Abstract #00300 ISMRM ABSTRACT

Learning Patient-Adaptive Undersampling Patterns for Cardiac MRI Using Nearest Neighbor Search

Primary: Acquisition & Reconstruction - Image Reconstruction: AI 〉 **Secondary:** Acquisition & Reconstruction - Subsampling: Parallel imaging, compressed sensing and low-rank modeling 〉 **Keywords:** IMAGE RECONSTRUCTION DEEP LEARNING RECONSTRUCTION SAMPLING PATTERN OPTIMIZATION CARDIAC CINE MRI ACCELERATED MRI RECONSTRUCTION

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Impact

Our approach learns patient-adaptive Cartesian sampling patterns that improve reconstruction quality and reduce acquisition time, enabling faster, personalized cardiac MRI and potentially lowering motion artifacts and patient discomfort.

Synopsis

Motivation: Long MRI acquisitions cause motion artifacts and patient discomfort.
Goals: Accelerate cardiac MRI via scan-adaptive undersampling and reconstruction.
Approach: We learn patient-specific Cartesian undersampling masks using a randomized subset-based iterative coordinate-descent (RB-ICD) algorithm and predict test-time masks through a nearest neighbor search.
Results: The proposed framework outperforms variable-density random sampling (VDRS) and equispaced masks in terms of NMSE, SSIM, and PSNR, improving anatomical sharpness and reconstruction accuracy.

Introduction

Dynamic cardiac MRI provides useful functional information but is limited by long scan times that can cause motion artifacts and patient discomfort. Conventional MRI acceleration approaches use population-adaptive or fixed undersampling patterns [1, 2, 3, 4] that may fail to capture patient-specific anatomy and motion. This work builds on our previous SUNO framework [5, 6], which introduced scan-adaptive sampling for static knee and brain MRI using iterative coordinate descent (ICD). We extend this approach to dynamic cardiac MRI by addressing its main limitation, which is high computational cost arising from the sequential optimization of one phase-encoding line at a time. To overcome this, we propose a randomized batched ICD (RB-ICD) algorithm that jointly updates subsets of k-space lines, enabling efficient and scalable sampling optimization for dynamic cardiac MRI. The resulting framework learns scan-specific Cartesian sampling masks using the RB-ICD algorithm and a reconstruction network trained on these masks. At test time, these scan-specific patterns are predicted by nearest-neighbor matching on aliased zero-filled reconstructions formed from the acquired low-frequency k-space, enabling personalized acceleration without retraining.

Methods

We jointly learn scan-adaptive Cartesian undersampling masks $\{\mathbf{M}_i\}$ offline and a reconstruction network f_θ over the training set. The optimization objective is

$$\min_{\boldsymbol{\theta},\, \{\mathbf{M}_i \in \mathcal{C}\}} \sum_i \left\| f_{\boldsymbol{\theta}}\left(\mathbf{A}_i^H \mathbf{M}_i \mathbf{y}_i^{\text{full}}\right) - \mathbf{x}_i^{\text{gt}} \right\|_2^2$$

where $\mathbf{y}_i^{\text{full}}$ denotes the fully sampled multi-coil k-space data for the i-th training case, $\mathbf{x}_i^{\text{gt}}$ is the corresponding ground-truth image sequence, $\mathbf{A}_i$ represents the encoding operator incorporating coil sensitivities and Fourier transforms, and $\mathbf{A}_i^H$ is its adjoint. Each $\mathbf{M}_i$ is a binary Cartesian mask selecting a subset of phase-encoding lines under a fixed sampling budget, and $\mathcal{C}$ is the set of all feasible masks that satisfy this constraint.

The optimization alternates between updating the reconstruction network using data undersampled by the current masks and refining the masks using a randomized batched iterative coordinate descent (RB-ICD) algorithm. In each RB-ICD step, small subsets of phase-encoding lines are jointly relocated to minimize reconstruction error with the current network held fixed. Each subset to be relocated is chosen randomly. The locations of the subset of lines is moved to are also chosen randomly. Among multiple such choices, the one producing the best reconstruction quality is selected for relocation.

At test time, the sampling mask is chosen from the ones optimized for the training set using a nearest neighbor search based on aliased zero-filled reconstructions obtained from the low-frequency test k-space.

Experiments and Results

The proposed sampling and reconstruction framework was evaluated on an in-house cardiac cine MRI dataset acquired at the University of Michigan using a 1.5T Sola scanner with a 30-channel receiver coil array and a standard 2D Cartesian protocol. The native acquisition matrix was approximately 440 × 240, acquired with a uniform 2×undersampling pattern in the phase-encoding direction. Higher accelerations (4× and 8×) were simulated by retrospectively applying additional undersampling masks to the original 2× data. All reconstructions were performed on this doubly undersampled k-space. For each training slice, an optimized undersampling mask was generated using the RB-ICD algorithm. During testing, each slice was matched to its most similar training slice based on the nearest neighbor search, and the corresponding SUNO mask was applied uniformly across all frames. This slice-adaptive configuration was used in all experiments.

SUNO masks were compared with conventional equispaced and variable-density random sampling (VDRS) [1] patterns combined with both classical and deep reconstruction methods. Equispaced masks were reconstructed using SENSE [7], while VDRS masks were paired with compressed sensing (CS) based reconstruction and the CTFNet reconstruction model [8]. For SUNO masks, reconstructions were performed using a trained MoDL reconstruction network [9]. CTFNet was also chosen due to its strong spatiotemporal modeling performance for dynamic MRI.

Representative reconstructions at 4× acceleration (Figure 1 and Figure 2) demonstrate reduced aliasing and improved temporal accuracy for SUNO-based sampling compared with equispaced and VDRS-based patterns. Quantitative comparisons (Figure 3) show that SUNO combined with MoDL achieved the lowest NMSE and highest PSNR and SSIM across all acceleration factors. The performance advantage increased at higher accelerations, where conventional and VDRS-based methods exhibited pronounced blurring and residual artifacts, while SUNO maintained stable reconstruction quality and temporal consistency.

Conclusion

We developed a scan-adaptive cardiac MRI sampling framework that jointly learns RB-ICD optimized Cartesian masks and a MoDL reconstructor first on training data, which are then used at test time with nearest neighbor-based sampling mask search. The proposed SUNO framework method outperforms equispaced and variable-density masks across multiple acceleration factors, demonstrating its potential for practical, scan-specific accelerated cardiac imaging.

Acknowledgements

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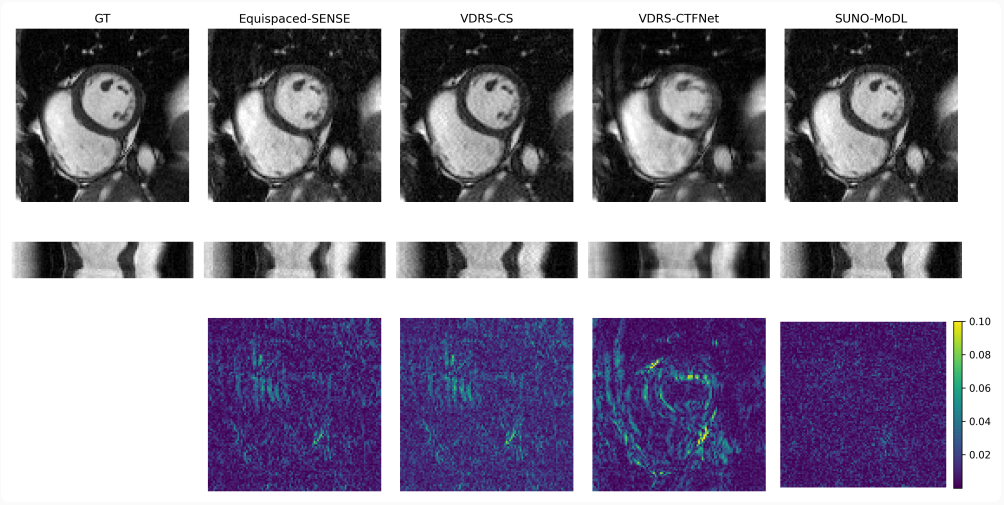
Figures and Tables



Scan for high-resolution version

Figure 1: *ROI-based qualitative comparison of different sampling techniques and reconstructions on two anatomically distinct slices at 4x acceleration (Slice-1). The figure includes: (i) cropped reconstruction over a region-of-interest (ROI) around the heart, (ii) spatial–temporal (Y–T) profile from a vertical stripe within the ROI to visualize cardiac motion fidelity, and (iii) ROI error maps showing the absolute difference from the ground truth.*

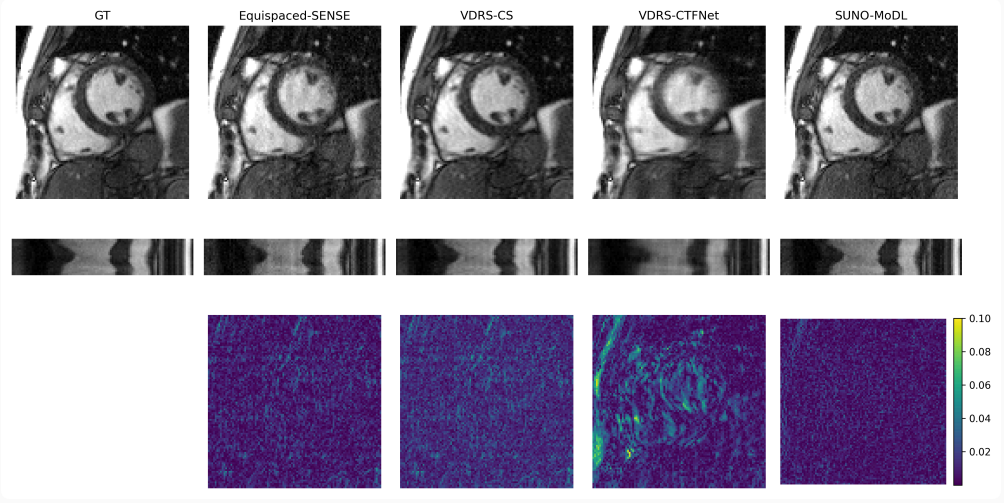


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Figure 2: *ROI-based qualitative comparison of different sampling techniques and reconstructions on two anatomically distinct slices at 4x acceleration (Slice-2). The figure includes: (i) cropped reconstruction over a region-of-interest (ROI) around the heart, (ii) spatial–temporal (Y–T) profile from a vertical stripe within the ROI to visualize cardiac motion fidelity, and (iii) ROI error maps showing the absolute difference from the ground truth.*

AF	Metric	Equispaced SENSE	VDRS CS	VDRS CTFNet	SUNO MoDL
4	NMSE	0.029	0.048	0.032	**0.026**
	PSNR (dB)	36.44	34.52	35.97	**37.26**
	SSIM	0.962	0.948	0.958	**0.968**
8	NMSE	0.186	0.215	0.109	**0.080**
	PSNR (dB)	28.14	27.63	30.72	**32.33**
	SSIM	0.862	0.857	0.893	**0.932**

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Figure 3: *Quantitative comparison of sampling and reconstruction methods on a test set of 52 slices at acceleration factors of 4× and 8×. The proposed SUNO–MoDL framework consistently outperformed all baselines, achieving the lowest NMSE and highest PSNR and SSIM across both accelerations.*