Deep learning-based acceleration for CEST parameter estimation

Chushu Shen[1,2], Karandeep Cheema[1,2], Yibin Xie[1], Debiao Li[1,2]

[1] Biomedical Imaging Research Institute, Cedars-Sinai Medical Center, Los Angeles, CA, USA. [2] Department of Bioengineering University of California, Los Angeles, CA, USA

INTRODUCTION: CEST quantification requires long saturation and scan time to acquire data at over 50 frequency offsets, making it infeasible for clinical applications. To accelerate CEST MRI acquisition, we propose to under-sampling in both frequency and spatial domains and leverage deep learning methods for frequency selection, resolution enhancement and parameter estimation.

METHODS: We propose to significantly reduce the number of frequency offsets needed for deep learning-based CEST parameter estimation using channel pruning. To select the most informative 10 out of 53 frequency offsets, a ResUNet was modified to add a batch norm (BN) layer right after the input. The ResUNet was trained for CEST parameter estimation using all 53 frequency offsets as 53 input channels, while sparsity regularization was enforced on the scaling factor γ of the BN layer for pruning purpose [1]. For each channel the BN layer would scale and shift the normalized data $\bar{\mathbf{Z}}$:$\mathbf{Z}_{\mathbf{out}} = \boldsymbol{\gamma}\bar{\mathbf{Z}} + \boldsymbol{\beta}$. We assume that channels with small scaling factors only contribute insignificantly to the final map prediction and can be pruned. 10 frequency offsets with large scaling factors were considered as crucial for parameter estimation and thus selected. To further accelerate acquisition, these 10 selected frequency offsets were acquired in a hybrid fashion, where 6 were sampled at full resolution and 4 were sampled at 4-times lower resolution. A super-resolution network (SR-Net) was implemented to recover full-resolution information for the down-sampled data. Then parametric maps of APT, NOE and MT were estimated by retraining the ResUNet, based on the hybrid of 6 acquired plus 4 SR rendered frequency. To evaluate the performance, 40 human subjects were used for training and 11 for testing, where ground-truth (GT) were generated using the conventional 53 frequency and 4-pool Lorentzian fitting. Normalized root mean squared error (NRMSE), structural similarity index (SSIM) and peak signal-to-noise ratio (PSNR) were calculated. Pearson correlation coefficients R were reported.

RESULTS: Figure 1 shows the distribution of scaling factors in the batch norm layer. Among all 53 channels, 43 channels have a scaling factor close to 0 and thus were considered as less important for parameter estimation. For the super-resolution network, the mean NRMSE, SSIM and PSNR of all 11 test subjects were 0.015,0.998 and 45.79. For the map prediction network, the mean NRMSE, SSIM and PSNR of all 11 test subjects ranges from 0.080-0.172, 0.947-0.952 and 27.0-33.0 for three parametric maps. Mean correlation coefficients R were 0.89, 0.93 and 0.93 for APT, NOE and MT respectively. Figure 2 shows predicted maps of one test subject (NRMSE ∈ [0.03,0.06], R∈ [0.97,0.99]).

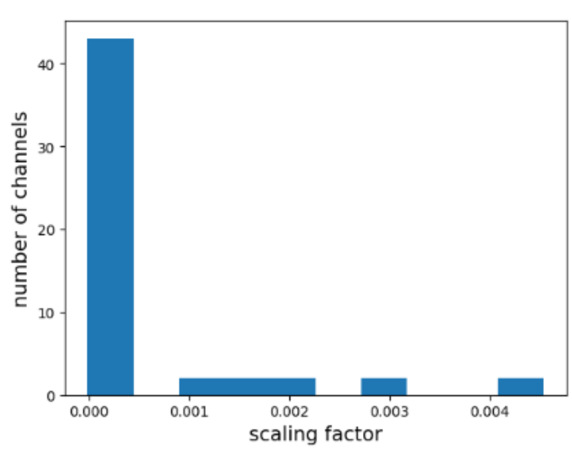

Figure 1 Histogram of the scaling factor γ for all 53 channels

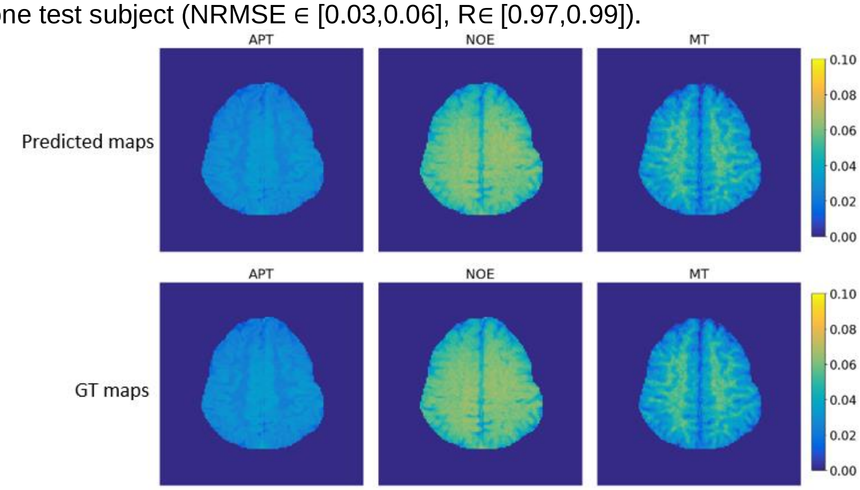

Figure 2 Predicted and GT maps of one test subject.

DISCUSSION: Distribution of scaling factors and comparison with GT maps suggested that the channel pruning method has successfully selected the informative frequency for deep learning based CEST parameter estimation. With the hybrid acquisition strategy where 4 frequencies were spatially down-sampled and effectively recovered by the SR-Net, a total acceleration factor of 7.6 can be achieved. While deep learning based CEST acceleration have been explored in other research, most of them achieved acceleration only by spatial under-sampling and super-resolution. Here we propose to combine both frequency and spatial under-sampling and leverage deep learning to achieve more efficient acceleration. Besides, the proposed channel pruning-based frequency selection is the first data-driven method for reducing CEST frequency offsets based on our knowledge.

CONCLUSION: The proposed deep learning-based acceleration method can accelerate CEST acquisition by a factor of 7.6. Future work will involve experimenting with higher under-sampling factors and network optimization to achieve further acceleration.

REFERENCES: 1. Z Liu, et al. IEEE International Conference on Computer Vision (ICCV) 2017 **2.**Guo C, et al. Magn Reson Med 2020; 84(6):3192-3205 **3.** Xu J, et al. Magn Reson Med 2024; 91: 583–599