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## eRAKI: Fast Robust Artificial neural networks for K-space Interpolation (RAKI) with Coil Combination and Joint Reconstruction

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### Synopsis

**RAKI can perform database-free MRI reconstruction by training models using only auto-calibration signal (ACS) from each specific scan. As it trains a separate model for each individual coil, learning and inference with RAKI can be computationally prohibitive, particularly for large 3D datasets. In this abstract, we accelerate RAKI by more than 200 times by directly learning a coil-combined target and further improve the reconstruction performance using joint reconstruction across multiple echoes together with an elliptical-CAIPI sampling approach. We further deploy these improvements in quantitative imaging and rapidly obtain  $T_2$  and  $T_2^*$  parameter maps from a fast EPTI scan.**

### Introduction

A number of machine learning approaches have been proposed for MRI reconstruction that allow high-quality reconstructions from highly undersampled data [1]. A promising approach in this direction is RAKI [2], which trains networks solely using autocalibration signal (ACS) data from each specific scan, without relying on a large training dataset. A drawback of RAKI is in the training and reconstruction time which can be prohibitively long as it needs to learn a model for real and imaginary components of each individual coil (e.g., 64 models for 32 channel data). This may be particularly problematic for large 3D datasets, impeding its clinical adoption. Self-consistent RAKI (sRAKI) [3,4] learns self-consistency using a single model for all the coils but the use of iterative optimization during reconstruction can still be time-consuming. In this abstract, we propose eRAKI to speed up RAKI by directly learning to reconstruct coil-combined target data using ESPIRiT-based sensitivity estimation[5]. We perform the learning/reconstruction in 3D k-space to benefit from 3D convolutions while utilizing the fully-sampled readout dimension to effectively increase the size of available ACS data. We show that the proposed eRAKI accelerates RAKI's computational speed by more than 200 times while improving reconstruction performance by taking the advantage of multi-echo joint reconstruction and elliptical-CAIPI [10] sampling. We further demonstrate the ability of eRAKI to speed-up the reconstruction of echo planar time-resolved imaging (EPTI)[9] acquisition by 10x times to provide distortion-free  $T_2$  and  $T_2^*$  parameter maps.

### Methods and Experiments

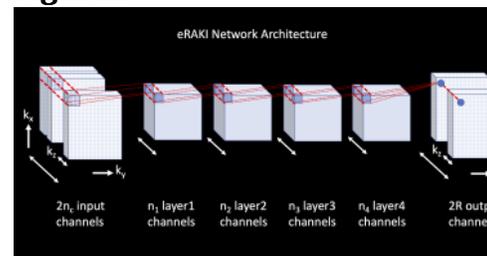
#### eRAKI Reconstruction

We use ESPIRiT to estimate coil sensitivities  $C$  from ACS data  $y_{acs}$  and perform coil combination to obtain single-channel ACS data in k-space,  $y_{combo}$ . We take  $y_{combo}$  as the network's target to learn and train a single model using the following objective function:

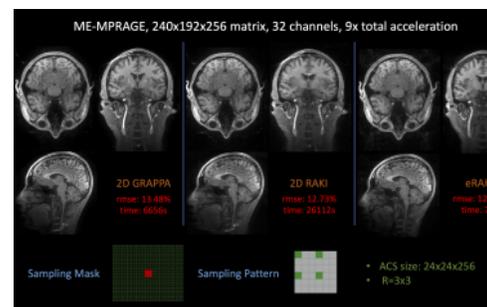
$$\operatorname{argmin}_{\theta} (\alpha \|y_{combo} - f_{\theta}(x_{acq})\|_1 + (1 - \alpha) \|y_{combo} - f_{\theta}(x_{acq})\|_2 + \beta \|\theta\|_2)$$

where  $f_{\theta}$  is the network,  $\theta$  are the network parameters,  $x_{acq}$  is the input under-sampled k-space. Regularization terms ( $\alpha = 0.5$  and  $\beta = 0.15$ ) are added to speed up the convergence. After training the network using ACS data, we apply the trained model to perform inference on the entire undersampled k-space and the network output is the reconstruction result. The whole process takes place in 3D k-space to benefit from 3D convolution to help compensate for any information loss during the coil combination process. This also further reduces the overall reconstruction time, as only a single network needs to be trained across the whole 3D imaging volume, rather than one model per slice. Figure 1 shows the implementation of the proposed eRAKI network.

### Figures



Our eRAKI uses 5-layer 3D CNN architecture. Since the learning target is coil-combined data, we need to learn R lines when the acceleration rate is R. The output channel is 2R so we only need to use one model to reconstruct all the data. Layer4 was followed by rectifier linear units (ReLU) as activation functions and we set  $n_1=n_2=n_3=n_4=64$ . The kernel sizes of the layers are  $3 \times 3 \times 7$ ,  $1 \times 1 \times 5$ ,  $1 \times 1 \times 3$ , and  $1 \times 1 \times 1$ , respectively.



Comparisons between 2D GRAPPA, 2D RAKI, and eRAKI reconstructions on 3D ME-MPRAGE data using  $24 \times 24 \times 256$  ACS and  $3 \times 3$  undersampling. We use Tikhonov regularization in GRAPPA and set parameter  $\lambda = 1 \times e^{-9}$ . Our eRAKI benefits from 3D convolutions and can achieve comparable performance with high-speed reconstruction.

### eRAKI with joint reconstruction and elliptical-CAIPI sampling

The proposed eRAKI is applied on 3D ME-MPRAGE data [6,7] and compared with 2D GRAPPA [8] and 2D RAKI as shown in Figures 2 and 3. To further improve reconstruction performance, we apply elliptical-CAIPI sampling while maintaining the same acceleration rate, and extend eRAKI to perform joint reconstruction across three echoes by concatenating echoes in the coil dimension.

### eRAKI with EPTI

EPTI [9] can rapidly acquire distortion- and blurring-free multi-contrast data using an efficient spatiotemporal CAIPI sampling  $k_y - t$  and B0-informed GRAPPA-like reconstruction. We apply RAKI and eRAKI on EPTI data for each acquired slice in  $k_x - k_y - t$  space. All the experiments were done on a workstation with an Nvidia TITAN V and an AMD Ryzen Threadripper 3970X 32-Core Processor. Code/data are available at <https://anonymous.4open.science/r/77eb09e7-8a65-4a57-b559-741d6f8d4f37/>.

## Results

Figure 2 shows that eRAKI achieves comparable performance as RAKI and GRAPPA, while improving the reconstruction speed >200-fold. Figure 3 shows that the reconstruction performance of eRAKI can be further improved by combining multi-echo joint reconstruction and elliptical-CAIPI sampling. Figure 4 shows that eRAKI can be applied to more complicated and advanced sampling methods where GRAPPA-like reconstruction can work, like EPTI, and achieve comparable performance while speeding up the computation by 10-fold. The table in Figure 5 summarizes the reconstruction times of the tested algorithms for these two datasets.

## Discussion and Conclusion

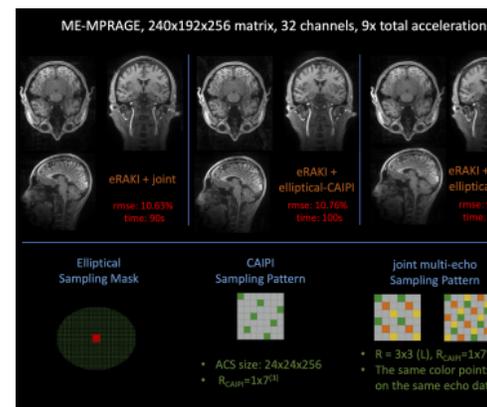
We accelerate RAKI reconstruction dramatically using a coil-combined target. For this, we capitalized on the fact that coil combination is a convolution in k-space, and can be well represented by a convolutional layer. Figure 5 shows the learning/inference time of each method. GRAPPA is implemented on CPU and RAKI and eRAKI run on GPU. Since GRAPPA needs to learn a model for each coil, it may not benefit significantly from a GPU implementation. In conclusion, eRAKI can reconstruct 3D volumes in a short timeframe and may facilitate the adoption of scan-specific deep learning on clinical scanners.

## Acknowledgements

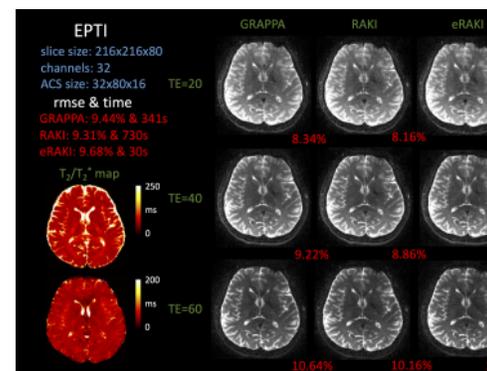
This work was supported by research grants NIH R01 EB028797, U01 EB025162, P41 EB030006, U01 EB026996 and the Nvidia Corporation for computing support.

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eRAKI's performance can be further improved using joint reconstruction across echoes and elliptical-CAIPI sampling. In joint reconstruction, shifted patterns are used between different echoes and all the echoes are reconstructed using one model. In this case, the number of output channels is  $2 \times R \times N_{\text{echo}}$ . Elliptical sampling provides  $\sim 4/\pi$  additional acceleration so that  $R_{\text{CAIPi}} = 1 \times 7^{(3)}$  sampling can maintain the total acceleration of  $R \approx 9$ .



Comparisons between GRAPPA, RAKI, and eRAKI reconstructions on EPTI data using  $32 \times 80 \times 16$  ACS. All three methods are implemented in  $k_x - k_y - t$  space and eRAKI can achieve comparable performance with GRAPPA but uses only two models to perform the whole learning/reconstruction process.

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ME-MPRAGE 240x192x256	2D GRAPPA	2D RAKI	eRAKI	eRAKI+ multi-echo (all 3 echoes)	ESPIRiT coil sensitivity estimation
Learning time	40s/slice x256 slices =10240s	100s/slice x256 slices =25600s	30s	75s	50s
Reconstruction time	8s/slice x256 slices =2048s	2s/slice x256 slices =512s	40s	100s	

EPTI 216x216x80	GRAPPA	RAKI	eRAKI	ESPIRiT coil sensitivity estimation
Learning time	11s	370s	20s	0.38s
Reconstruction time	330s	360s	10s	

Summary of learning and reconstruction time between GRAPPA, RAKI and eRAKI reconstructions. Proposed eRAKI significantly reduces the overall reconstruction time since low-resolution ESPIRiT coil sensitivities can be estimated rapidly. Note that GRAPPA is implemented on CPU while RAKI and eRAKI are implemented on GPU. But simply putting GRAPPA on gpu won't help much, since it still needs 64 different models for the typical 32 channel receiver coil data while eRAKI needs only one model.