

Adaptive Neural Network for Direct Quantification of Longitudinal Relaxation Rate Change (ΔR_1) in T One by Multiple Read Out (TOMROP) Sequence

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Introduction:

Direct and accurate measurement of the temporal change in the longitudinal relaxation rate R_1 ($R_1=1/T_1$) after injection of a paramagnetic contrast agent (CA) has become increasingly important to the estimation of hemodynamic parameters associated with tissue physiological parameters – e.g., perfusion, capillary permeability in dynamic contrast-enhanced MRI (DCE-MRI) [1-5]. In the past, we have used TOMROP, an imaging variant of the Look-Locker sequence, to generate estimates of the temporal variation of contrast agent concentration in tissue and blood [6]. The Look-Locker (LL) sequence provides accurate T_1 estimates, with the advantages of having a shorter acquisition time, and a wide range of sampling times post-inversion [7]. Estimating T_1 from LL data is generally accomplished by nonlinear multi-dimensional curve fitting for estimating a set of model parameters (T_1 , tip-angle, M_0) in the LL signal [7]. However, these fitting methods are sensitive to initial guesses, and the errors of the parametric estimates generally have a high co-variance, so a biased estimation of one parameter will usually bias estimates of the other parameters. In this study, two Adaptive Neural Networks (ANNs) were trained and employed as unbiased estimators of T_1 and ΔR_1 in 3T and 7T. These estimators were trained and tested by simulating the LL signals at different levels of Signal-to-Noise Ratio (SNR). Following this, the model-trained ANNs were applied to dynamic contrast enhanced (DCE) data in a 9L rat model of experimental tumor data acquired in 3T and 7T, and their temporal estimates of T_1 were compared with those of the conventional method (Simplex-least squares fitting) and the values of ΔR_1 and T_1 for 3T and 7T reported by the literature [7].

Materials and Methods: We hypothesized that, given a signal generated by a LL model, an ANN could be trained to directly estimate T_1 and ΔR_1 . The analytical equation of the Look-Locker signal in 7T (with an exponential kernel in 3T) was used for signal simulation in 3T and 7T. For each T_1 value, LL signals with 16 (for 3T) and 24 (for 7T) echoes were generated in the synthetic model (T_2^* , M_0 etc) and all were normalized to their first echo to form a training set. Gaussian noise at different ranges (SNRs of 5, 10, 15, 20, 35, 30, and 50) was added to all simulated signals; simulated signals were input to the ANNs and their T_1 values were used as the ANN training outputs. To characterize the generalization errors, the ANNs were trained and validated by the K-Folding Cross Validation (KFCV) method [8-9]. The average errors, calculated by the Area Under Receiver Operator Characteristic (AUROC) of the ANNs validated on the K (K=25 with 20000 sample per fold) omitted subsets then served as the estimate of the generalization errors for all 500,000 samples. To test the ANNs' accuracy, they were also applied to the experimental LL data (GE Signa-3T MR and Bruker-7T, respectively 16 and 24 echoes at 80 and 50 ms intervals, TR/TE =1800/6.77 and 801/3.4, FOV 4X4 and 3.2X3.2 cm², 8 and 3 slices of 2.6 mm thickness for 3T and 7T respectively) of 8 Fisher rats (female, 5wks) with 9L cells (16 days). Following two baseline image sets, (0.1mM/Kg) Gd-DTPA was injected to the tail vein and LL data was gathered in 4 sets (for 3T) and 10 sets (for 7T) of acquisitions each ~3 minutes apart. Data was reconstructed and input to the two model-trained (15:5:3:1) ANNs (3T and 7T) to generate T_1 maps. Figure 1 illustrates an example of pre and post contrast T_1 maps estimated by the model-trained ANN, and maps of ΔR_1 in different time points for 3T experiments. Figure-2 shows T_1 maps estimated by the model trained ANN and Simplex optimization before and after CA concentration injection for 7T. To check the accuracy of the ANNs in temporal estimations, the ΔR_1 maps for each slice were constructed and the lesion time signatures, in the normal and leaky areas were plotted and compared for all animals scanned in 3T and 7T.

Results and discussion: This study presents an application of the ANN for direct estimation of CA concentration in soft tissue. Since the ANNs are less sensitive to noise and can model nonlinearity effects, they can serve as stable and reliable estimators for CA concentration in DCE studies. In this study an accurate estimator for direct and rapid quantification of longitudinal T_1 relaxation time is proposed. It was also applied to the animal model of the LL signals acquired at different field strengths (3T and 7T). Results of the ANNs in leaky areas were compared to the conventional method (least squares fitting-Simplex optimization).

The resting T_1 values and their changes estimated by both methods (ANN and Simplex) are highly correlated ($r=0.94$, $p<0.0001$ for 3T and $r=0.96$, $p<0.0001$ for 7T). However the averaged ANNs' estimates of T_1 in the lesion (1420ms for pre and 610ms for post injection in 7T, 850ms for pre and 430ms for post in 3T) and normal areas (1130ms for pre and 1090ms for post injection in 7T, 750ms for pre and 380ms for post in 3T) are more in agreement with the values reported by the literature [7] compared to the Simplex-Optimization technique which is underestimating T_1 values in normal and lesion areas in both 3T and 7T. Therefore the proposed method has a very good potential to be used as a fast (producing a 256X265 T_1 map in a fraction of second) and accurate T_1 or ΔR_1 map estimator from LL data in DCE studies which plays an important role in quantification of physiological parameters.

References:

- [1] Deichmann R. Magn Reson Med 2005; 54:20–27.
- [2] Henderson E et al., Magn Reson Imaging 1999; 17:1163–1171.
- [3] Ordidge RJ et al., Magn Reson Med 1990;16:238–245.
- [4] Zhu DC et al., Magn Reson Med 2005; 54:725–731.
- [5] Bishop CM. Oxford University Press; 1997.
- [6] Clare S et al., Magn Reson Med 2001; 45:630–634.
- [7] Bagher-Ebadian et al., Magn Reson Med 2007; 58:290–297.
- [8] Neil Gelman et al., Magn Reson Med 2001; 45:71–79.
- [9] Gurney K. London Press: Routledge; 1997

