A Serial Artificial Neural Network Model for TrueFISP Sequence Design

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

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

Target Audience:
MR scientists who design pulse sequences.

Purpose:
The goal of this study is to introduce an efficient and accurate approach for predicting the user controllable MR sequence settings, such as Repetition Time (TR) and Flip Angle (FA) in order to achieve desired signal characteristics from a pulse sequence. By utilizing Artificial Neural Networks (ANNs), the suggested method makes it possible to develop systems that can automatically design MR pulse sequences. The potential of ANNs in predicting required MR sequence parameters for a desired signal output has been demonstrated previously[1, 2]. Here, we propose a new simplified model that is capable of handling signal evolutions with arbitrary initial magnetizations. This method can be a useful tool to accelerate quantitative imaging in general and MR fingerprinting (MRF) [4] in particular. In the latter case the extreme flexibility in sequence designed and acceptable signal behavior means that sequence design purely by intuition about MR sequences is likely to yield inefficient and sub-optimal results.

Methods:
Based on the properties of biological neural systems, ANNs are composed of highly interconnected elements (neurons) operating in parallel[4]. ANNs are trained from available data to perform a particular function (e.g. prediction). In ANNs using optimization methods, training is performed via a Backpropagation algorithm that seeks to minimize an error function defined as the absolute difference between the target and predicted value. As proposed previously[1], the ANN models utilized for this work were trained with the transverse magnetization signal evolutions of the TrueFISP pulse sequence, calculated via Bloch simulations. These signal evolutions can be quickly and accurately calculated for nearly infinite sets of sample training data.

Our model consists of individual blocks of ANNs, each specific to a TR value. Due to redundancies in the inverses of trigonometric functions over the entire range of FAs, each ANN in the block is constrained to a small FA range. The ANN's inputs in a block are $[M_{xi}, M_{yi}, M_{zi}]$ and $[M_{xi+1}, M_{yi+1}, M_{zi+1}]$, which are the magnetization before and after the i+1[th] excitation, respectively. M_0 indicates the initial magnetization. The ANN output is a $\widetilde{FA}_{n,m}$ (predicted FA of ANN n at block m). The optimum $\widetilde{FA}$ is that which minimizes $\| S(i) - BE(\widetilde{FA}_{n,m}, TR_{n,m}) \|$. $S(i)$ is the signal at the i^{th} excitation in transverse plane, $TR_{n,m}$ is the specific TR of the n[th] ANN in the block m and $BE(\widetilde{FA}_{n,m}, TR_{n,m})$ is the result of the Bloch simulation of $\widetilde{FA}_{n,m}$ and $TR_{n,m}$. Bloch Simulation is used once more to create the next magnetization using the predicted FA and TR. Figure 1 depicts the architecture of this system.

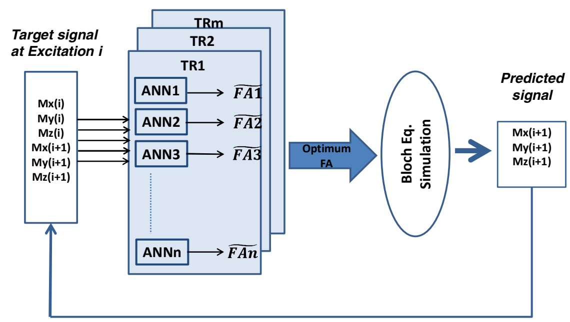

Figure 1: Architecture of the system

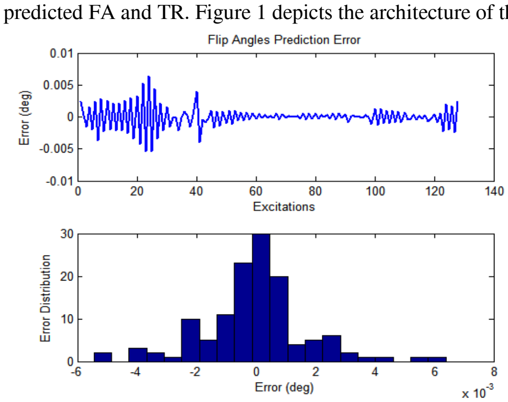

Figure 2a: Errors between target and ANN predicted flip angles (top) and histogram of the errors (bottom)

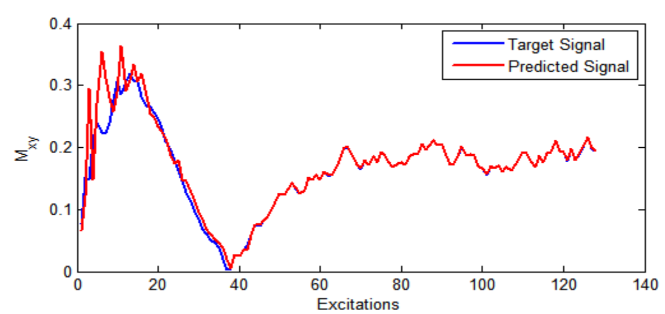

Figure 2b: Predicted and target Transverse magnetization evolution

Results and Discussion: ANNs were trained with 40000 transverse magnetization evolutions from the True-FISP pulse sequence with arbitrary initial magnetizations. Each signal evolution consisted of random flip angles (range: 0 to 30 degrees), TR (range: 5-10 ms) and T1 and T2 of three different tissues of T1/T2=[300/40, 600/70, 900/90]. To evaluate the system, the model was then used to predict the settings for sequence constructed from an initial magnetization of [0, 0,-1] and randomly selected flip angles in the range of 0 to 6 degrees, and 128 excitations. Figure 2a depicts the errors between target and ANN predicted flip angles over the entire sequence (top) and a histogram of the errors (bottom) Figure 2b depicts the target transverse magnetization and the signal obtained using these predicted FAs). The overall prediction performance is acceptable both for FA and Transverse magnetization with MSE less than or equal to $1x10^{-3}$.

Conclusion: Artificial Neural Networks can open the door to automatic MR pulse sequence design. This approach can be particularly helpful for sequences where a wide array of signal evolutions are possible and desirable, and sequences must be tailored in a non-intuitive way to achieve an optimal signal evolution. Once the system is properly trained, it provides a relatively accurate and fast prediction tool for sequence settings needed for a desired signal evolution.

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Reference: [1] N Geshnizjani et al, Conference Abstract: ISMRM 2013, 2380; [2] H Marschner et al, Conference Abstract: ISMRM 2013, 4239; [3] D Ma et al., Nature 2013-495.; [4]. S Haykin, Neural networks: A comprehensive foundation, Prentice Hall, 1998, ISBN 0-1327-3350-1;