## MRzero – Fully automated invention of MRI sequences using supervised learning

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**Abstract**

**Purpose:** We propose a supervised learning approach to automatically generate MR sequences and corresponding reconstruction from scratch without providing sequence programming rules. This enables elegant target based optimization of existing MR sequences as well as exploration of novel MR sequence strategies.

**Methods:** The entire scanning and reconstruction process is simulated end-to-end in a fully differentiable fashion in terms of RF events, gradient moment events in x and y, delay times, acting on the input model spin system given in terms of PD, T1 and T2, and ΔB0. As proof of concept we use a conventional MR image as a target and optimize from scratch using the loss defined by data fidelity, SAR, and scan time.

**Results:** In a first attempt, outgoing from existing sequences, MRzero is able to reduce scanning time of fully relaxed sequence down to few ms TR, and to reduce SAR by 40 % by lowering flip angles in the outer k-space. In a second attempt, MRzero learns all gradient and RF event from zero, and is able to generate the target contrast. Both experiments could be translated for image acquisition at a real system (3T Siemens, Prisma) and could be verified in phantoms and in vivo. Resolution is only limited by computation time, yet 3mm in plane resolution could already be achieved.

**Discussion/Conclusion:** We have developed a fully automated MRI sequence generator based on the Bloch equation simulations and supervised learning. While we focus on basic image generation herein, having such a tool at hand paves the way to a novel way of generating optimal MR sequence and reconstruction solely governed by the target provided, which could be a certain MR image, but the possibilities for targets are limitless, e.g. quantification, segmentation or contrasts of other image modalities.

**INTRODUCTION**:

Generation of Magnetic Resonance (MR) images requires profound knowledge on the dynamic of magnetization in the presence of RF excitation fields as well as spatially encoding magnetic gradient fields, not only for signal generation, but as well for the reconstruction of images from the frequency space to the real space. This profound knowledge is given by the very compact Bloch equations, which can describe most effects spins undergo in a static or dynamic external magnetic field. For this reason, Bloch equation simulations were inevitable for optimization and tests of novel pulse sequences, and as well sophisticated reconstructions. For pulse sequences, optimal control of excitation and refocusing pulses, optimization of k-space trajectories or improving homogeneity using parallel transmit pulses are such as non-uniform Fourier transform, parallel imaging, or compressed sensing as well as neural network based reconstruction approaches. Given this successful pathway, an approach where both signal generation and image reconstruction are optimized simultaneously is plausible. Especially with regard to current developments in various machine learning approaches, were high dimensional functions and large networks of functions are optimized efficiently, using novel approaches such as backpropagation, as well as sophisticated highly parallel hardware. First approaches of an automatic sequence generation using MRI were already suggested based on deep reinforcement learning. Here something about RL. A bottleneck of RL is the large parameter space that has to be explored. In this work we present a supervised learning approach to automatically generate MR sequences and corresponding reconstruction from scratch without providing sequence programming rules. The trick is here to have a fully differentiable Bloch simulation at hand, and by this be able to calculate a gradient in the high dimensional parameter space which then can be exploited using gradient descent methods.

**METHODS**

The entire scanning and reconstruction process is simulated end-to-end as a fully differentiable concatenated sequence of tensor operations. Each tensor operation from the stack implements: RF events (RFE) (i.e. flip angles and phases), gradient moment events (GME) in x and y, delay times, and a weighting for an ADC, acting on the input model spin system (given in terms of PD, T1 and T2, and ΔB0).  At the sequence learning step, we use Adam[1] optimizer to find the sequence parameters given the loss function specified with respect to data fidelity and SAR cost terms.  
**Task and target**  
We evaluate the proposed method on a simple task: match a target GRE-derived image by optimizing the gradients and flip angles and putting a penalty on SAR. Target sequence details: transient RF- and gradient-spoiled gradient echo readout with linear phase encoding, 24x24, TR = 20 ms, TE =3 ms, FA=5°. Low FA decreases image blurring due to the signal decay of the transient readout. As task sequences we used the same timing pattern and ADC as the target sequence, where for gradients and flip angles we approached four different tasks:  
Task 1: clone target GME and RFE, optimize only RFE with SAR penalty   
Task 2: clone target RFE, set GME to 0, optimize GME only  
Task 3: set RFE and GME to 0, optimize both RFE and GME   
Task 4: set RFE and GME to 0, optimize both RFE and GME with SAR penalty

**RESULTS**:

The result of task 1 displayed in figure 1a-e shows that the optimizer prefers to lower flip angles in the outer k-space lines to reduce SAR by 40 % keeping a small image error. Figure 1f-j shows how spatial encoding is learned from scratch (Task 2). Figure 2abc shows that when learning both RFE and GME, too high flip angles are chosen (Task 3). This can be mitigated by putting an additional penalty on SAR. Figure 3cde shows the full potential of MRI zero: the invention of a complete MRI sequence (Task 4) that is applicable for image acquisition at a real system (3T Siemens, Prisma) in phantoms and in vivo (Figure 3). 

Figure 1: (a-e) Task 1, (f-j) Task 4. a,f: Training error (percent NMSE) curves and SAR over iterations. b,g: k-space sample locations at the last iteration. c,h: flip angles at the last iteration (red) compared to target flip angles (green). (d,i) target images, (e,j) invented sequence images.



Figure 2: First row: Task 3, second row: Task 4. a,d: Training error curves and SAR over iterations. b,e: k-space sampling at the last iteration. c,f: flip angles at the last iteration (red) compared to target flip angles (green).

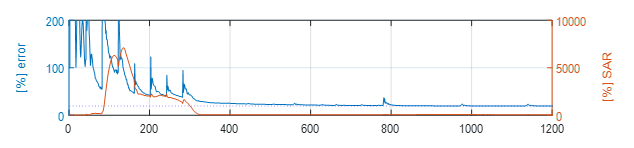
 

Figure 3: Row 1: training error curve, Row 2: k-space sampling at different iterations, Row 3: flip angles over measurement repetitions. Row 4: simulation-based reconstruction at different iterations 3, 30 80,280 and 1100. row 5: phantom measurement, row 6: in vivo brain scan. An animated version for 48x48 matrix size can be found on [www.tinyurl.com/y4z9qlhz](http://www.tinyurl.com/y4z9qlhz)

**DISCUSSION** / **CONCLUSION:**

We have developed a fully automated MRI sequence generator based on the Bloch equation simulations and supervised learning. Resolution (24x24) is only limited by computation time. While we focus on basic image generation herein, having such a tool at hand paves the way to a novel way of generating optimal MR sequence and reconstruction solely governed by the target provided, which could be a certain MR image, but the possibilities for targets are limitless, e.g. quantification, activation, segmentation or contrasts of other image modalities.

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