

## Generalized High-Pass-Filtered GRAPPA Reconstruction

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**Introduction:** Parallel imaging techniques [1] have been widely used to reduce total acquisition time and subject motion in clinical application by using the spatial information inherent in a multiple receiver coils. However, with increasing acceleration factors, they lead to residual artifacts and amplified noises over the whole image due to corrupted data with noise. To overcome these problems, several regularization approaches have been proposed using the framework of Tikhonov regularization, such as prior-regularized GRAPPA [2], but a direct tradeoff between image blurring and noise amplification still remains substantially. From a different perspective, high pass GRAPPA (HP-GRAPPA)[3] addressed this problem by controlling low frequency energy with high pass filter (HPF). However, it is still challenging to find an optimal high pass band in k-space, resulting in a tradeoff between calibration data fidelity and numerical conditioning. Thus, the purpose of this work is to develop a novel generalized high pass (GHP) GRAPPA reconstruction algorithm to resolve the high pass band problems.

**Theory:** In conventional HP-GRAPPA [3], calibration was performed employing a single high pass filter to suppress low spatial frequency signals and thus reduce image support. The image support reduction is favorable in GRAPPA calibration with increasing acceleration factors. In HP-GRAPPA, the range of narrow pass band is a weight to balance the data fidelity and noise amplification like Tikhonov regularization. The use of large high pass band generates low noise in the reconstructed image, but lowers data fidelity by suppressing available information in k-space. The use of wide high pass band generates low aliasing artifacts, but noises spread out over the whole image due to numerical instability in k-space. It is a key factor to find an optimal high pass band balancing between aliasing and noise artifact level. Based on these observations, a flow chart of the proposed GHP-GRAPPA is shown in Fig. 1. A single low pass filter (LPF) followed by multiple HPFs with different high pass bands are applied to k-space, and then GRAPPA reconstructions are performed through interpolation kernel obtained from filtered calibration signals. To employ different properties obtained from multi-filters, multi-coil signals are transformed to single k-space signals by SNR optimized coil combination. To choose the optimal pass band signals among the multiple filtered signals, the inverse filter assumes that the measured signals are on the subspace spanned by a set of filtered signals and neighboring signals close to measured ones are also present on the same space [4]. To achieve automatic procedure for choosing the space, the measured signals can be modeled as follows:  $s^{\text{MEAS}}(k) = s_{\text{LP}}(k) + s_{\text{HP,comb}}^{\text{RECON}}(k)$ , where  $s^{\text{MEAS}}$  denotes measured signals,  $s_{\text{LP}}$  is k-space signal with LPF, and  $s_{\text{HP,comb}}^{\text{RECON}}$  is the weighted combination of the high pass filtered signals,  $s_{\text{HP,f}}^{\text{RECON}}(k) = \sum_{f=1}^{N_f} \alpha_f s_{\text{HP,f}}^{\text{RECON}}(k)$ , where  $N_f$  denotes the number of high pass filter,  $\alpha_f$  is the parameter of the inverse filter. Here, projection onto measured signals is achieved by parameter set  $\alpha$  of inverse filter by solving the least squares algorithm  $\min_{\alpha} \|s_{\text{HP,comb}}^{\text{RECON}} - s_{\text{HP,f}}^{\text{RECON}} \alpha\|_2^2$ , and missing signals adjacent to measured ones can be reconstructed by projection onto the space of the measured ones, that is, it is reconstructed by applying parameter set of inverse filter to reconstructed signals with filter. k-space signals with LPF are used as the baseline signals suppressing noise amplification in the process of inverse filter. To perform regionally optimized inverse filtering process, k-space is divided into sub-region, and the parameter sets of inverse filter are calculated locally and reconstructed locally. The procedure is repeated for all segmented region.

**Materials and Methods:** To demonstrate the feasibility of the approach, a brain *in vivo* data is acquired volunteer at 3T whole-body scanner (MAGNETOM Trio, Siemens Medical Solutions, Erlangen, Germany) using 2D spoiled gradient echo imaging with following parameter: FA, 70°; TE, 2ms; TR, 22ms FOV, 220mm x220mm; in-plane acquisition matrix, 256x256; slice thickness, 4mm. A twelve-channel head coil is used for signal reception. To emulate under-sampling for the proposed method, the fully acquired data are decimated using a factor of 4 with 32 self-calibrating lines in the central k-space respectively, and three different high pass bands are used.

**Results and Conclusion:** We proposed the generalized formulation and solution for HP-GRAPPA under a framework of the regularization. Figure 2 compares three images reconstructed using conventional GRAPPA, HP-GRAPPA, and the proposed GHP-GRAPPA (top row) and the corresponding image difference between the reference and reconstructed images (bottom left), and the corresponding geometry factor (bottom right). The proposed GHP-GRAPPA outperforms conventional GRAPPA and HP-GRAPPA in suppressing residual artifacts and noises over the entire image and reducing local geometry factors.

**References:** [1] Griswold et al., MRM 47:1202-10 (2002), [2] F-H. Lin, ISMRM 2006, p.3656, [3] F. Huang et al., MRM 59: 642-649 (2008), [4] Nowak et al., IEEE TIP 7: 1068-1074.

**Acknowledgements:** Mid-career Researcher Program (2011-0016116) and World Class University (WCU) (R31-10008), NRF, Korea.

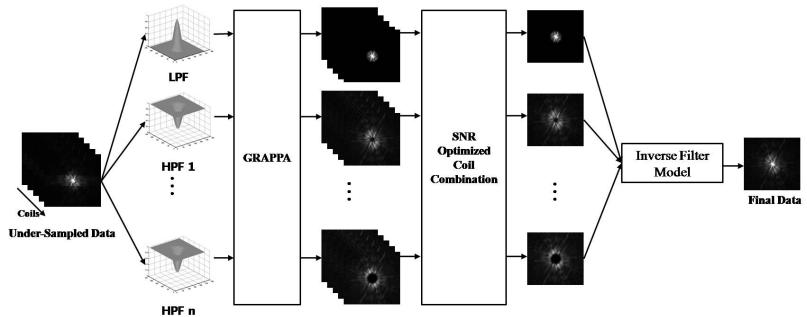


Figure 1: An overall schematic of the generalized high pass filtered GRAPPA

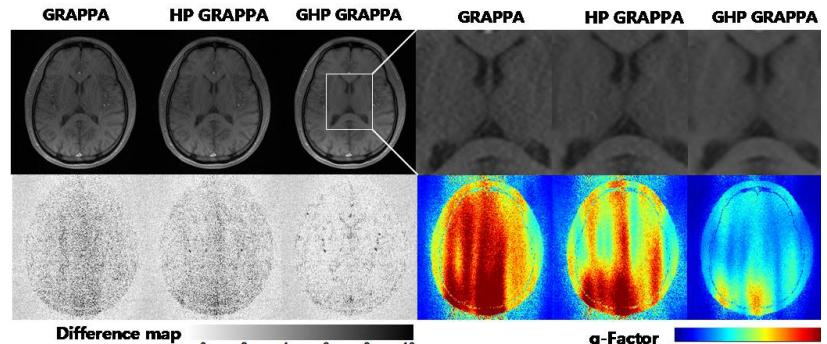


Figure 2. Comparison of images using three different reconstruction methods. Top Left: The reconstructed images. Top Right: The corresponding zoomed images. Bottom Left: Image difference between reference and reconstructed images. Bottom Right: geometry factor images.