Iterative optimization method for accelerated acquisition and parameter estimation in quantitative magnetization transfer imaging

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Target audience: Researchers interested in quantitative MRI, in particular quantitative magnetization-transfer imaging.

Purpose: Information about macromolecules, such as myelin or cartilage, can be obtained indirectly via magnetization transfer (MT). There are several MT imaging techniques, but to be independent on hardware and sequence parameters, quantitative MT (qMT) is preferable [1]. The most common model for quantification is the binary spin bath described by six parameters (relative pool sizes, relaxation times, and exchange rate constants). A drawback of the qMT method is the necessity for acquiring multiple images at various MT offset frequencies and saturation amplitudes. Recently, it was found that using artificial neural networks (ANNs), MT parameters can be obtained form reduced MT data sets while still maintaining the quality of parameter estimation as obtained with conventional fitting of large MT data sets [2]. This study presents a method for automatically selecting MT scanning parameters using backward elimination [3] that achieves *(i)* efficient sampling and *(ii)* optimized parameter estimates using ANNs.

Methods: ***MRI Scans:*** Experiments in 7 healthy volunteers were performed at 3T (MAGNETOM TIM Trio, Siemens) using a 32-channel head array as recently described [4]. Measurements comprised *(i)* multiple MT-prepared gradient echo acquisitions; *(ii)* a B_0 map for correcting for the influence of field inhomogeneities on the off-resonance frequencies; *(iii)* a Look-Locker sequence to measure $T_{1,obs}$ for extracting M_{0b}. qMT scanning parameters were 19 acquisitions with flip angle 10°; TR=33.6 ms; TE=6.7 ms; Gaussian off-resonance saturation with 200 Hz ≤ $\Omega/2\pi$ ≤ 40 kHz; $\omega_{1,max}$=1003 and 3010 rad/s. RF spoiling was used and spoiler gradients were applied before and after each MT pulse. ***Conventional MT Parameter Fitting:*** Parameter fitting was performed as described recently [4]. The two-pool model [1] was used, consisting of a liquid pool *"a"* (Lorentzian lineshape) and a semi-solid pool *"b"* (super-Lorentzian lineshape [5]). Fitting was performed using a Levenberg-Marquardt algorithm with 5 parameters (T_{1b}=1s): T_{2b} (transverse relaxation time of the semisolid pool); $M_{0b}\cdot T_{1a}$ (pool size of the semi-solid pool weighted by the longitudinal relaxation time of the liquid pool); T_{1a}/T_{2a} (ratio of the relaxation times of the liquid pool); R (rate constant describing exchange processes between both pools); and a scaling factor. ***ANN Training:*** Data from 3 randomly selected subjects were used for ANN training. Data exceeding an error bound in fitting were removed. As initial input, all MT images were included and in the process reduced to 4 optimal MT images. B_0, B_1, and $T_{1,obs}$ values were also part of the input and were not removed during the optimization resulting in an initial 22-dimensional and an optimized 7-dimensional input vector. Targets were the 6 conventionally fitted qMT parameters each assigned to a different ANN to minimize the workload during training and to increase the estimation quality per qMT parameter. The chosen network design was a feed-forward network with 5 hidden layers including 12, 20, 25, 20, and 10 neurons. Hyperbolic tangent sigmoid transfer functions between the layers and linear transfer functions for the output layer were kept as standard. Levenberg-Marquardt back-propagation training with early stopping to prevent overfitting was performed including data distribution in training, test, and validation sets with 70, 15 and 15% data partition. For the optimization process, the final error after training for each network was normalized and summed up for all networks per input set. ANNs were implemented in the Neural Network Toolbox™ of MATLAB (Natick, USA). ***Iterative Optimization Process:*** Optimization was performed iteratively by training the ANNs on a set of input scans while removing a single scan from the input vector. This step was repeated for every single scan while tracking the error after each training. This error was calculated as the sum of single errors of the 6 individual networks allowing setting weights for the single errors to modify the resulting choice of scan for removal. The scan whose removal caused the least increase in the error was permanently removed. The next iteration was performed with the smaller set of input scans. The process was repeated until the desired minimum number of scans was reached.

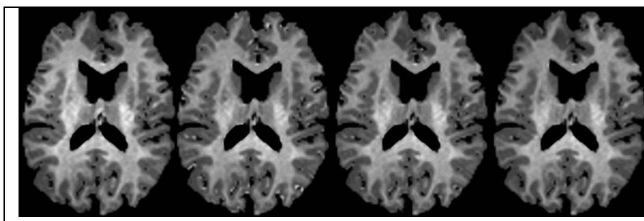

Figure 1. *M_{0b} maps of the same slice (left to right: conventional fit and ANN estimations using 10 scans, 8 scans, and 5 scans).*

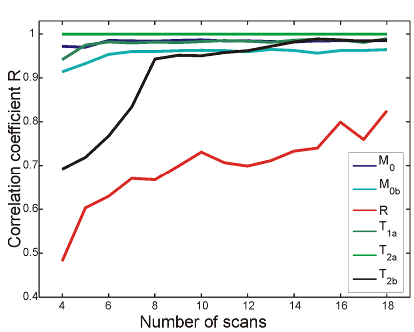

Figure 2. *Plot of the qMT parameter correlation vs. input vector size for parameter estimation using ANNs; estimated parameters were correlated with conventional fitting results.*

Results and Discussion: Fig. 1 shows the examples of optimization for the qMT parameter M_{0b}. Apparent are the high agreement in white matter and the also very good results in grey matter even when using only 5 input images. Fig. 2 shows the progression of correlation over the optimization experiment and reveals a higher sensitivity of the T_{2b} estimation to the number of scans as compared to other parameters, suggesting 8 scans for optimal estimation results. All other parameter estimates were obtained already with only 5 scans. Further acceleration (reduction of the input to only 4 scans) might be possible if saturation parameters are more widely spread as in the current data set. Depending on the desired estimation accuracy and specific importance of individual qMT parameters different optimized settings for specific sequence parameters are obtained.

Conclusion: It was shown that qMT experiments can be optimized close to the theoretical limit of input dimensions for unique determination of all qMT parameters.

References. [1] R.M. Henkelman et al. *Magn. Reson. Med.* 29: 759-766 (1993). [2] H. Marschner et al., *Proc. ISMRM* 21: 4239 (2013). [3] R. May et al. *Artificial Neural Networks–Methodological Advances & Biomedical Applications*, InTech, Shanghai (2011), 19-44. [4] D.K. Müller et al. *J. Magn. Reson.* 230: 88-97 (2013). [5] C. Morrison et al., *Magn. Reson. Med.* 33: 475-182 (1995).

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