Iterative auto-calibrated reconstruction of 3D non-Cartesian trajectories

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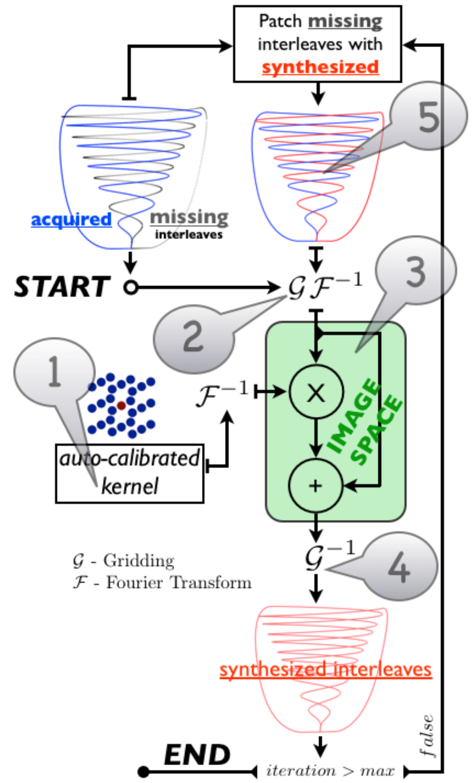
INTRODUCTION – Traversing k-space with 3D Cones trajectories is a very SNR-efficient way of reading out data. Due to the higher-density sampling at the center of k-space they are ideal for reconstruction algorithms that rely on a fully sampled small center portion of k-space for auto-calibration, such as 3D GRAPPA and, L1-SPiRiT [1,2]. However, unlike trajectories such as 3D stack of spirals or 3D Cartesian (e.g. CAIPIRINHA), 3D sampling strategies (including 3D Cones, 3D Spirals, FLORET, and yarns) cannot be simplified to a 2D reconstruction problem because it will produce varying undersampling patterns in 3D k-space with aliasing artifacts in all three dimensions. Here, we introduce an iterative POCS algorithm for reconstructing arbitrary 3D k-space data and apply it to 3D Cones trajectories. This work extends on the recently published 2D/hybrid 3D L1-SPiRiT[1], which didn't present a POCS approach for non-Cartesian trajectories.

Figure 1: POCS implementation of the proposed reconstruction algorithm. *(1)* - 3D SPiRiT kernel is estimated from the gridded acquired data. *(2)* - The acquired data is gridded and inverse Fourier transformed. *(3)* - The inverse Fourier transformed auto-calibrated adjoint kernel is multiplied with this data in image space. This operation computes for each coil channel, a weighted sum over all coils and voxels, which is then added to the undersampled volume in image space. *(4)* - Inverse gridding is performed to synthesize all interleaves (acquired and missing). *(5)* - In preparation for the next iteration step and to enforce data consistency in the non-Cartesian k-space, only missing interleaves are replaced with a subset of the synthesized ones. The rest of the synthesized interleaves are discarded. The algorithm stops after a predefined number of iterations (undersampling factor R + 1).



MATERIALS & METHODS – Data acquisition: Imaging was performed using a MR 750 HD (GE Healthcare) unit with a 32-channel receive-only head coil. A GRE sequence was used to acquire 12760 interleaves (FA=25°, TR/TE=12ms/0.3ms, FOV 32cm, 1mm^3) with a 8ms 3D Cones readout [2]. Undersampling was performed retrospectively by either eliminating every other interleave (R=2) or randomly (R=4). Reconstruction: The reconstruction algorithm is shown in **Figure 1**. First, coil-compression to 13 virtual coils and gridding was performed to compute a 9x9x9 3D GRAPPA kernel from a 30x30x30 calibration-area at the center of k-space that estimated the center sample point from its N=9^3-1 surrounding samples. Then, the adjoint kernel was inverse Fourier transformed into image space and multiplied with the inverse Fourier transform of the gridded undersampled data. Subsequently, the original undersampled volume or the volume from the previous iteration was added to the data set that was produced by the kernel multiplication in image space. Finally, inverse gridding was performed to synthesize all (acquired and missing) interleaves. In the next iteration step, a subset of the synthesized interleaves replaced the missing (undersampled) interleaves. For the randomly undersampled data set, an additional soft-threshold was applied to the synthesized interleaves during each iteration to suppress incoherent aliasing artifacts.

RESULTS – The proposed reconstruction algorithm shows greatly reduced artifacts when compared to a zero-padded reconstruction of the same data (**Fig. 2**). Some residual aliasing artifacts remain for the randomly undersampled R=4 data set. The kernel computation took ~400sec, and each iteration step took ~1000sec (8x Intel Xeon 2.93GHz). 3-5 iterations were sufficient for the algorithm to converge.

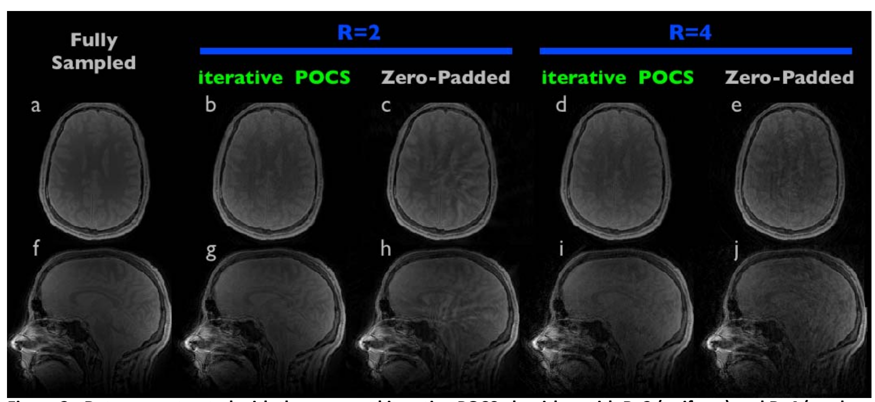


Figure 2 - Data reconstructed with the proposed iterative POCS algorithm with R=2 (uniform) and R=4 (random undersampling). Also shown, the zero padded reconstruction and the fully sampled data set. Residual artifacts are barely visible in R=2 case (b, g) compared to the zero-padded reconstruction (c, h). Minor artifacts are visible in the R=4 case (d, i).

CONCLUSION & DISCUSSION – This work shows that this iterative POCS algorithm is a promising method for reconstructing arbitrary undersampled 3D MR data. The image quality of the reconstructed images could be further improved by enforcing additional penalties, such as Wavelet or TGV2, and is part of forthcoming work. This could be especially beneficial for higher undersampling factors. This algorithm is not restricted to the 3D Cones trajectory, allowing the reconstruction of any auto-calibration-compatible 3D k-space trajectory and is also easily extendable to 4D.

References: [1] Gurney PT, et al., MRM 2006; 55: 575-582. [2] Lustig M, et al., MRM 2010; 64:457–471. **Acknowledgements:** The authors would like to thank John Pauly for helpful discussions. This work was supported in part by the NIH (2R01 EB00271108-A1 , 5RO1 EB008706, 5R01 EB01165402-02), the Center of Advanced MR Technology at Stanford (P41 EB015891), Lucas Foundation, Oak Foundation.