MR Pulse Sequence Design with Artificial Neural Networks

Nahal Geshnizjani[1], Kenneth A. Loparo[1], Dan Ma[2], and Mark A. Griswold[2,3]

[1]Dept. of Electrical Engineering and Computer Science, Case Western Reserve University, Cleveland, Ohio, United States, [2]Dept. of Biomedical Engineering, Case Western Reserve University, Cleveland, Ohio, United States, [3]Dept. of Radiology, University Hospitals of Cleveland and Case Western Reserve University, Cleveland, Ohio, United States

Target Audience: MR scientists who design MRI pulse sequences as part of their research projects or clinical work.

Purpose: The novel concept of MR Fingerprinting (MRF) [1] has opened the door to use nontraditional, randomized pulse sequences for quantitative imaging. However, traditional methods of MRI pulse sequence design lack the efficiency to handle these types of complicated signals that could be used for quick and accurate quantitative imaging. The aim of this study is to design a system to automatically design MR pulse sequences that could be applied even outside of MRF. The approach is to develop an Artificial Neural Network (ANN) based model to design MR sequence parameters such as TR and Flip Angle (FA) for a given set of target signal evolutions.

Methods: ANNs inspired by biological nervous systems are composed of highly interconnected elements (neurons) operating in parallel [2]. ANNs are trained from available data to perform a particular function (e.g. prediction). The training process starts by presenting the network with some sample data and then modifying the weights to better approximate the desired output. In our design, ANNs are trained with transverse magnetization evolution signals of True-FISP pulse sequence that are generated by Bloch equation simulation that can be quickly and accurately calculated for a nearly infinite set of training data. The ANN structure plays a significant role in the accuracy of the model, so we propose a sequential block model with the same number of blocks as the number of excitations in the pulse sequence. Each block is assigned to one of the excitations, and consistent with known MR physics, each block's inputs are the transverse magnetization signal during its assigned excitation block and the pulse sequence parameters from all the previous blocks. In our current configuration, each block includes multiple ANNs that are trained for random FA, where each individual ANN is optimized for a constant TR. Once the model is trained, it can be used to predict TR and FA for any desired target signals. At the prediction stage, the desired signal S is fed to the model and multiple predictions of the FA are offered. The model then selects the solution that minimizes $\| S(i) - BE(\tilde{FA}_n, TR_n) \|$. $S(i)$ is the signal at the i^{th} excitation, $\tilde{FA}$ is the predicted FA, TR_n is the specific TR of the nth ANN in the block i and $BE(\tilde{FA}_n, TR_n)$ is the result of Bloch equation simulation of $\tilde{FA}$ and TR_n. Figure 1a shows a schematic view of this system's architecture and figure 1b depicts a block structure.

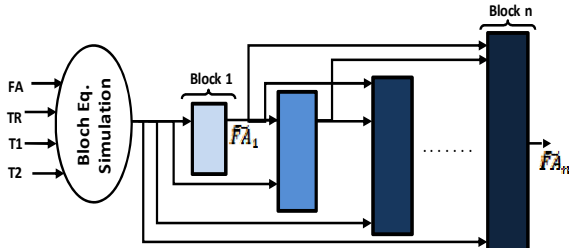

Figure 1a Architect of the system, each block i receives the Bloch equation's outputs specific for i excitations

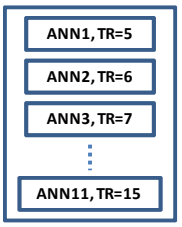

Figure 1b: Enlarged view of one Block

Results and Discussion: The proposed method was evaluated by training ANNs with 1000 transverse magnetization evolution signals of True-FISP pulse sequence of 128 excitations with random flip angles (range: -180 to 180 degrees), TR (range: 5-15ms) and T1 and T2 of six different tissues of WM, GM, CSF, Fat, Blood and Muscle. The prediction stage was tested with signal S= $e^{(-(TR/2)/\beta T_2)}$, β=1.2, TR=10, T1=[300 900 1300 1500 1600 4500] and T2=[50 90 120 250 40 750], which would provide a pure, but extended T2-weighted signal from a TrueFISP sequence. Figure 2a depicts the predicted flip angles and TRs and Figure 2b demonstrates the predicted signal and desired target signal. Outside of a few time points, the sequence provides a good match to the target signal evolution. The total time for the generation of this MR pulse sequence was 20.65 seconds.

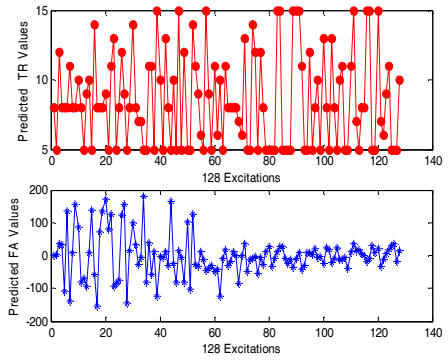

Figure 2a: Up, predicted TR values, Bottom, predicted Flip Angle values

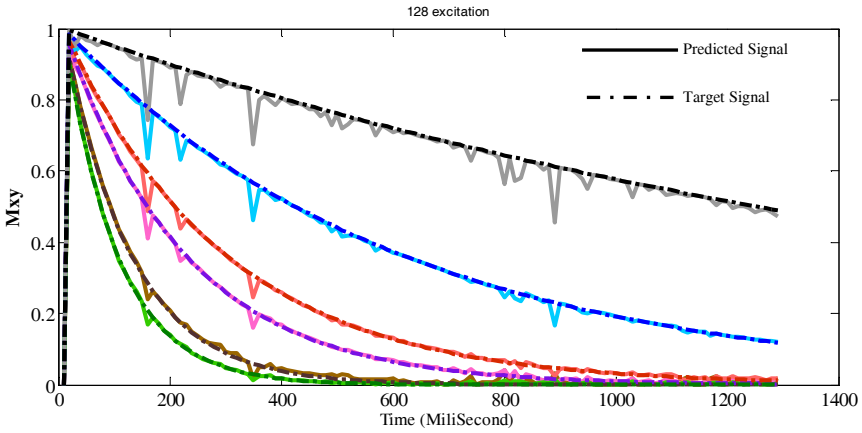

Figure2b: Predicted Transverse magnetization evolution of 6 tissues, solid lines show the predicted signal and dashed-solid lines show the target signal

Conclusion: The result of this study demonstrates the potential of Artificial Neural Networks to automatically design MR pulse sequences. The ability of the proposed ANN structure to generate MR pulse sequences with arbitrary and difficult signal evolutions confirms the viability of this concept.

Reference: [1]. D Ma et al., Conference Abstract: ISMRM 2012, 0288; [2]. S Haykin, Neural networks: A comprehensive foundation, Prentice Hall, 1998, ISBN 0-1327-3350-1. **Acknowledgements:** The authors would like to acknowledge funding from Siemens Medical Solutions and NIH grants.