Impact of Coil-Neighbors of Target points in Autocalibration of ESPIRiT

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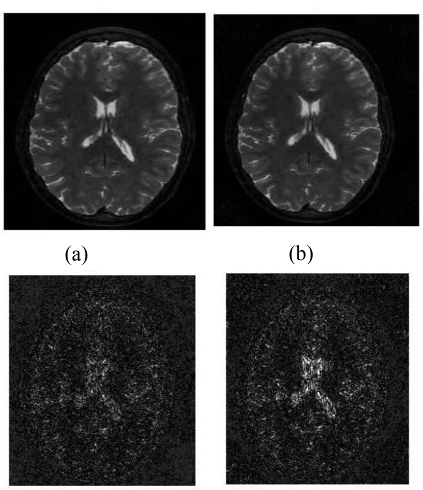
Introduction:
Compressed Sensing and Parallel imaging based MRI reconstruction algorithms like L1-SPIRiT[1], and an efficient version of it called ESPIRiT[2] have been proposed in the recent past. ESPIRiT addresses the computational challenges with the use of an image-domain eigenvector-based Parallel imaging (PI) operator obtained from fully sampled convolution kernel, in place of performing computationally expensive convolution with the kernel in k-space. The kernel-weights are computed by obtaining a least squares fit for predicting target points in the calibration region using the entire set of neighbors within the kernel as source points. In this procedure, a linear system needs to be solved separately for each coil. If we avoid using a target point's coil-neighbors(which are the corresponding points in the rest of the coils), we can avoid the multiple computations of the computationally expensive solver. We study the impact of avoiding the use of coil neighbors on the final image quality and the computational performance.

Theory:
The autocalibration procedure for ESPIRiT generates reconstruction weights $\boldsymbol{w}$ by fitting a source matrix $\boldsymbol{A}$ to a target matrix $\boldsymbol{B}$ using generalized matrix inversion. The number of rows $\boldsymbol{m}$ of $\boldsymbol{A}$, are the number of points in the calibration region. For $\boldsymbol{k1} \times \boldsymbol{k2} \times \boldsymbol{k3}$ kernel and $\boldsymbol{N}$-channel dataset, the number of columns $\boldsymbol{n}$ are $\boldsymbol{k1}\times\boldsymbol{k2}\times\boldsymbol{k3}\times\boldsymbol{N}$. The weights for each coil are obtained by solving Moore-Penrose pseudo inverse i.e., solve for $\boldsymbol{Cw}=\boldsymbol{D}$, where $\boldsymbol{C}=\boldsymbol{A}^T\times\boldsymbol{A}$, $\boldsymbol{D}=\boldsymbol{A}^T\times\boldsymbol{B}$. In a typical approach, the weights, $\boldsymbol{w}_i$ correspoinding to source points of a target location in a coil $\boldsymbol{c}_i$, are obtained by solving $\boldsymbol{C}_2\boldsymbol{w}_i=\boldsymbol{D}_2$, where $\boldsymbol{C}_2$ is obtained by removing a row and column corresponding to the target location. In the proposed approach, we use only $\boldsymbol{k1}\times\boldsymbol{k2}\times\boldsymbol{k3}\times\boldsymbol{N}$ –N source points for calculating the kernel weights, avoiding the coil-neighbors of a target point. By doing so, we will need to compute the solver only once, thus giving us a speed up of $\boldsymbol{N}$x. We expect that for a high-channel count dataset, where we already have large number of source points from all coils, the impact is minimal and will not be visible on the final reconstructed images. We compare the two approaches: the typical approach and the proposed one.

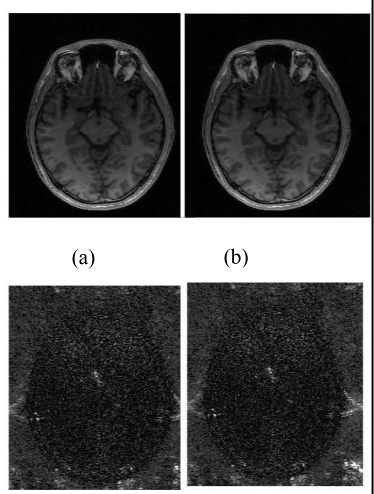
Methods:
Based on the above theory, the calibration step mainly consists of the following operations. 1) Forming the $\boldsymbol{A}$ matrix. 2) Finding the correlation matrices $\boldsymbol{C}=\boldsymbol{A}^T\times\boldsymbol{A}$, $\boldsymbol{D}=\boldsymbol{A}^T\times\boldsymbol{B}$ 3) Solving for the kernel weights for each coil. Creating the matrix $\boldsymbol{A}$ and finding the correlation matrix takes up significant memory and involves redundant computation. We exploit the redundancy and directly compute the correlation matrix as proposed in [3]. For the first approach, we create the matrices $\boldsymbol{C}_i$ and $\boldsymbol{D}_i$ corresponding to coil *'i'*, by removing a row and column corresponding to the target location . The linear system $\boldsymbol{C}_i\boldsymbol{w}_i=\boldsymbol{D}_i$ is solved using a linear solver, for each coil. For the second approach, we remove the rows and columns corresponding to the target locations and the corresponding locations in the rest of the coils. We solve this once, and find the weights corresponding to the rest of the source points.

Results:
We experimented the approaches on T2w brain MRI using 8 channel and 32-channel datasets. For an 8-channel dataset, we observed differences in the coilmaps as in figures 3(a) and 3(b), and thus the final image quality, as shown in figures 1(a) and 1(b). For a 32-channel dataset, the coilmaps are similar (as in 4(a) and 4(b)) and there is no perceptual difference in image quality, as shown in figure 2(a) and 2(b).

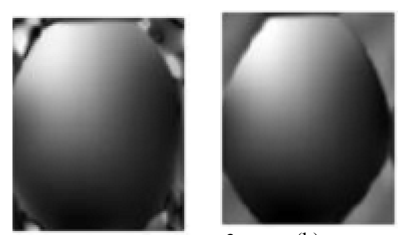
Discussion:
We studied the impact of avoiding the use of coil-neighbors of a target point as source points, for finding the kernel weights as part of the autocalibration step of ESPIRiT. From our experiments on high-channel datasets, we see that the image quality is not compromised, as it still has large number of source points spanning across all coils.



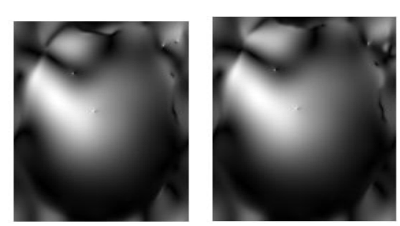
(a) (b) (c) **Figure 1** (d)



(a) (b) (c) **Figure 2** d)



(a) **Figure 3** (b)



(a) **Figure 4** (b)

Figure 1,2: ESPIRiT output for T2w brain MRI for 8-channel and 32 channel datasets respectively (a) Uses coil-neighbors (b) doesnot use coil neighbors (c) &(d) are difference images scaled corresponding to (a) and (b) with respect to fully sampled datasets. Figure 3,4: Coilmap outputs for 8-channel and 32-channel channel datasets (a) uses coil-neighbors (b) doesnot use coil neighbors

References:[1]Lustig ISMRM, 2009,p334; [2]Peng Lai ISMRM 2010:345 [3]P.J. Beatty, ISMRM 2007,p1749