T2 Shuffling Fast 3D Spin-Echo Reconstruction with Score-Based Generative Modeling

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Target Audience: MRI researchers interested in image reconstruction and deep learning.

Introduction: Volumetric fast spin-echo (3DFSE) is desirable for multi-planar reformatting, but it has not been routinely used clinically due to T2-decay induced blurring[1-3]. Recently, a method called T2 Shuffling (T2Sh) has been proposed which generates images along the FSE signal relaxation curve, thus reducing blur and providing multi-contrast images[4]. While this approach has been shown to be noninferior to clinical 2D FSE[5,6], it still requires scan times in excess of 7 minutes[5]. Recently deep learning-based score models have been applied to MRI with promising reconstruction results with under-sampling, exceeding the performance of traditional compressed sensing methods.[7] In this work, we train the score model to learn a prior that is used to reconstruct T2Sh data through posterior sampling[8]. We use the basis coefficient images from the low-rank T2Sh reconstruction to train the score model and apply posterior sampling to retrospectively accelerated data with no model mismatch. We show performance over different acquisition signal-to-noise (SNR) levels in this setting. Finally, we show preliminary results of our approach for experimentally acquired under-sampled T2Sh data.

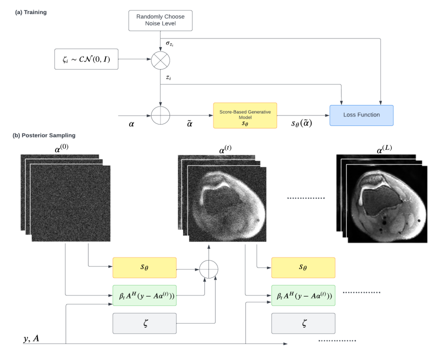

Fig 1. A) Overview of the training process of the score model. Training involves choosing random noise levels at different steps and adding them to the training samples and making the score model predict the gradient. B) Basis coefficient estimation using posterior sampling from a given k-space measurements

Methods: For this work, we trained the score model on 5000 basis coefficient knee images, which were acquired with IRB approval and informed consent/assent. As the score model is only trained on basis images, it is agnostic to MRI sampling and hence it can be customized to different sequence parameters. The T2Sh forward model is as follows: $y = PFS\Phi\alpha + w,\ \ w \sim N\,(0, \sigma^2 I)$ where $\alpha \in C^K$ are the basis coefficient images, $\Phi \in R^{T\times K}$ is the basis, S is the coil sensitivity maps, F is the Fourier transform operator, P is the k-space sampler, and w is Gaussian noise. T is the FSE echo train length (ETL) and K is the number of basis coefficients. We define the forward operator as $A = PFS\Phi$. The MRI reconstruction is done using posterior sampling which uses Annealed Langevin Dynamics[7] as follows: $\alpha^{t+1} \leftarrow \alpha^t + \eta_t\left(s_\theta(\alpha^t) + \beta_t A^H(y - A\alpha^t)\right) + \sqrt{(2\eta_t)}\,\zeta_t\,,\ \zeta_t \sim N(0, I)$ where α^t are the estimated basis coefficient images at step t, η_t is the learning rate, s_θ is the score model output, β_t is the weight of the data consistency term, A^H is the adjoint of the forward operator, and ζ_t is the annealing noise. For the first set of experiments, the under-sampled k-space data is generated from the forward model as a proof of principle to show that the score model-based posterior sampling can reconstruct coefficient images, noting that this is an inverse crime[9]. For this set of results, we treat T2Sh reconstruction as a "ground truth." In the second set of results, we incorporate varying SNR levels in the forward model and compare the reconstruction results. For the third set of results, we run the posterior sampling on experimental under-sampled T2Sh k-space data.

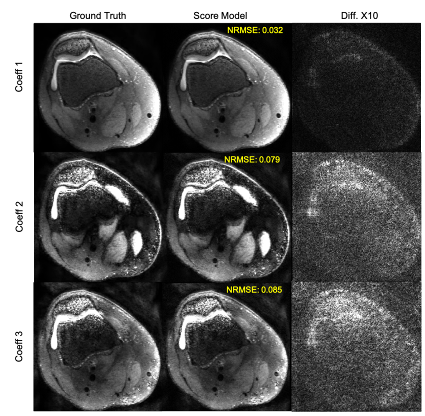

Fig 2. Reconstructed basis coefficient images and ground truth coefficient images along with difference image with 10X zoom.

Results and Discussion: Fig. 2 shows the reconstructed basis coefficient images after posterior sampling using the prior provided by the score model. The reconstructed coefficient images and the ground truth coefficients agree very well as corroborated by the low normalized root mean squared error (NRMSE). Fig. 3 shows the effect of different SNR levels. Noise is added to the under-sampled k-space data corresponding to different SNR values. It can be observed that as SNR increases, the NRMSE for all 3 coefficients decreases. Fig. 4 shows the comparison between the output from T2Sh and the score-based posterior sampling on the experimental data. Coefficient images seem to qualitatively match both methods except for the 3rd coefficient image. For future work, we will focus on improving score model posterior sampling to handle variation in SNR across the basis images and experimental k-space data.

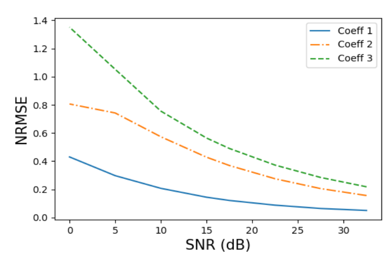

Fig. 3. NRMSE vs SNR for reconstructed basis coefficient images.

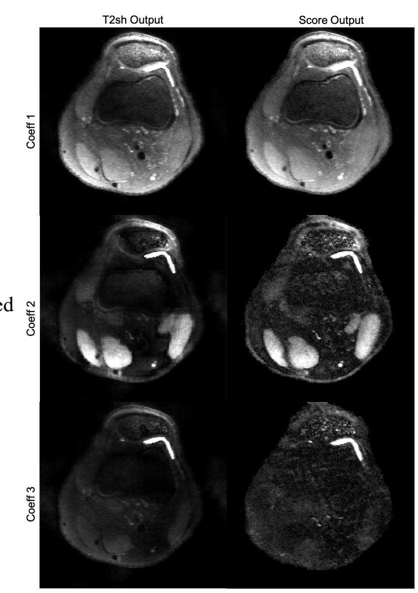

Fig. 4. Score model and T2Sh output images on experimental k-space data.

References: **1.** Busse, MRM 60(3), 2008. **2.** Mugler, JMRM 39(4), 2014. **3.** Busse, MRM 55(5) 2006. **4.** Tamir, MRM 77(1) 2017. **5.** Tamir, JMRI 49(7), 2019 **6.** Bao, MRM 74(2), 2015 **7.** Jalal, NeurIPS, 2021. **8.** Song, NeurIPS, 2020. **9.** Shimron, PNAS, 119(13), 2022.