Estimation of Parameters from Sparsely Sampled in-vivo Magnetization Transfer Data Using Artificial Neural Networks

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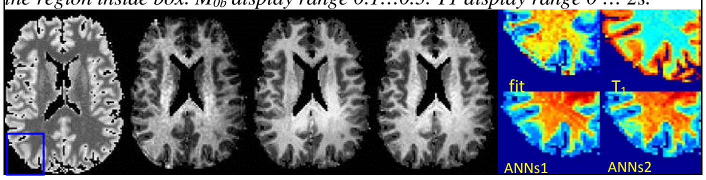
Target audience: Researchers interested in quantitative MRI, in particular quantitative magnetization-transfer imaging.

Purpose. Signals from protons bound to macromolecules are not directly visible to MRI due to their very short transverse relaxation times. However, information about macromolecules can be obtained indirectly from magnetization-transfer (MT) experiments [1]. To be independent of hardware and MRI sequence parameters; quantitative MT techniques (qMT) are preferable [1]. Quantification is typically based on the assumption of the binary spin-bath model described by 6 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 powers. Even for optimal configurations of sample points, the number of images required is in the order of 10 [2]. Furthermore, to obtain truly quantitative MT parameters, B_1 and B_0 field maps are mandatory. A $T_{1,obs}$ map obtained from a suitable MR sequence is necessary to obtain the relative pools sizes [1]. Reduction of the number of sample points is not advisable, because parameters have to be fitted by non-linear multi-dimensional least-square fitting [1]. Purpose of this study was to examine if Artificial Neural Networks (ANNs) can be trained to estimate parameter sets from sparsely sampled MT data. ANNs were trained using densely sampled MT data from healthy volunteers as input and MT parameters obtained from conventional fitting as target values. Test data sets were generated from previously unseen densely sampled MT data by choosing a few data points. After training, MT parameters estimated by the ANN for unseen test datasets were compared to those obtained by conventional fitting of entire unseen dataset.

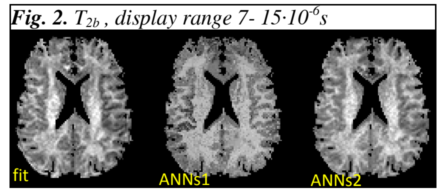
Methods. *MRI Scans:* Experiments in 7 healthy volunteers were performed at 3T (Magnetom TIM Trio, Siemens, Germany) using a 32-channel head array as recently described [3]. Measurements comprised multiple MT-prepared gradient echo acquisitions (19 off-resonance frequencies; 2 MT pulse flip angles 180° and 540°; NAE=8); a B_0 map, and a $T_{1,obs}$ map. The B_0 map was used for considering the effect of field inhomogeneities on the off-resonance frequencies in the MT parameter estimation. *Conventional MT Parameter Fitting:* Implementation of parameter fitting was described recently [3]. The standard two-pool model was used, consisting of a liquid pool *"a"* (Lorentzian lineshape) and a semi-solid pool *"b"* (super-Lorentzian lineshape [1]). Fitting was performed using a Levenberg-Marquardt algorithm with 5 parameters (T_{1b}=1s): T_{2b} (transverse relaxation time of the semisolid pool); $M_{0b}\cdot T_{1a}$ (the pool size of the semi-solid pool weighted by the longitudinal relaxation time of the liquid pool); (T_{1a}/T_{2a} the ratio of the relaxation times of the liquid pool); k (rate constant describing exchange processes between both pools), and a scaling factor. *ANN Training:* Data from 3 subjects were randomly selected for network training. Voxels exceeding an error bound during fitting were excluded, resulting in a training sample of approx. 15,000 voxels. Two sets of ANNs were trained. Input values for each voxel were 3 or 5 experimental data points. ANNs1: data measured with MT pulse flip angle of 540° and nominal frequency of 1170 Hz, 6840 Hz, 40000 Hz, respectively. ANNs2: same as ANNs1 plus data measured at 12323 Hz (540°) and 360 Hz (180°). In addition, the respective B1 values, frequency correction value and $T_{1,obs}$ were provided, resulting in an input vector of 6 or 8 values per voxel. For each MT parameter obtained from conventional least-squares fitting, feed-forward ANNs were independently trained. They consisted of 5 hidden layers with 12, 20, 25, 20, 10 neurons. The hyperbolic tangent function and the linear function were used as transfer function for hidden and output neurons, respectively. Training was performed by scaled conjugate gradient backpropagation with early stopping to prevent over-fitting. For this, the data set was split into a training, a test, and a validation set, consisting of 70, 15, and 15% of the included voxels, respectively. Voxels in each set were equally distributed throughout the brain. ANNs were implemented in the Neural Network Toolbox™ of MATLAB (Natick, USA).

Fig. 1. *$T_{1,obs}$ (left) and pool size of the semisolid pool M_{0b}. Color images: zoom of the region inside box. M_{0b} display range 0.1…0.3. T1 display range 0 … 2s.*



Results and Discussion. The trained ANNs were used to estimate the MT parameters of the 4 previously unseen data sets, whereby only data matching the training conditions were used. In general, the MT parameters estimated by both methods are highly correlated in all subjects (R>0.9703 for all parameters and ANNs), demonstrating that the parameter estimation from sparse data using ANNs works well. A key parameter of qMT is M_{0b}, often displayed as the bound-pool fraction, because of its relation to the myelination. It is found (Fig. 1), that already the ANNs using just 6 input values (ANNs1) permitted estimation of this parameter. The definition of the gray/white-matter boundary was better than obtained by conventional fitting (see colored zoom). It seems surprising that already 3 MT data are sufficient. However, as argued in [4], the number of free fitting parameters can be reduced, if the remaining parameter space is sufficiently constrained. In our approach these constraints are learned by the ANNs from the training data. The performance of ANNs could be improved if more data were considered (ANN2s). Similar performance was observed for estimation of the other MT parameters. As an example, the T_{2b} map is shown in Fig.2.

Fig. 2. *T_{2b} , display range 7- $15\cdot10^{-6}$s*



Conclusion. It was shown that the ANNs, if sufficiently trained by a few densely sampled data sets, enable parameter estimation from sparsely sampled MT data. As an added advantage, the parameter estimation is much fast compared to conventional fitting. The method needs no *a priori* assumptions of any parameter. Further work will employ estimation of optimized MT data sampling schemes and 3D imaging.

References: [1] Morrison et.al, JMR(B) 108 (2), p.103; 1995.; [2] Cercignani et.al, MRM 56 (4), p.803; 2006.; [3] Müller et al., ISMRM 2010#2996; [4] Underhill et.al, NeuroImage 54 (3), p.2052; 2011.