An end-to-end Complex-valued Neural Network Approach for k-space Interpolation in Parallel MRI

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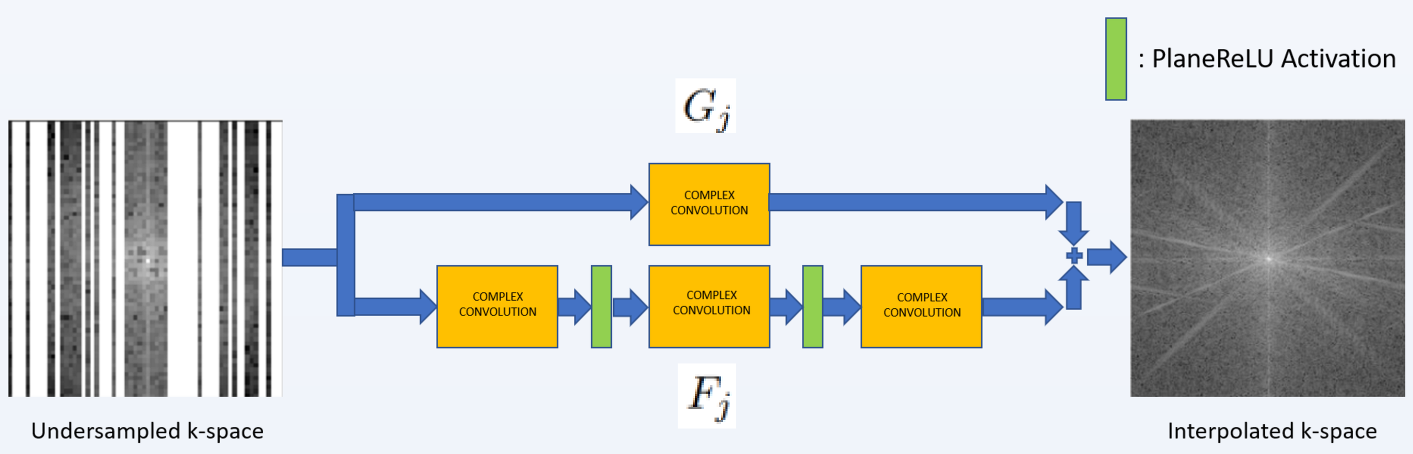
INTRODUCTION

- Parallel MRI is a method to speed up otherwise slow MRI scans using multiple MRI sensors (coils)
- In MRI, the sensor observations correspond to Fourier transform (k-space)
- Parallel MRI acquires fewer k-space samples than Nyquist frequency to speed up the scan and exploits the redundancies in samples from the coils to get a good quality image
- GRAPPA estimates missing samples in the k-space by assuming they are linearly dependent on their neighboring acquired k-space samples
- Residual RAKI is a neural network approach to improve GRAPPA by learning potentially non-linear dependence
- Residual RAKI uses a CNN to estimate noise in the linear GRAPPA reconstruction

OBJECTIVES

- Neural network approaches like Residual RAKI use real-valued weights to process the complex k-space as 2-D real data
- This discards the rich algebraic structure of the complex input
- Some previous works have used complex arithmetic in neural networks to address this
- But they try to denoise poor-quality reconstructions in image domain. When the noisy reconstructions have lot of artefacts, fine details may be lost, thus making it important to use k-space data as input.
- Also they rely on huge datasets for training
- We explore complex arithmetic in the Residual RAKI (rRAKI) CNN which operates on k-space in a single MRI scan
- The contributions of our work are –
  1. an end-to-end complex-valued neural network called **Complex rRAKI**
  2. We propose a novel activation function, the **PlaneReLU**, which is a generalized version of the ReLU activation function on the complex plane

PROPOSED METHOD AND MATERIALS



Complex rRAKI Model

- The Complex rRAKI uses complex convolution and proposed PlaneRELU activation function blocks
- Complex convolution utilizes 50% fewer parameters than real convolution with the same input and output size
- The proposed PlaneReLU function is defined as follows

$$PlaneReLU(x+iy) = \begin{cases} x+iy, & if\ ax+by+c \geq 0 \\ \frac{a+b+c}{\alpha}(x+iy), & otherwise \end{cases}$$

where $a, b, c \in \mathbb{R}$ are learnable parameters and $\alpha \in \mathbb{R}$ is a hyperparameter that we set to 3

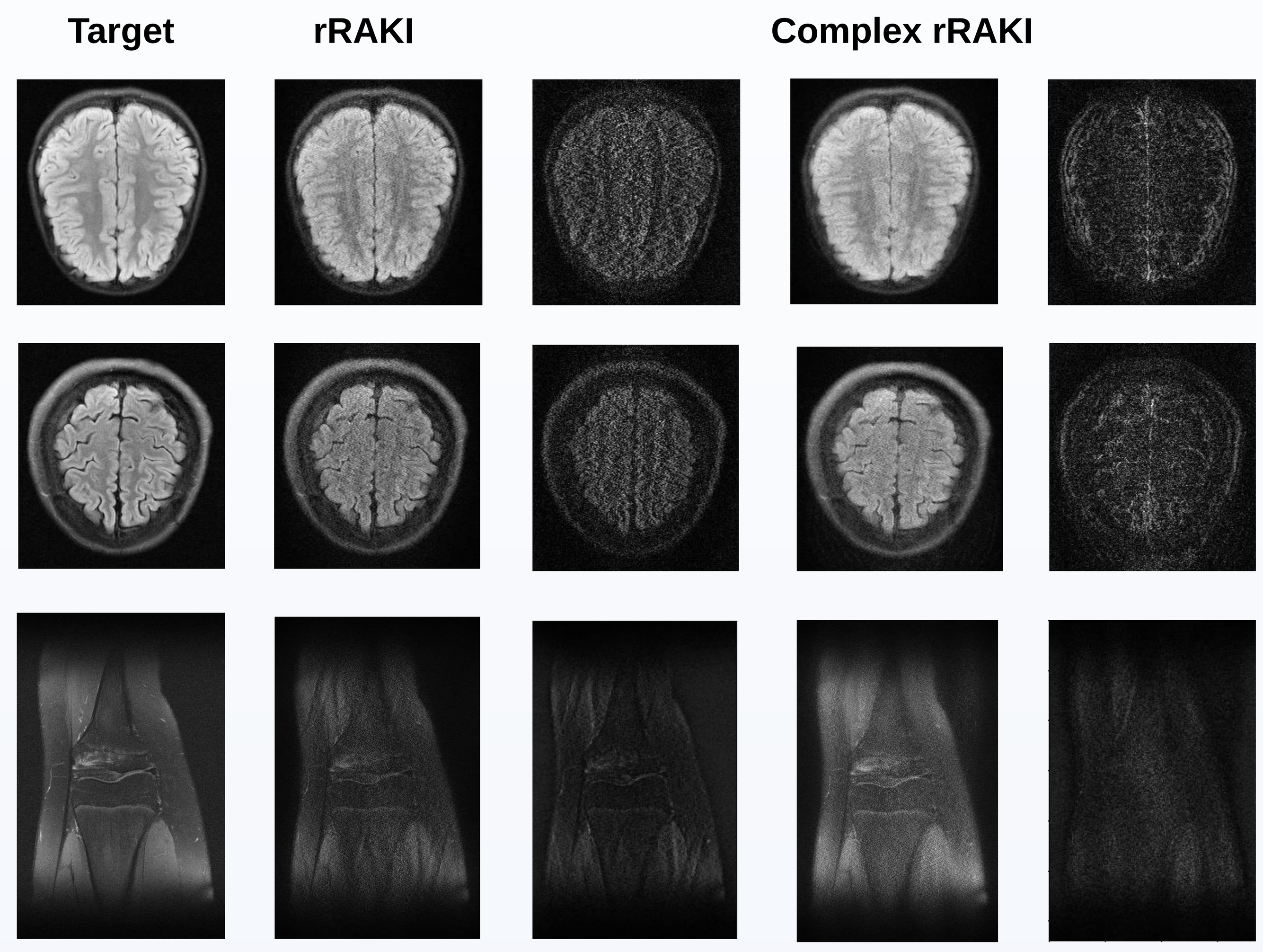
- The PlaneReLU divides the complex plane into two parts about a learnable line $ax+by+c=0$ like the ReLU divides the real line into two parts about the fixed origin
- It takes the firing decision based on both input magnitude and phase unlike other complex-valued activation functions which take the firing decision based on magnitude or phase information only

EXPERIMENTS AND RESULTS

- Two datasets are used –
  1. fastMRI multicoil brain dataset (FLAIR contrast)
  2. fastMRI multicoil knee dataset (proton density contrast with fat suppression)
- Cartesian undersampling with acceleration factor 5
- Optimizer: SGD with lr = 0.001 and momentum = 0.9
- Loss:

$$\mathcal{L}(\gamma_j,\theta_j) = \min_{\gamma_j,\theta_j} \|y_j - G_j(y_{source};\gamma_j) - F_j(y_{source};\theta_j)\|_2 + \lambda\|y_j - G_j(y_{source};\gamma_j)\|_2$$

Metric	PSNR	NRMSE	SSIM
fastMRI Brain Dataset			
rRAKI	31.51 ± 1.3	0.20 ± 0.041	0.84 ± 0.036
Complex rRAKI	31.83 ± 0.79	0.23 ± 0.08	**0.87 ± 0.027**
fastMRI Knee Dataset			
rRAKI	28.7 ± 0.73	0.45 ± 0.09	0.60 ± 0.07
Complex rRAKI	29 ± 0.49	**0.35 ± 0.047**	**0.67 ± 0.05**



DISCUSSION AND CONCLUSION

- The Complex rRAKI approach shows improved performance w.r.t. the SSIM metric and comparable performance w.r.t. other metrics with rRAKI using 50% fewer parameters on brain and knee datasets
- The performance improvement of Complex rRAKI is attributed to the structure of its network which respects the complex-valued algebraic structure of the input, thus constraining the degrees of freedom in the neural network and assisting improved learning.
- The proposed PlaneReLU activation function shows promising potential for use in complex-valued neural networks in k-space and other complex-valued domains

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ACKNOWLEDGEMENTS

The authors gratefully acknowledge the financial support of this project through the Mphasis F1 foundation.