MR Estimation of Longitudinal Relaxation Time (T1) in Spoiled Gradient Echo Using an Adaptive Neural Network

H. Bagher-Ebadian[1,2], S. P. Nejad-Davarani[1,3], R. Paudyal[1], T. Mikkelsen[4], Q. Jiang[1,2], and J. R. Ewing[1,2]

[1]Neurology, Henry Ford Hospital, Detroit, MI, United States, [2]Physics, Oakland University, Rochester, MI, United States, [3]Biomedical Engineering, University of Michigan, Ann Arbor, MI, United States, [4]Neurosurgery, Henry Ford Hospital, Detroit, MI, United States

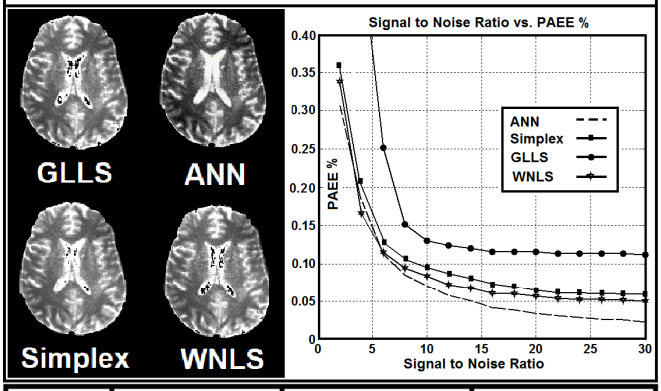
Introduction: The acquisition of high-resolution T_1 maps in a clinically feasible time frame has been demonstrated with Driven Equilibrium Single Pulse Observation of T_1 (DESPOT1) [1-3]. DESPOT1 derives the longitudinal relaxation time, T_1, from two or more spoiled gradient recalled echo (SPGR) images acquired with a constant TR and different flip angles [2, 3]. In general, T_1 can be estimated from two or more SPGR images [2, 3]. Estimation of MR parameters (T_1, M_0, etc.) from these sequences is challenging and susceptible to the level of noise in signal acquisition [2, 3]. Methods such as Simplex Optimization, Weighted Non-Linear Least Squares (WNLS), Linear Least Square (Gupta's LLS or GLLS), and Intensity based Linear Least Square (ILLS) method have been employed to estimate T_1 [2-6]. In both linear and non-linear methods, the estimated T_1 values are dependent on defining the weighting factors, which may result in a biased estimate of T_1 [3-6]. Herein, an adaptive neural network (ANN) is introduced, trained and evaluated as a T_1 estimator from the SPGR signal. The ANN was trained using an analytical model of the SPGR signal in the presence of different levels of signal to noise ratio (SNR). Receiver Operator Characteristic (ROC) analysis with K-fold cross-validation (KFCV) were employed for training, testing, and network optimization.

Materials and Methods: We hypothesized that an ANN could be trained to directly estimate T_1 for a simulated signal generated by a DESPOT1 pulse sequence. For training, the SPGR signal constructed using a wide range of T_1 values (10ms to 3000ms) from its analytical equation (Equation 1) was used. The Gold Standard for the ANN training was the T_1-value of the simulated signal. In the experiment, the measured SPGR signal intensity, *S(i)*, is a function of the longitudinal relaxation time (T_1), repetition time (T_R), the flip angle (θ), and the equilibrium longitudinal magnetization, (M_0). For each T_1 value, SPGR signal inputs were generated by varying the other independent parameters (T_2*, M_0 etc) in the synthetic model of the signal [3], Gaussian noise with an SNR range of 2 to 30 was added to all simulated signals. The simulated signals were then input to the ANN and their T_1 values were used as the ANN training output. To assess the ANN's accuracy for analysis of the experimental SPGR data, the model-trained ANN was applied to SPGR sequences acquired from eight patients with 16 slices each (3T, Matrix size: 256X256, FOV=240 cm^2, TR=5.834 ms, TE=0.888 ms). The same data was analyzed using conventional methods (Simplex, WNLS, and GLLS) and the results were compared to that of the ANN. Using simulated SPGR signals (Eq. 1), a feed-forward multilayer perceptron (MLP) with a back propagation training algorithm was trained and tested to estimate T_1. The ANN was trained using a gain insensitive input set (μ_k) described as Equation 2. The input vectors are presented to the ANN, and the output result is compared to the class identifier (*i.e.*, the value of T_1 in SPGR simulation). To quantify the accuracy and performance of the trained ANN compared to conventional techniques (WNLS, GLLS, and Simplex), the Percentage of Average Error of Estimation (PAEE) was calculated for each technique over a wide range of SNRs (2 to 30). The PAEE value is the measure of under or over-estimation of the trained ANN. Equation 3 was used to calculate the PAEE for each technique for different values of T_1 (1 to 3000 ms with 1ms interval) with different SNRs. In Eq. 3, T_{1E} denotes the T_1 estimated by the trained ANN and T_{1A} the actual T_1 value and H is the maximum number of T_1 samples in the simulation (H=2000, with 1 ms interval). Finally, to check the accuracy of the trained ANN, the ANN and the conventional methods were all applied to an experimental MR data set of eight patients and the T_1 values of different areas of the brain in the estimated T_1 maps were calculated and compared (see Table-1).

$$S_i = M_0 \frac{(1-e^{\frac{-T_R}{T_1}})\sin\theta}{(1-e^{\frac{-T_R}{T_1}}\cos\theta)} e^{\frac{-TE}{T_2^*}}, \quad i \in \{1,2,3,..N\} \quad (1)$$

$$\mu_k = \frac{S(k)}{S(1)}, k \in \{1,2,3,..N\} \quad (2)$$

$$PAEE = \frac{1}{H}\sum_{k=1}^{H}\left|1-\frac{T_{1E}^k}{T_{1A}^k}\right| \quad (3)$$



	White Matter	Gray Matter	CSF
GLLS	920 ± 55 msec	1330 ± 355 msec	3710 ± 855 msec
ANN	786 ± 55 msec	1149 ± 263 msec	2151 ± 14 msec
Simplex	810 ± 82 msec	1210 ± 302 msec	4820 ± 755 msec
WNLS	762 ± 93 msec	1130 ± 315 msec	3523 ± 655 msec
Literature	832 ± 93 msec	1331 ± 13 msec	[6]2180± 25 msec

Results and Discussion: The ANN was trained with a stopping error of 0.013, learning rate of 0.01 and momentum of ~0. Figure 1 shows the PAEE curves for the trained ANN, Simplex, WNLS, and GLLS versus SNR, and demonstrates that the average estimation error for T_1 by the ANN is about 7% to 4% for SNR of 10 to 15. The PAEE changes from 9% to 7% for the WNLS, 10% to 8% for the Simplex, and 13% to 12% for the GLLS. This figure also illustrates an example of a T_1 map estimated by the model-trained ANN, and all other techniques. As shown in Table-1 and Figure-1, the model-trained ANN estimates the T_1 map accurately and in a stable manner. To evaluate the accuracy of the model-trained ANN against real data, experimental results of the ANN for different areas of the brain in eight patients were also compared to the results of the conventional methods (Simplex, WNLS, GLLS and values reported in the literature- see Table-1); ANN and conventional methods yielded highly correlated estimates of T_1, independent of tissue type. For the trained ANN, the number of operations needed to produce a single T_1 value from one SPGR signal is about 20 (for an ANN with 5:3:1). This is much shorter than the many thousands of operations required in the iterative and multi-dimensional Simplex method. A map of T_1 with a dimension of 256X256 can be estimated by the ANN in a few seconds, whereas the time required for creating the same map using the simplex, GLS and WILS methods is roughly around 5, 2 and 2 minutes respectively.

References:

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