Kernel regression for fast myelin water imaging

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Synopsis: This work examines the use of kernel regression for myelin water imaging. Parameter estimation by kernel regression (PERK) is a machine learning method that is very fast to train and apply for quantitative MRI problems. This abstract presents the first *in vivo* comparison of myelin water fraction (MWF) estimates from standard multi-echo spin echo (MESE) scans and fast-relaxing compartmental fraction (ff) PERK estimates from an optimized set of dual-echo steady state (DESS) scans. Results demonstrate that PERK is practical for *in vivo* use.

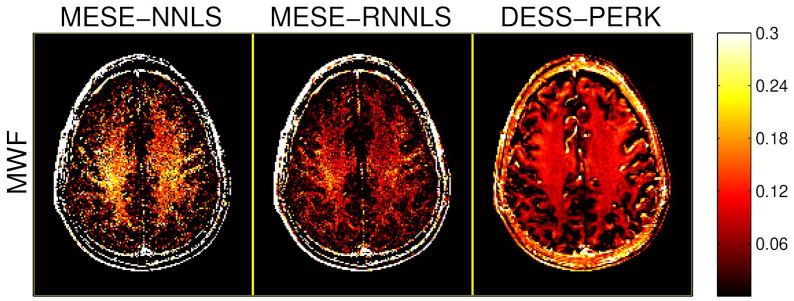
Introduction: Myelin water imaging is important for a variety of neurological disorders. The conventional method for myelin water imaging consists of estimating MWF from a MESE acquisition [1]. To address long scan times due to long MESE repetition intervals (TR ~1-2s), researchers have estimated ff from two-compartment models of fast steady-state scans [2,3]. There are two main challenges in ff quantification: (1) collecting data that is informative about both the fast- and slow-relaxing water compartments, and (2) processing that data to produce accurate myelin water images. We optimized the TR and flip angle values for DESS scans [3]; we previously applied PERK to such scans [3] anecdotally without comparison to MESE results.

Several groups have applied neural-net (NN) methods for estimating MRI parameters from a sequence of MR images having different contrasts, including MR fingerprinting scans. Training kernel regression is very fast and well-understood, whereas training a NN takes much longer and involves many hand-selected hyperparameters including network architecture. PERK [4] uses simple data-driven methods for tuning the few adjustable hyperparameters for gaussian kernels, leading to a simple turn-key approach for nonlinear regression that is far faster to apply than dictionary-based matching or nonlinear least-squares optimization methods [4] and is easier to train than NN methods. The speed benefit increases when estimating more parameters, and for two-compartment myelin water imaging there are 6 parameters: ff, spin density M0, and four compartment-specific relaxation times, neglecting exchange as in [3].

Methods: We acquired *in vivo* data using a 3T GE scanner with a 32-channel Nova receive head array. We acquired our precision-optimized DESS data with optimized flip angles and repetition times, holding all other scan parameters fixed across DESS scans. We acquired 32-echo MESE data using slab-selective refocusing pulses, minimal TE=9.2ms echo spacing, and TR=1s to limit scan time. We estimated B1 maps using Bloch-Siegert (BS) SPGR scans [5,6]. To compensate for incomplete recovery in MESE only, we estimated single-compartment T1 using nine SPGR scans with variable flip angles. All scans used a fully-sampled 3D Cartesian k-space grid and were reconstructed onto a 200x200x8 matrix over a 240x240x24 mm^3 field of view. DESS, MESE, BS, and SPGR scans respectively took 3m15s, 53m26s, 4m30s, and 3m32s.

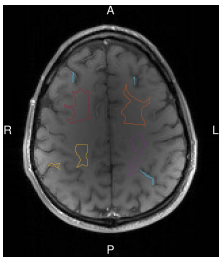
We reconstructed all coil images by 3D FFT and processed one image slice centered within the excitation slab. We combined coil images by extending JSENSE [7] to multiple datasets. We estimated ff maps from magnitude DESS images via PERK [4], using B1 estimates to compensate for flip angle variation. Using both B1 and T1 estimates, we estimated MWF maps from MESE echo images via nonnegative least-squares (NNLS) [8] and a l2-norm regularized variant of NNLS (RNNLS) used in [9] to reduce MWF variability, using extended phase graphs to compensate for stimulated echo contributions. PERK training and testing respectively took 33.4s and 0.7s, while NNLS and RNNLS respectively took 46.8s and 104.6s.

Results: This figure shows NNLS and RNNLS MWF estimates from a MESE scan and PERK ff estimates from optimized DESS scans. PERK ff estimates more clearly delineate cortical white/gray matter (WM/GM) boundaries and exhibit less WM variation than MESE MWF estimates. RNNLS MWF and PERK ff estimates appear visually similar in lateral WM regions, but both NNLS and RNNLS estimates are elevated in medial regions, possibly due to overlap of the myelin water and cellular water T2 peaks in internal capsules [10].



The table compares sample statistics of NNLS, RNNLS, and PERK estimates, computed over four WM and one cortical GM region of interest (ROI) that are color-coded in the adjacent anatomical image (key: Anterior, Posterior, Right, Left). Overall, estimates are quantitatively similar. PERK estimates exhibit the lowest variation within WM ROIs and the most similar sample means across WM ROIs. RNNLS estimates are consistently lower but less variable than NNLS estimates. As expected, none of the estimators measured significant myelin water content in GM.

ROI	MESE-NNLS	MESE-RNNLS	DESS-PERK
AR WM	0.10 ± 0.09	0.06 ± 0.05	0.11 ± 0.02
AL WM	0.11 ± 0.07	0.06 ± 0.04	0.10 ± 0.02
PR WM	0.16 ± 0.09	0.10 ± 0.06	0.09 ± 0.01
PL WM	0.14 ± 0.08	0.08 ± 0.06	0.09 ± 0.01
GM	0.01 ± 0.04	0.02 ± 0.03	0.02 ± 0.06



Conclusion: Kernel regression (PERK) with optimized DESS scans produces myelin water images with much faster scan times and improved SNR efficiency over conventional MESE. MESE MWF and DESS ff estimates are in reasonable agreement. PERK is applicable to *in vivo* data with only 33.4s training even with unoptimized Matlab code and no GPU processing.

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