf{x})} \cdot C_{i}^{*}(\mathbf{x}) \cdot e^{i(-\mathbf{k})\mathbf{x}} d\mathbf{x} = FT[\rho(\mathbf{x}) \cdot D_{i}^{*}(\mathbf{x})]$$
 [Eq. 2]

This means, the actually measured data base can be extended by adding calculated data from virtual coils: $S_{j+N}(\mathbf{k}) = S_j^*(-\mathbf{k}); \ D_{j+N}(\mathbf{x}) = D_j^*(\mathbf{x})$ [Eq. 3]

With this extended data and sensitivity sets, all conventional PI reconstruction algorithms can be applied and g-factor calculations from the 2N sensitivities are possible with

$$g_i = \sqrt{((\mathbf{D}^H \mathbf{D})^{-1})_{i,i} (\mathbf{D}^H \mathbf{D})_{i,i}}$$
 [Eq. 4]

If the background phase φ contained in the effective sensitivities D is not entirely zero, the virtual coil approach provides additional information to the reconstruction algorithm. It can be shown, that there exists an optimal distribution of the background phase with which the virtual coil set ideally complements the actual one.

Methods: Such an optimal phase distribution can be found and adapted for its generation with PEX by the 3 following steps: **A)** Firstly, all image locations are identified that fold into one pixel in the undersampled dataset. **B)** Afterwards, using an exhaustive brute-force variation, a phase combination is selected that yields a minimum g-factor (using Eq. 4 and the 2N sensitivities) when multiplying the actual sensitivities by this combination at the folding locations from A before calculating the extended sensitivity vector. **C)** This procedure typically results in critical phase steps and wraps, especially at the edges of the folding regions. Since for realization by PEX smooth profiles are required, each two folding regions were connected by a phase ramp maintaining the relative phase offsets between the folding pixels.

Experiments were performed on a 9.4 T Bruker BioSpec system with an 8-element transceive coil array in a water bottle (Fig. 1a) and a mandarine-orange (Fig. 3a). From the water bottle, 5-fold undersampled data was acquired in a spin echo sequence. Receive sensitivities were calculated from the fully sampled pilot scan acquired with equal imaging parameters (Fig. 1a). Afterwards, virtual data and virtual coil sensitivities were calculated by Eq. 3. A SENSE reconstruction was performed first with the data of the 8 actual coils only and afterwards with the data extended from the 8 additional virtual coils.

From the measured sensitivity maps which include the "accidentally" existing background phase and which correspond therefore to the effective sensitivities D, an optimal background phase offset distribution was calculated. Afterwards a 2-dimensional PEX pulse for 8 transmit channels was designed based on a spiral transmit k-space trajectory in order to generate this phase distribution during excitation. With this parallel excitation pulse the SENSE acquisition and reconstruction with the virtual coils was repeated.

For the mandarine, GRAPPA experiments were performed with 6-fold undersampling. Although the GRAPPA kernel is supposed to have an impact on the optimal background phase, again the SENSE g-factor was used as a measure to find an optimized background phase.

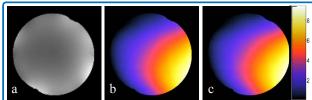


Fig. 1: (a) pilot scan of the water phantom. (b) calculated optimal background phase. (c) generated and measured background phase.

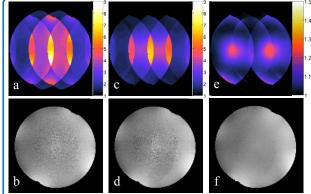


Fig. 2: g-factor maps (top row) and reconstructed images (bottom row) from 5-fold accelerated SENSE in the water phantom: (a,b) conventional reconstruction from 8 receive coils. (c,d) reconstruction from 16 (8 real + 8 virtual) coils and unmodified background phase. (e,f) reconstruction from 16 coils and background phase modulated by parallel excitation according to the optimal phase distribution (note the different scaling of the g-factor maps!).

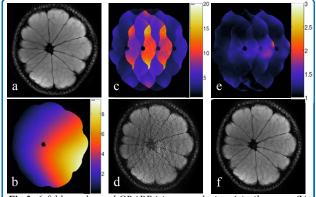


Fig. 3: 6-fold accelerated GRAPPA in a mandarine. (a) pilot scan. (b) optimal background phase distribution. (c,d) (SENSE-)g-Factor map and conventionally reconstructed image from 8 coils. (e,f) for reconstruction from 16 coils with optimal background phase.

Results: The optimal background phase distribution found for the 5-fold accelerated SENSE experiments in the water phantom is depicted in Fig. 1b. For verification, the phase as generated by the PEX pulse was measured and a nearly identical distribution compared to the target profile was observed (Fig. 1c). As the comparison of the g-factor maps and images in figures 2a,b and 2c,d reveal, the virtual coil concept improves reconstruction quality only moderately (the maximum g-factor is reduced from 9.4 to 6.9) as long as only the "accidentally" existing background phase is involved. In contrast, modulating the background phase by

PEX lowers the g-factor dramatically to values smaller than 1.2 (Fig. 2e). Consequently, the noise enhancement is reduced significantly as demonstrated by Fig. 2f. A similar behavior was observed in the GRAPPA experiments with the mandarine. Acceleration factors of 6 were unfeasible with the conventional reconstruction due to g-factors up to 20.8 (Fig. 3c) leading to images completely degraded by noise (Fig. 3d). However, applying the virtual coil concept with the optimal background phase (which is depicted in Fig. 3b), the g-factor is reduced below 2.3 (Fig. 3e) and reconstructed images are of remarkable quality for such high acceleration factors.

Discussion & Conclusion: This study presents the modulation of the background phase by parallel excitation which dramatically improves PI performance in combination with the virtual coil concept. Significant benefits for SENSE as well as for GRAPPA were demonstrated. The background phase is tailored to yield minimum g-factors. To this end, it is adapted to several experimental parameters like coil sensitivity profiles, acceleration factors, object geometries and already existing background phases. It was shown, that the phase profiles can be generated by PEX with very high accuracy. Due to the smooth distributions, very low spatial resolution of the PEX pulses is sufficient resulting in short and very robust pulses. Even so-called spokes trajectories [2] may be applied for PEX allowing the generation of such smooth phase modulations in combination with slice-selection.

References: [1] Blaimer M., et al.; MRM 61:93, 2008 [2] Saekho S, et al.; MRM 55:719, 2006

Acknowledgements: This work is part of the INUMAC project supported by the German Federal Ministry of Education and Research. Grant #13N9207.