Dynamic 3D MRI Reconstruction from Single-Spoke via Motion-Compensated Neural Representation

Dynamic 3D Magnetic Resonance Imaging (MRI) is an essential tool for motion management and MR-guided radiotherapy, offering both excellent soft-tissue contrast and the ability to capture dynamic changes in tissue. However, the long acquisition time creates an inherent trade-off between the temporal and spatial resolution. Current reconstruction methods address this trade-off using two primary approaches. The first is to reduce the dimension (i.e., 1D navigator echo) to increase temporal resolution. However, these methods cannot accurately capture motions beyond breathing, which is usually complex and high-dimensional. On the other hand, in order to reconstruct high-dimensional dynamic MRI images, current methods assume that multiple spokes share a single motion state and use consecutive spoke grouping, window shifting, or motion signal-based sorting to group continuously acquired radial spokes into several motion states, increase spatial resolution, and alleviate the ill-posedness of the reconstruction problem. However, this assumption fails to capture precise physiological motion, causing inaccurate motion signal estimation and image blurring artifacts. In this work, we address a more challenging scenario: each spoke is assigned its own motion state, and dynamic 3D MRI is reconstructed from a single spoke. A spoke refers to a stack of spokes from stack-of-stars, golden-angle radial sampling with an acquisition time of $\sim$170ms, which is aligned with the latency of MR-guided radiotherapy. However, this single-spoke motion modeling further exacerbates the inherent ill-posedness of the inverse problem of dynamic MRI reconstruction by requiring the recovery of instantaneous images from single-spoke k-space data.

In dynamic MRI reconstruction, motion-compensated methods decompose dynamic images into a canonical (or template) volume and a sequence of canonical-to-observation deformation vector fields (DVFs), which can effectively constrain the solution space of the inverse problem. Current motion-compensated methods represent the canonical image as a discrete matrix and use the learned DVFs to interpolate the canonical image and generate the image sequence. However, this discrete interpolation may lose high-frequency details and thus limit reconstruction quality. Recently, implicit neural representation (INR) has demonstrated an exceptional ability to represent continuous functions parameterized by neural networks. It uses a multi-layer perceptron (MLP) to model the underlying signal by mapping coordinates to signal responses. Moreover, the inductive bias of MLPs toward low-frequency signal components also provides implicit regularization. Therefore, we adopt an INR framework to represent both the canonical volume and the DVFs, and jointly optimize the two networks to fit all acquired spoke measurements. However, relying solely on the implicit learning bias of the INR cannot produce satisfactory performance in this extremely ill-posed problem, where only one spoke is available to reconstruct the 3D volume at each time point. To address the issue, we propose a motion-ignoring static initialization strategy. Specifically, the core idea is to initially disregard motion and exploit all aggregated spoke measurements to train an initialization of the canonical INR that represents a motion-ignoring static volume. This initialization not only provides low-frequency anatomical information to the canonical network but also allows the DVF INR to focus on extracting temporal changes. As the DVF INR captures the changes, blurring artifacts are reduced and the canonical INR gradually learns intricate details and high-frequency structures.

In summary, we propose SPINER, which is, to the best of our knowledge, the first single-spoke motion-compensated dynamic 3D MRI reconstruction method. We conduct experiments on our in-house abdominal MRI dataset to evaluate the performance. Fig. 1 shows the qualitative results of reconstruction. The first column shows the intensity profile along the blue line over time. Our method reconstructs dynamic 3D MRI with high spatiotemporal resolution. Table 1 shows the quantitative results aligning with the above qualitative comparisons.

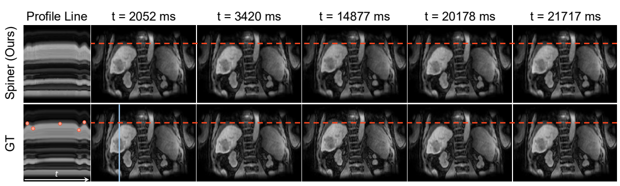

Figure 1. Qualitative results reconstructed by SPINER.

Table 1. Quantitative comparison of dynamic 3D images.

	NUFFT [2]	TD-DIP [3]	Naïve INR [1] (single-spoke)	Naïve INR [1] (20 spokes)	SPINER (w/o Init.)	SPINER (w/ Init.)
PSNR	10.64	23.83	19.16	27.13	<u>32.59</u>	**38.99**
SSIM	0.3309	0.6539	0.2113	0.7339	<u>0.7564</u>	**0.9664**

[1] J. Feng, R. Feng, Q. Wu, X. Shen, L. Chen, X. Li, L. Feng, J. Chen, Z. Zhang, C. Liu, Y. Zhang, and H. Wei. Spatiotemporal implicit neural representation for unsupervised dynamic mri reconstruction. *IEEE Transactions on Medical Imaging*, 2025.

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[3] J. Yoo, K. H. Jin, H. Gupta, J. Yerly, M. Stuber, and M. Unser. Time-dependent deep image prior for dynamic mri. *IEEE Transactions on Medical Imaging*, 40(12):3337–3348, 2021.