STEP: Self-supporting Tailored k-space Estimation for Parallel imaging reconstruction

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Target audience: MR researchers and clinical scientists interested in reconstruction and fast imaging studies.

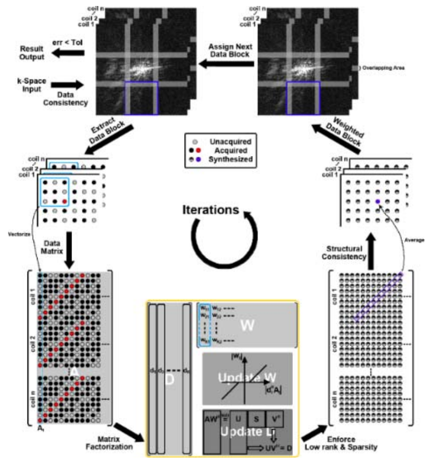
Introduction: Parallel Imaging (PI)[1,2] has been the most popular technique to reduce MR scan time in clinical applications. The PI methods without a pre-scan for sensitivity profile estimation can eliminate inter-scan motion and small FOV issues and are thus more robust. PI methods such as GRAPPA[2] and SPIRiT[3] usually acquire several central autocalibration signals (ACSs) to form a calibration matrix for interpolation kernel extraction. PRUNO[4] further generalized this idea by finding the null space basis of the calibration matrix via Singular Value Decomposition (SVD), while ESPIRiT[5] exploited the complementary signal subspace for PI reconstruction. One limitation for these proposed subspace methods is the mismatching that the subspace basis calibrated from the central ACSs data might not be optimal for the peripheral k-space. SAKE[6] attempted to solve this problem based on the global subspace established for the entire k-space data. However, the signal-to-noise characteristic varies in k-space particularly for imaging sequences with gradually evolved signals due to T1 and/or T2 relaxation[7,8]. In this work, we developed a Self-supporting Tailored k-space Estimation for Parallel imaging reconstruction (STEP) technique to address the problems of subspace parallel imaging reconstruction in the case of insufficient data for calibration and spatially varying correlation.

Theory and Methods: *Local signal characteristics promotion constraints:* To adapt the spatially varying signal characteristic, two tailored schemes were proposed on the basis of a simplified SVD matrix factorization of calibration matrix A, where $A = U\Sigma V^H = U_{||}\Sigma_{||}V_{||}^H + U_{\perp}\Sigma_{\perp}V_{\perp}^H \approx U_{||}\Sigma_{||}V_{||}^H \approx DW$. 1). k-space partition (e.g. 3-by-3 overlapping blocks as shown in Figure 1 when total # of partitions $L = 9$) can make each local basis $D_l, l = 1, \cdots, L$ provide more localized data features in k-space. 2) apply a Laplace a priori model on weighting matrices $W_l, l = 1, \cdots, L$ to further promote local basis selection[9]. *Image reconstruction:* Based on the previous considerations, STEP was designed to restore the undersampled k-space with the following optimization problem: $\min_{x,D_1,W_1,\cdots,D_L,W_L} \sum_{l=1}^{L}\frac{1}{2}||R_l(P^T y + \bar{P}^T x) - D_l W_l||_F^2 + \lambda||W_l||_1$, where y and x are the acquired and un-acquired k-space data respectively, P^T and $\bar{P}^T$ are operators to project the acquired and un-acquired data onto the Cartesian grids in k-space, R_l is the operator to extract the lth data block in Cartesian k-space and reshape it into the structured low rank data matrix. It is noteworthy that the ACSs data is also not required in STEP which therefore retains its self-supporting property similar to SAKE. The proposed method was implemented in an iterative Projection-Onto-Convex-Sets (POCS) fashion and its main steps were illustrated in Figure 1. *Data acquisition:* To validate algorithm performance, one 8 channel T1 weighted brain dataset was obtained from author's webpage[3] and another 3D isotropic 0.6mm Proton Density (PD) weighted knee dataset was acquired on a Philips 3T scanner (Philips Healthcare, Best, Netherland) with an 8 channel dedicated knee coil.

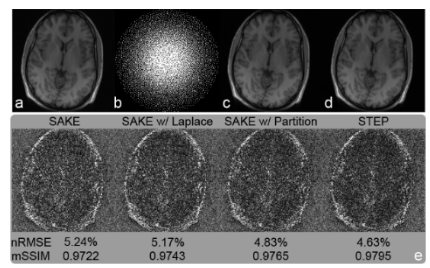
Results and Discussion: STEP was compared to SAKE and Tikhonov regularized SPIRiT in both calibrationless and autocalibrating experiments. Figure 2 demonstrates that two tailored schemes adopted in STEP can improve the accuracy of SAKE method in calibrationless condition for 8 channel T1 weighted brain dataset. Moreover, Figure 3 showes that STEP can better reduce noise amplification and residual aliasing artifacts in uniform undersampling case. Figure 4 indicates that improved delineation of popliteal arterial vessel wall boundary can be found at R = 5.6 for high resolution PD weighted knee dataset. In addition, quantitative image quality measured by normalized Root Mean Square Error (nRMSE) and mean Structural SIMilarity index[10] (mSSIM) further demonstrated the ROI based image quality improvement of STEP.

Conclusion: In this work, we presented a novel PI reconstruction framework called STEP that can be implemented in both autocalibrating and calibrationless conditions. Experimental results demonstrated that STEP can reduce noise amplification and aliasing artifacts while preserving structural information.

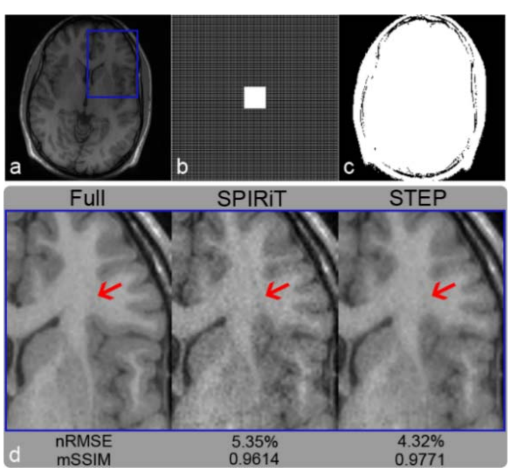
References: [1] Pruessmann KP, et al. MRM 1999. [2] Griswold MR, et al. MRM 2002. [3] Lustig M, et al. MRM 2010. [4] Zhang J, et al. MRM 2011. [5] Uecker M, et al. MRM 2014. [6] Shin PJ, et al. MRM 2014. [7] Guo JY, et al. MRI 2006. [8] Park S, et al. MRM 2012. [9] Malioutov D, et al. IEEE TSP 2005. [10] Wang Z, et al. IEEE TIP 2004.



(↑)**Figure 1.** Flowchart of the STEP algorithm.



(↑)**Figure 2.** Performance comparison in calibrationless experiment. (a) Fully sampled reference image. (b) vd-PDS pattern with net reduction factor of 4. (c) and (d) correspond to reconstruction result of SAKE and STEP respectively. (e) The reconstruction errors of SAKE, SAKE+Laplace a priori, SAKE+k-space partition and STEP in comparison to the reference image. The ROI (Figure 3(c)) based nRMSE and mSSIM measurements are also shown at bottom.



(←)**Figure 3.** Performance comparison in autocalibrating experiment. (a) Full data as reference. (b) 3.8-fold uniform undersampling pattern. (c) ROI used for quantitative image quality measurement. (d) The zoom-in view of a local area marked with blue square in (a). Note that less aliasing artifacts can be seen in STEP (as shown by red arrows). The ROI based nRMSE and mSSIM values are also provided at bottom.

(→)**Figure 4.** Demonstration of improved vessel wall delineation. (a) Fully sampled axial slice of knee dataset. (b) 5.6-fold vd-PDS undersampling pattern. (c) ROI used for quantitative image quality measurement. (d) Zoomed-in results as indicated by blue square in (a). The nRMSE and mSSIM measured within ROI are also presented at bottom.