# Image support reduction technique for self-calibrated partially parallel imaging

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## *Introduction*

The signal to noise ratio (SNR) of images reconstructed by using Partially Parallel Imaging (PPI) techniques is decided by the coil geometry factor (g-factor) for a given folding factor. If the image has a reduced image support, then the coil sensitivity maps have more zeros and the factor of folding is smaller than the acceleration factor. Hence the geometry factor is improved and it results in better SNR. This explains why images with reduced support have better PPI performance. The image support can be artificially reduced before applying PPI techniques and recovered after PPI reconstruction. This idea has been applied in dynamic imaging [1]. In this work, a simple image support reduction technique is introduced for static PPI. This technique can dramatically improve the quality of images reconstructed by self-calibrated PPI techniques, such as GRAPPA[2] or mSENSE [3], by applying a filter before and after the PPI. Since the kernels of the PPI algorithms need not be changed, this technique can be easily adopted.

## *Method*

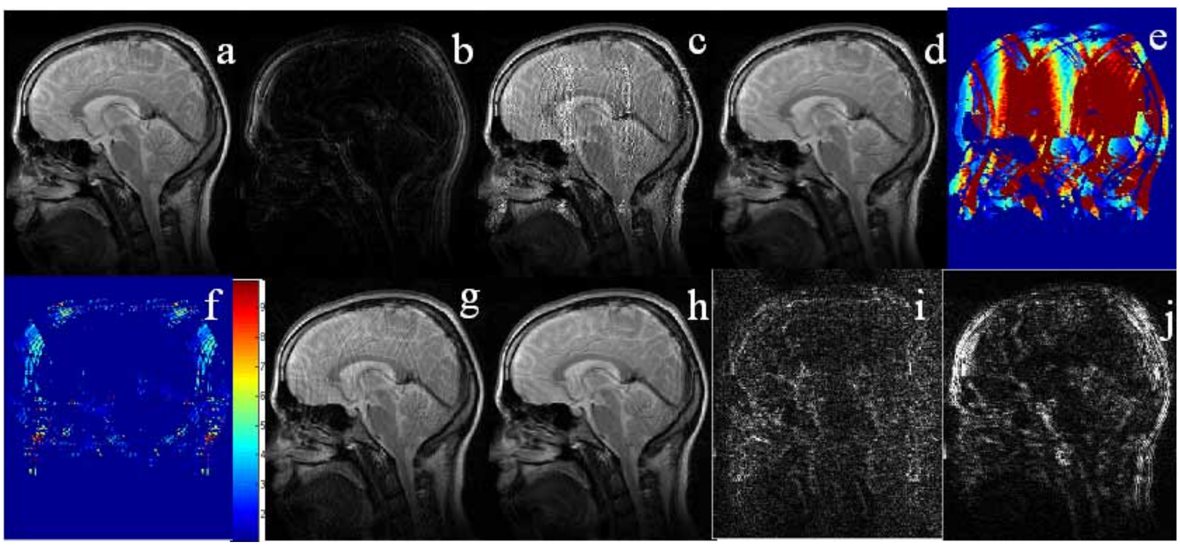
Most of the low frequency information of the image is located at the center of *k*-space. If a high pass filter is applied to the *k*-space, then the filtered *k*-space corresponds to an image with reduced image support. PPI techniques have better performance on the image corresponding to the filtered *k*-space. For self-calibrated PPI techniques, extra auto calibrated signal (ACS) lines are acquired. And usually ACS lines are located at the center of the *k*-space. A high pass filter can be applied to the partially acquired *k*-space before PPI to generate a *k*-space corresponding to an image with reduced image support. The filtered ACS lines provide corresponding sensitivity maps for reconstruction. After PPI, the inverse of that high pass filter is applied to the output of PPI to generate the final result. The high pass filter should be chosen in a way that the image corresponding to the filtered *k*-space has reduced support and the filtered ACS lines can provide enough sensitivity information.

## *Results*

Brain images (matrix size 224×256×4) were collected on a 1.5T SIEMENS system with a 4-channel head coil (Invivo, Gainesville, FL). Full *k*-space data were acquired. Only partial *k*-space data were used for reconstruction. In the experiments, the high pass filter was chosen as 1-*L*, where $L = \left(1+e^{(ky-c)/w}\right)^{-1} - \left(1+e^{(ky+c)/w}\right)^{-1}$ [4]. *ky* is the count of phase encoding lines from –111 to 112 for this data set, *c* and *w* are two parameters to adjust the filter. In this experiment, $c = 13$, $w = 2$. The inverse of the high pass filter used after PPI is 1/(1-*L*). The proposed method was applied to both mSENSE and GRAPPA techniques, and the corresponding methods are called high pass mSENSE and high pass GRAPPA. The acceleration factor was 4 and 64 ACS lines were used, hence the actual reduction factor was 2.15. Figs. a to h show the results.

*References*

[1] Huang F, *et al*, ISMRM 2004, p 2690; [2] Griswold M *et al*., MRM 2002, 47:p1202-1210; [3] Wang J, *et al*, 1st Wurzburg workshop on parallel imaging, p92; [4] King KF. ISMRM 2004, p 2418; [5] Park J, *et al*, MRM 2005,53: p186-193





Figures: a) The image reconstructed with full *k*-space; b) The image corresponding to the filtered *k*-space; c) The image reconstructed by using mSENSE, e) shows the corresponding g-factor map; d) The image reconstructed by using high pass mSENSE, f) shows the corresponding g-factor map; g) The image reconstructed by using GRAPPA; h) The image reconstructed by using high pass GRAPPA; i) The difference between a) and h); j) The difference between a) and the image reconstructed by using sum of squares with full 112 central *k*-space lines and zeros outside(reduction factor 2); k) The image reconstructed by using high pass segmented GRAPPA. a), b), c), d), g), h), k) are in the same intensity scale; e) and f) use the same intensity scale; i) and j) are brightened 10 times to make them visible;

## *Discussion*

An image support reduction technique is introduced to improve the performance of partially parallel imaging techniques. From Fig. b, it can be seen that the image corresponding to the filtered *k*-space does have reduced image support. When the acceleration factor is high, images reconstructed by using PPI (Fig. c and g) may have significant artifacts. By using the proposed method, artifacts are dramatically reduced (Fig. d and h) without changing the PPI algorithm, and the g-factor is also dramatically improved (comparing Fig. e and f). By comparing Figs. i) and j), it can be seen that the image reconstructed using high pass GRAPPA has higher spatial resolution than the image using full central *k*-space with more acquisitions. It means higher spatial resolution (comparing with no PPI) and higher SNR (comparing with PPI) can be both achieved by using high pass self-calibrated PPI. One potential problem of this technique is that it may reduce the spatial resolution. The choice of filter will balance spatial resolution and artifacts level. Smaller *c* and *w* can reduce artifacts more, but it may also damage the spatial resolution more. Bigger *c* and *w* reduce artifacts less, but it protects the spatial resolution better. One way to further improve spatial resolution is to combine this technique with other techniques. For example, this technique can be combined with the segmented GRAPPA [5] to get even higher spatial resolution and lesser artifacts (Fig. k).