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Accelerating Phase and Quantitative susceptibility mapping with Scan-Specific Complex Convolutional Neural Networks

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Introduction: In recent years, the MR image reconstruction task has been successfully performed with deep learning strategies. Most studies focus on magnitude and disregard phase images. However, it is crucial to know the phase of MRI for many applications, such as field mapping, Quantitative Susceptibility Mapping (QSM) [2], phase contrast velocity mapping etc. Typically, reconstruction networks separate real and imaginary components into real-valued channels, which is suboptimal to represent complex numbers, as well as the derived phase information. Recent studies suggest that deep neural networks based on complex-convolutions have high representational power and accuracy, which will allow them to be applied to MRI reconstruction [1], including for phase-based applications based on highly undersampled data. We propose a novel crRAKI, a scan-specific complex-valued residual convolutional neural network (CNN) for 2D MRI data as well as its extension for 3D for phase-mapping and QSM. It is compared to GRAPPA [3] and rRAKI [4] for accelerated MRI reconstructions.

Methods: Reconstruction Network, crRAKI aims to produce a fully sampled k-space from undersampled k-space. The network is trained using AutoCalibration Signal (ACS) [3] which is fully sampled in the center of k-space. Fig. 1a illustrates a Train-Validation Partition (TVP) scheme for early stopping in order to avoid overfitting.

Standard GRAPPA estimates the missing k-space lines in each coil by a linear combination of its neighbourhood acquired data overall coils, which can be formalized as a one-layer complex convolution. RAKI [5] non-linearly estimates the missing k-space lines using multiple convolutional layers and non-linear activation layers Rectified Linear Unit (ReLU). This reconstruction is similar to GRAPPA but uses CNNs instead of linear convolutional kernels for interpolation in k-space. Recently the proposed rRAKI (residual RAKI) utilized both linear convolutions and a CNN that takes the sampled lines as input. However, it treats the convolution by concatenating the real and imaginary parts and may only support 2D MRI data. Here, we investigate the use of crRAKI (for 2D) and crRAKI3D (its 3D extension) which support a true complex implementation for 2D/3D MRI data respectively as shown in Fig. 1b. crRAKI is Line-by-Line complex-2D-CNN, with 3 complex-conv-blocks of the size Conv(5x2), Conv(1x1), Conv(3x2) with LeakyReLU with the residual connection. Similarly, crRAKI3D is a 3-layer CNN as shown in Fig. 1b and 1c.

Interleaved multi-slice (24) 2D GRE multi-echo (6 echos) with an in-plane resolution of 1 mm, slice thickness 3 mm matrix size 256x256, TR=802 ms, Tacq=1.4 min, at 3T with a 20-channel coil array were acquired. Acquisitions with acceleration factors R=2 were performed with 24 ACS lines. Multi-echo (6) 3D GRE brain acquisitions with isotropic voxel-size of 1 mm, matrix size of 256x256x160, at 3 Tesla (Siemens Vida) with a 64-channel coil array were performed (TR=35 ms). Acquisitions with various acceleration factors were acquired (R=2 and 4x3 shown, with Tacq=10 min and 2 min, respectively) with 64x64 ACS lines. ACS region and undersampled data are acquired on a healthy volunteer in a separate mode.

Results and Discussions:

2D results: Fig. 1c & 1d show the qualitative comparison of crRAKI reconstructed magnitude and phase maps along with GRAPPA_{TVP} and rRAKI, for R=2 and 4 and for the first and last echoes. GRAPPA_{TVP} and rRAKI reconstruction have significant undersampling artifacts at R=4 whereas the crRAKI reconstruction has almost no artefacts on magnitude/phase images. Filtered field maps corroborate this point with artefact-free crRAKI images. Our method can perform phase-mapping reconstruction up to R=4 in these 2D acquisition settings.

3D results: Fig. 1e shows the echo combined magnitude image, R2* and QSM for the default GRAPPA reconstruction for R=2, as well as with the GRAPPA_{TVP} and crRAKI accelerated at R=4x3. Despite a visible reduction of SNR, both methods are able to perform reconstructions for R=4x3 and display similar paramagnetic deep grey matter structures.

In this study, a qualitative preliminary evaluation of the reconstruction was conducted. Standard GRAPPA was adapted to the neural network to leverage the train-validation scheme that can improve reconstruction quality. Our results showed less undersampling artefacts at high acceleration rates on phase in the 2D case for crRAKI, and similar performance in 3D for GRAPPA_{TVP} and crRAKI. Subsequent QSM was successfully performed on accelerated 3D GRE data with a preserved contrast as well as with an expected loss of SNR. It demonstrates that phase maps from these highly accelerated 3D multi-echo scans can be exploited for QSM. R=4x3 is a significant gain in terms of acquisition times as compared to the usual 2x-3x clinical routine used GRAPPA.

Conclusions: crRAKI achieves superior image quality both for magnitude and phase as compared to real-valued CNNs rRAKI and GRAPPA on multi-echo gradient echo 2D acquisition in which phase is of primary importance for multiple applications. We are able to perform reconstruction at an acceleration rate of 4 in a scan-specific manner in 2D. GRAPPA was also revisited to prevent overfitting during training by using a train-validation partition specific to uniform undersampling. This reconstruction strategy has been extended to 3D and is able to perform reconstruction, R2* and QSM at a higher acceleration rate of 4x3. Further work will focus on quantitatively validating these reconstruction strategies, as well as assessing end-user ratings of images.

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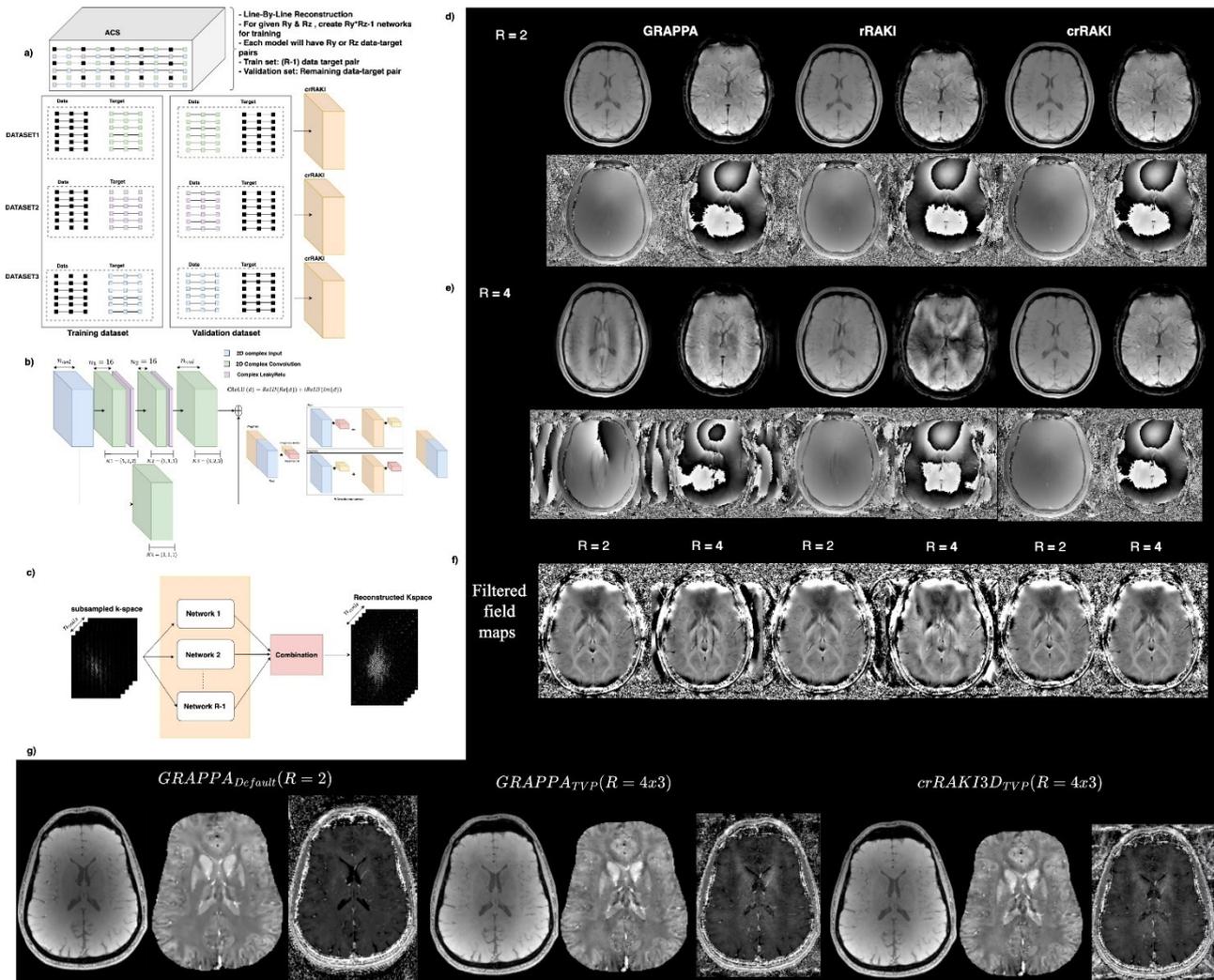


Figure 1: (a) Train-Validation scheme for 3D, (b) crRAKI3D architecture, (c) After the training is performed, the weights are applied on the undersampled k-space data to each echo, (d) Magnitude and phase at R=2 for 1st and last echoes, (e) Magnitude and phase at R=4 for 1st and last echoes, (f): Filtered field maps for GRAPPA, rRAKI, crRAKI at R=2 & 4, Fourier-transform images were combined using an estimation of coil sensitivities from a low pass filtered version of the first echo image. (g) Magnitude, QSM (MEDI [6]) and R2* at R=2,4x3 for GRAPPA and crRAKI3D.

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