Optimizing Non-Cartesian Sampling Patterns via Gradient Methods

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Target Audience: researchers interested in fast imaging and efficient sampling

Purpose: Efficient sampling trajectories are important for fast imaging. This abstract presents a method named SNOPY (**S**tochastic Optimization of **No**n-Cartesian Sam**p**ling Trajector**y**). SNOPY proposes a gradient method for optimizing non-Cartesian sampling patterns, enabled by an efficient NUFFT's Jacobian approximation approach [1]. SNOPY has several optimization objectives, including reconstructed image quality, compliance to hardware constraints (maximum slew rate and gradient strength), reduction of peripheral nerve stimulation (PNS), and parameter-weighted contrast. SNOPY is versatile for different applications, such as optimizing gradient waveforms or optimizing rotation angles of radial/spiral trajectories. SNOPY uses several computational strategies to relieve the high computation demand brought by this non-convex and large-scale problem.

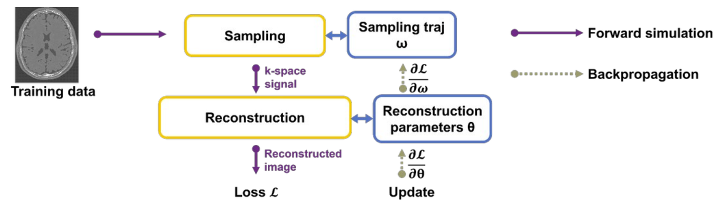

Figure 1. Diagram of SNOPY

Methods: SNOPY uses stochastic gradient descent (or its variants) to learn sampling trajectories and other reconstruction parameters. The method utilizes differentiable programming to compute the gradient w.r.t. the sampling trajectories. The training loss includes several terms. The image quality loss calculates the distance between images reconstructed from undersampled k-space signals and the reference image. By minimizing this loss, the trajectory (and possibly the reconstruction method) learns to generate high-quality images. The optimization also includes 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). One may optimize existing trajectory parameters, such as rotation angles or (continuous) phase-encoding locations. It is also possible to directly optimize gradient waveforms. Additionally, SNOPY allows multiscale optimization to avoid sub-optimal local minima and further improve optimization results. SNOPY proposes several techniques for more accurate and efficient optimization. See [2] for more details.

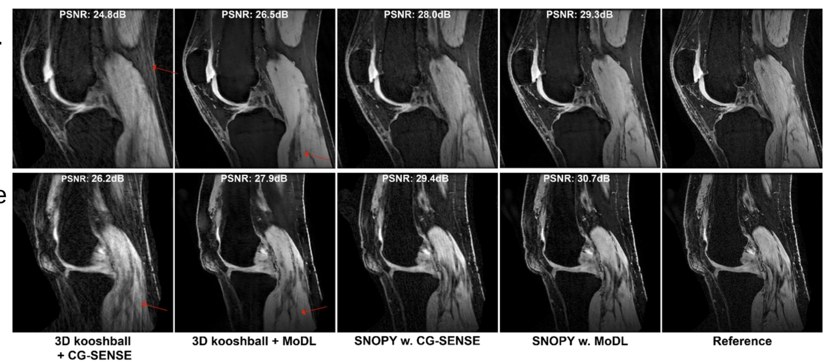

Figure 2. Slices of reconstructed images in simulation experiments.

Results: The first simulation experiment compares the reconstruction quality of SNOPY-optimized trajectories versus its kooshball initialization. The trajectories were jointly optimized with reconstruction algorithms (CG-SENSE and MoDL [3]). As is shown in Fig. 2, SNOPY improved the image quality. The second experiment optimizes the in-plane rotation angles of a Stack-of-Stars sampling trajectory. Fig. 3 shows the prospective experiment results. SNOPY-optimized trajectories led to reduced aliasing artifacts. Experiment 3 optimized waveforms of a rotational EPI trajectory [4], to reduce the high-PNS effect. Fig. 4 reports the participants' subjective rating of the PNS effect, which was dampened by SNOPY optimization.

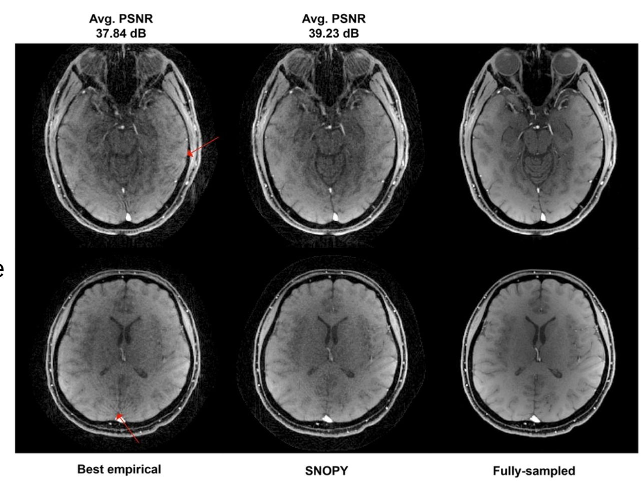

Figure 3. Prospective results of the second experiment, optimizing the rotation angles of the stack-of-stars (6× acceleration). 'Best empirical' uses the design from a previous study [6].

Discussion: SNOPY tailors sampling trajectories to specific training datasets and reconstruction algorithms, which may raise concerns about overfitting. In experiment 2, the training set used an MP-RAGE sequence, while the prospective sequence was an RF-spoiled GRE. In a 2D experiment [5], we found that trajectories learned with one anatomy (brain), contrast (T1w), and vendor (Siemens) still improved the image quality of other anatomies (like the knee), contrasts (T2w), and vendors (GE). These empirical studies indicate that trajectory optimization is robust to a moderate distribution shift between training and inference.

Conclusion: SNOPY presents a novel yet intuitive approach to optimizing non-Cartesian sampling trajectories. Various applications and in-vivo experiments showed the applicability and robustness of SNOPY.

References: [1] Wang G & Fessler JA. arXiv:2111.02912, 2021. [2] Wang G, et al. arXiv:2209.11030, 2-22. [3] Aggarwal HK, et al. arXiv:1712.02862, 2017. [4] Rettenmeier CA, Maziero D & Stenger VA. MRM, 2020. [5] Wang G, et al. IEEE T-MI, 2022. [6] Zhou Z, et al. MRM, 2017.

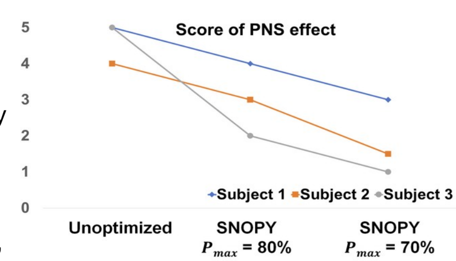

Figure 4. The subjective score of the PNS effect.