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Stochastic optimization of 3D non-Cartesian sampling trajectory (SNOPY)

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Synopsis

Keywords: New Trajectories & Spatial Encoding Methods, Machine Learning/Artificial Intelligence

Efficient k-space trajectories are crucial for accelerated MRI. SNOPY proposes a generalized gradient-based method for optimizing 3D non-Cartesian sampling patterns. The algorithm can simultaneously tune multiple properties of sampling patterns, including image quality, hardware constraints (maximum slew rate and gradient strength), reduced peripheral nerve stimulation (PNS), and parameter-weighted contrast. The proposed method applies to various scenarios, such as optimizing gradient waveforms or optimizing rotation angles of radial/spiral trajectories. We adopted several computational strategies to address this non-convex and large-scale problem. Various simulated and in-vivo experiments demonstrated the effectiveness of SNOPY.

Introduction

In MRI, efficient sampling strategies can accelerate acquisition and improve image quality. This abstract introduces a data-driven method for automatic trajectory tailoring. SNOPY combines gradient-based and data-driven approaches to learn optimal sampling trajectories from data. SNOPY includes several optimization objectives, including image quality, hardware constraints, PNS suppression, and image contrast. The composite objective enables the simultaneous optimization of multiple characteristics. It is also viable to jointly optimize sampling trajectory with trainable reconstruction algorithms to improve both simultaneously [1]. The algorithm can optimize different attributes of a given sampling trajectory, such as the readout waveform, or the rotation angles of different shots. We introduced several techniques to improve the efficiency of optimization for this large-scale problem. We also tested the proposed methods with multiple imaging applications, including structural and functional imaging. These applications benefited from the SNOPY-optimized sampling trajectories in both simulation and prospective studies.

Methods

Generally, SNOPY is a machine learning framework that adopts differentiable programming to compute the Jacobian/gradient w.r.t. sampling trajectories required in the gradient-based methods, as shown in Fig 1. SNOPY uses stochastic gradient descent-like algorithms to update sampling trajectories and other parameters, such as the reconstruction weights.

The algorithm uses composite optimization objectives to ensure that the optimized sampling trajectories have certain desired properties. The first type of objective is image quality, which encourages images reconstructed from sampled k-space signals to be close to the reference image. The optimization also considers physical constraints, including gradient strength, slew rate, and peripheral nerve stimulation (PNS) effect. We formulated such constraints as soft penalty terms. To maintain certain parameter-weighted contrasts, SNOPY may also include a penalty on the echo time (TE).

Users can optimize various attributes of sampling trajectories via the proposed method. One may optimize existing trajectory parameters, such as rotation angles or (continuous) phase-encoding locations. This approach is easier to implement and compatible with existing reconstruction and correction methods. The second approach, spline-based freeform optimization [1], can directly optimize gradient waveforms. Additionally, it enables multiscale optimization to avoid sub-optimal local minima and further improve optimization results.

SNOPY proposes several techniques for more accurate and efficient optimization. SNOPY uses stochastic gradient Langevin dynamics (SGLD) as the optimizer to accelerate training. One may also pre-calculate the Toeplitz embedding kernel to further reduce memory use [2]. We derived a fast and accurate approximation for Jacobian involving NUFFTs [3]. Without the aforementioned techniques, optimizing 3D trajectories would cost hundreds of GBs of memory. SNOPY enables solving this otherwise prohibitively large problem on a single graphic card (GPU). Table 1 (a) shows the memory efficiency improvement brought by these techniques.

Experiments

We experimented with multiple scenarios to show the broad applicability of the proposed method. Experiment 1 optimized the gradient waveforms initialized by a 3D radial ('kooshball') trajectory. Experiment 2 optimized the rotation angles of stack-of-stars trajectories [4]. The third application aims to dampen the PNS effect of rotation EPI (REPI) trajectories [5], which provide an efficient sampling strategy for 3D fMRI at the cost of a high PNS effect.

We used two publicly available datasets to optimize the trajectories; both of them contain 3D multi-coil raw k-space data. SKM-TEA (exp. 1) is a 3D quantitative double-echo steady-state (qDESS) knee dataset [6]. The Calgary brain dataset (exp. 2 and 3) is a 3D brain T1w MP-RAGE k-space dataset [7].

In the prospective studies, we programmed the sampling trajectory with a 3D T1w fat-saturated GRE sequence for experiment 2 using TOPPE [8]. The experiment included 4 healthy subjects. For experiment 3, to rate the PNS effect, we asked 3 participants to score the nerve stimulation with a 5-point Likert scale from 'mild tingling' to 'strong muscular twitch.' All subjects gave informed consent under local IRB approval.

Results and Discussion

For the spline-based freeform optimization experiment, Table 1 (b) shows the quantitative image quality in the simulation experiment. Across reconstruction methods (CG-SENSE and model-based deep learning, MoDL [9]), SNOPY improved image quality (PSNR) by ~4dB. Fig. 2 shows example slices. Fig. 3 shows the prospective results of experiment 2, optimization of rotational angles of SOS. SNOPY effectively reduced streak artifacts. PSFs of different trajectories also support this finding. Fig 4 displays the PNS effect reduction brought by SNOPY both in simulation studies and patients' ratings (exp. 3). SNOPY efficiently reduced the severe PNS effect of REPI.

In summary, SNOPY provides an effective tool for optimizing 3D non-Cartesian trajectories while satisfying hardware constraints and controlling PNS.

Acknowledgements

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Figures



Figure 1. SNOPY learning workflow. The sampling trajectory (and possibly reconstruction parameters) are optimized by gradient-based methods. SNOPY uses differentiable programming to compute the gradients required in the update.

(a)	+Efficient Jacobian	+In-place ops	+Toeplitz embedding	+Low-res NUFFT
Plain	5.7GB / 10.4s	272MB / 1.5s	253MB / 1.6s	268MB / 0.6s
				130MB / 0.2s
(b)	CG-SENSE	PLS	MoDL	
3D kooshball	28.2 dB	28.2 dB	30.1 dB	
SNOPY	32.5 dB	32.5 dB	33.7 dB	

Table 1. Sub-table (a) lists the memory/time use reduction brought by proposed techniques. The test case here uses a 2D 400×400 slice, and CG-SENSE reconstruction. '+' means adding the technique to previous columns, thereby reducing the memory needed. Sub-table (b) shows the average PSNR of experiment 1.

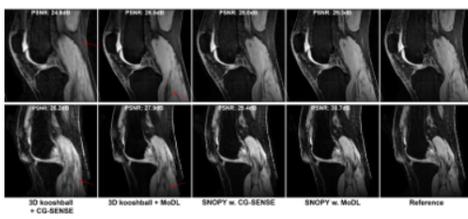


Figure 3. Examples of the reconstructed images for two knee slices in experiment 1.

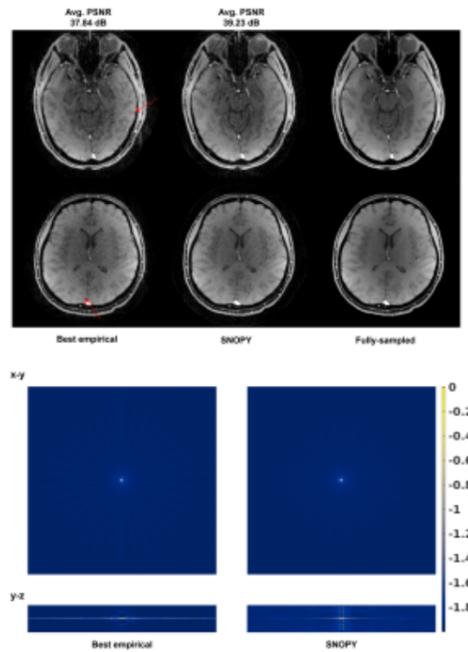


Figure 4. Results of experiment 2, optimizing the rotation angles of the stack-of-stars (6x acceleration). 'Best empirical' uses the design from a previous study [4]. We also labeled the average PSNR of the 4 subjects compared to the fully sampled reference. The lower subfigure shows the log-scaled PSF (single-coil) of two trajectories.

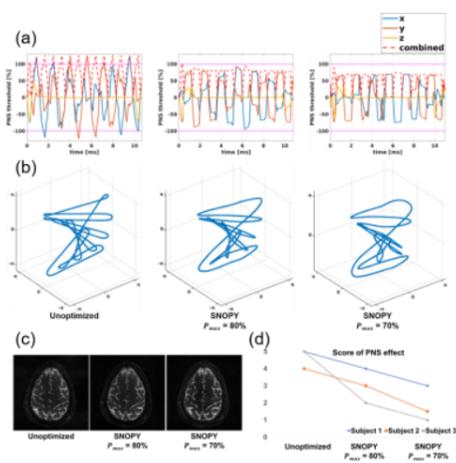


Figure 5. Prospective results of experiment 3. The figure shows three different trajectories: the unoptimized REPI, SNOPY-optimized with the PNS threshold of 80%, and SNOPY-optimized with the PNS threshold of 70%. Sub-figure (a) plots the PNS effect calculated by the convolution model [10]. Sub-figure (b) shows one readout trajectory before/after the SNOPY optimization. Sub-figure (c) shows one slice of reconstructed images. Subfigure (d) shows the subjective score of the PNS effect.