

# Schedule design for parameter quantification in the transient state using Bayesian optimization

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**Abstract**—Magnetic resonance fingerprinting (MRF) is a new quantitative imaging paradigm, which simultaneously acquires multiple tissue parameters in an efficient experiment. MRF can map several parameters simultaneously including  $T_1$ ,  $T_2$ , and spin density [2]. However, it is important to underline that specific sequences may be better suited for certain parameter ranges or sampling patterns. This work aims to introduce a framework for pulse sequence optimization, individually optimizing for  $T_1$  or  $T_2$  relaxation times. We demonstrate a new method, including undersampled acquisitions, by simulating the MRI signal encoding, gridding, and pattern recognition directly in the optimization. The design framework could obtain efficient schedules for  $T_1$  and  $T_2$  acquisition.

**Index Terms**—Magnetic resonance imaging, MR fingerprint, Bayesian Optimization

## I. INTRODUCTION

MR fingerprinting is a novel approach for multi-parametric quantitative mapping in MRI. This method is based on a pseudorandom acquisition scheme in the transient state, used to obtain unique signal evolutions for different tissue properties. Using a pattern matching algorithm with a precomputed dictionary of possible signal evolutions, this technique allows to obtain multiple parametric maps within a single acquisition. As this technique accurately models the physics of the system, the correlation between the parameters is calculated and eliminated from the estimate of the individual parametric maps. However, the accuracy of each parametric map heavily relies on the characteristics of the acquisition scheme. For example, when using SSFP MRF, the accuracy of  $T_2$  maps depends critically on the length of data acquisition and on the quality of stimulated echoes, while  $T_1$  accuracy crucially depends on the quality of the data from first two seconds after the inversion pulse [4]. Here, we propose a framework to individually optimize  $T_1$  and  $T_2$ , including aliasing and noise in our estimates. The goal of this sequence design framework was to optimally select the varied sequence parameters (flip angles and TRs) to maximize parameter sensitivity while maintaining the shortest possible experiment duration.

## II. METHODS

To perform our optimizations, we used a Bayesian Optimization [3]. To work on a realistic dataset, we used a numerical brain phantom to simulate single-channel MR fingerprint experiments, using  $T_1$ ,  $T_2$  and proton density map  $M_0$  from the Brainweb database [1] as the ground truth. For a given acquisition scheme, the phantom values were used to generate signal evolutions with the Extended Phase Graph formalism [5]. Undersampling artefacts were simulated by applying forward and inverse non-uniform Fourier transform, using the same spiral trajectory as in [4]. Complex Gaussian noise with a sigma of 0.02 was added to the signal evolution in the image space. Finally, the simulated dataset was matched to a precomputed dictionary of signal evolutions (in order to mimic an actual MRF experiment) and the resulting parametric maps were compared to

ground truth values. In our dictionary 250  $T_1$  and  $T_2$  values were linearly spaced generated respectively from 200 to 2600ms and from 20 to 330ms.

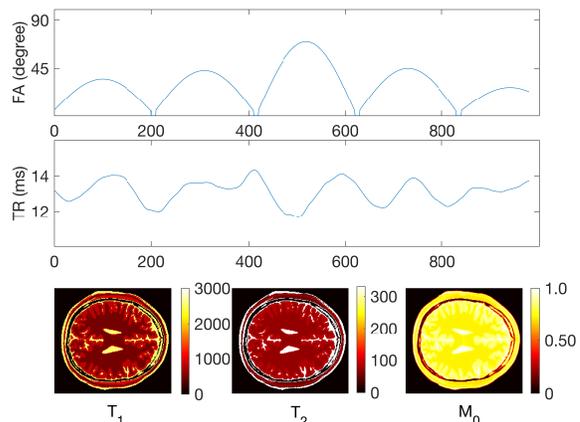


Fig. 1: Flip angles and repetition times from [4]. Ground truth parameter maps for the brain phantom [1]. Times in ms.

The single relative error in  $T_1$  or  $T_2$ , averaged over the whole brain avoiding background, was used as the cost function (norm of the difference between maps). We optimized the acquisition method to allow a better acquisition of  $T_1$  and  $T_2$  parameters individually. As commonly used acquisitions are based on empirical schedules [4], to avoid any bias we did not use any initialization.

We considered two ways of generating the function  $f$  consisting of  $m$  excitations for flip angle or TR sequences:

- Method 1: It has been previously reported that slow-varying periodic patterns are effective as flip angle functions [6]. We used the first  $n = 4$  coefficients from the Fourier transformation of  $f$  to estimate a zero-padded the remaining  $m - n$  coefficients. The parameters in input to our optimization model were: the schedule length  $m$ , the  $n$  Fourier coefficients for TR and flip angle respectively and an overall scaling factor for TR and flip angle respectively.
- Method 2: Several MRF works have used Perlin noise [4]. To generate Perlin noise we generated normally distributed random numbers and interpolated them with  $\cos$  function. The parameters in input to our optimization model were: the schedule length  $m$ , the amplitude and the wave length of Perlin noise signal, a seed for random generation and an overall scaling factor for TR and flip angle respectively.

We compared the best  $T_1$  and  $T_2$  schedules between the two methods and with the one in [4].

### III. RESULTS

A global optimization with 70 iterations was computed in 180 minutes on an Intel® Xeon® processor E5-2600 v4.

Figure 2 shows the results from  $T_2$  optimization using Method 1 in terms of achieved schedules, accuracy of maps and convergence. Our efficiency metric was 3.3568 in our method compared to 3.4984 in the benchmark method. Figure 3 shows the results from  $T_1$  optimization using Method 1 in terms of achieved schedules, accuracy of maps and convergence. Our efficiency metric was 19.27 in our method compared to 19.843 in the benchmark method. Figure 4 shows the results from  $T_2$  optimization using Method 2 in terms of achieved schedules, accuracy of maps and convergence. Our efficiency metric was 3.5465 in our method compared to 3.4984 in the benchmark method. Figure 5 shows the results from  $T_1$  optimization using Method 2 in terms of achieved schedules, accuracy of maps and convergence. Our efficiency metric was 18.6137 in our method compared to 19.843 in the benchmark method. For  $T_2$  estimation, Method 1 performed better than Method 2. For  $T_1$  estimation, Method 2 performed better than Method 1, despite of a larger number of acquisition frames.

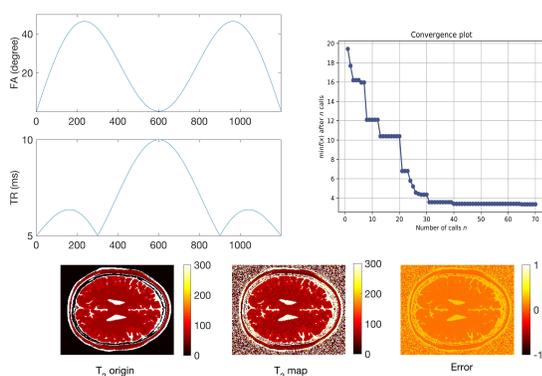


Fig. 2: Flip angles, repetition times and convergence plot from optimization Method 1.  $T_2$  ground thru map, reconstructed  $T_2$  map from the undersampled MR fingerprint experiments using the above acquisition parameter and relative error maps.

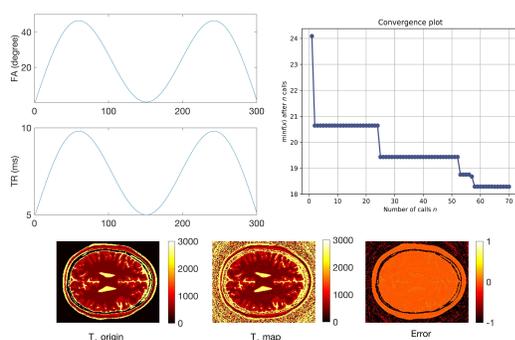


Fig. 3: Flip angles, repetition times and convergence plot from optimization Method 1.  $T_1$  ground thru map, reconstructed  $T_1$  map from the undersampled MR fingerprint experiments using the above acquisition parameter and relative error maps.

### IV. DISCUSSION

Our framework could obtain new MRF schedules in a reasonable timeframe. Importantly, compared to previous literature, our approach did not assume that the aliasing was noise-like, but we included both

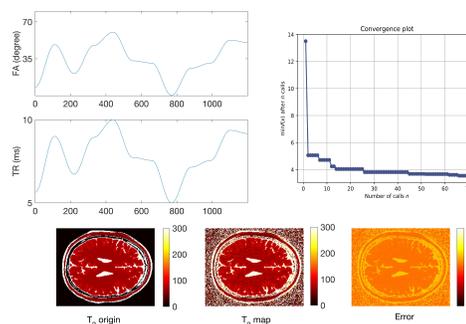


Fig. 4: Flip angles, repetition times and convergence plot from optimization Method 2.  $T_2$  ground thru map, reconstructed  $T_2$  map from the undersampled MR fingerprint experiments using the above acquisition parameter and relative error maps.

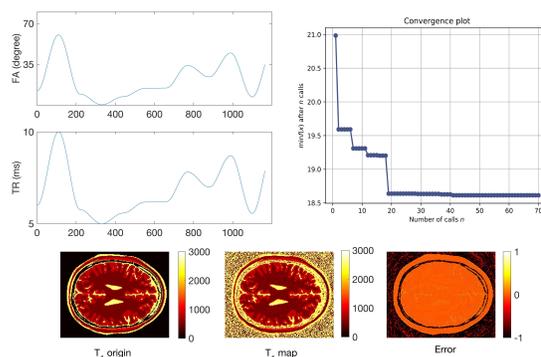


Fig. 5: Flip angles, repetition times and convergence plot from optimization Method 2.  $T_1$  ground thru map, reconstructed  $T_1$  map from the undersampled MR fingerprint experiments using the above acquisition parameter and relative error maps.

aliasing and noise. Here, rather than optimizing the acquisitions for all the physics modelled, we focussed on optimizing a single parameter at a time. This could be useful in the future for regressing novel acquisition strategies. Recently, a few different accounts have used different methods for optimising schedules in MRF, and comparing our method with others was beyond the scope of the current work. In this work, we were limited to  $T_1$  and  $T_2$ , but extensions of these optimization methods can be performed including other parameters such as  $T_2^*$ ,  $B_0$  and  $B_1$ , perfusion diffusion or chemical shift. After validation in-vivo, schedules here reported can be used for research studies, with the promise of ultimately improving the efficiency of quantitative MRI protocols.

### REFERENCES

- [1] D. Louis Collins et al. "Design and Construction of a Realistic Digital Brain Phantom." In: *IEEE Trans. Med. Imaging* 17 (1998).
- [2] Dan Ma et al. "Magnetic resonance fingerprinting". In: *Nature* (Mar. 2013).
- [3] J Mockus, Vytautas Tiesis, and Antanas Zilinskas. *The application of Bayesian methods for seeking the extremum*. Sept. 2014.
- [4] Yun Jiang et al. "MR fingerprinting using fast imaging with steady state precession (FISP) with spiral readout". In: *Magnetic Resonance in Medicine* (2015).
- [5] Matthias Weigel. "Extended phase graphs: Dephasing, RF pulses, and echoes - pure and simple". In: *Journal of Magnetic Resonance Imaging* (2015).
- [6] Jakob Asslinder et al. "Relaxation in Spherical Coordinates: Analysis and Optimization of pseudo-SSFP based MR-Fingerprinting". In: *Magnetic Resonance in Medicine* (Mar. 2017).