# End-to-end Adaptive k-space Sampling, Reconstruction and Registration for Dynamic MRI

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## Motivation

**Dynamic MRI supports cardiac function assessment, motion correction, and MR-guided radiotherapy. Yet the time needed to acquire fully sampled k-space conflicts with physiological motion. Undersampling accelerates acquisition but can degrade both reconstructed images and the deformation fields estimated from them.**

## Introduction

### Problem

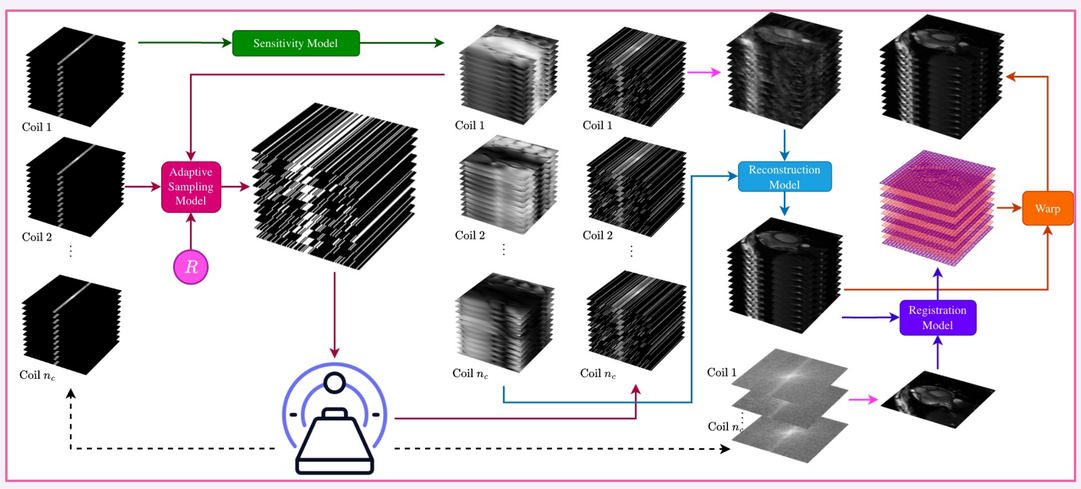
**Most accelerated MRI pipelines optimize sampling and reconstruction for image fidelity, then run registration afterwards. Our target is motion estimation from the undersampled dynamic acquisition.**

### Approach

**We extend End-to-end Adaptive Dynamic Sampling and Reconstruction (E2E-ADS-Recon) [1] with deformable registration. Sampling, reconstruction, and registration form one trainable pipeline, so registration gradients can modify the acquisition policy and reconstruction network.**

## Method

### Pipeline overview




Initial ACS data provide a small acquisition and a fully sampled central k-space region. The model predicts the remaining samples for the requested acceleration.

### Joint training objective

$$L = \alpha\, L_{rec} + \beta\, L_{reg}$$

**Reconstruction loss:** reconstructed image fidelity (2D SSIM, 3D SSIM, L1)
**Registration loss:** warped-image similarity and spatial deformation smoothness

### Experimental Setup

- **Evaluation:** CMRxRecon 2023 cine MRI, 471 scans and 3,185 slices [4]. We train and test at R = 4, 6, and 8.
- For each sequence, phase 6 is the end-systolic registration reference; the other 11 phases form the moving sequence.

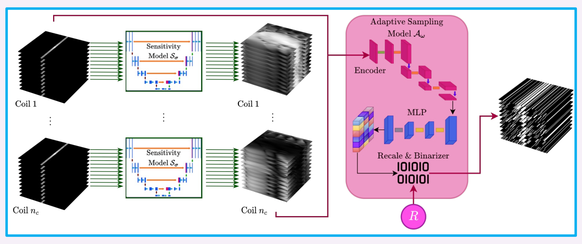
### Implementation details

#### 1. Sensitivity estimation

A 2D U-Net refines coil sensitivity maps from the 4% ACS region. These maps enter both the sampler and data-consistency updates.

#### 2. Adaptive dynamic sampling (ADS)

ADS takes the initial measurements, sensitivities, and target R, then predicts a separate binary 1D mask for each moving phase. A straight-through estimator enforces the sampling budget while allowing end-to-end gradients [1].

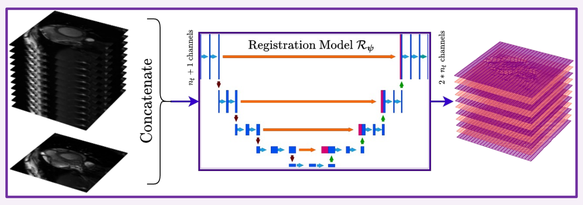



#### 3. Reconstruction

vSHARP reconstructs the dynamic multi-coil measurements using 10 unrolled ADMM iterations, a 3D U-Net denoiser, and data-consistency updates [2]. This produces a dynamic image sequence for motion estimation.

#### 4. Registration

A lightweight 2D U-Net receives the reconstructed moving frames and a static end-systolic reference concatenated in the channel dimension. It predicts one deformation field per moving phase; a spatial transformer warps the reconstruction to the reference [3].

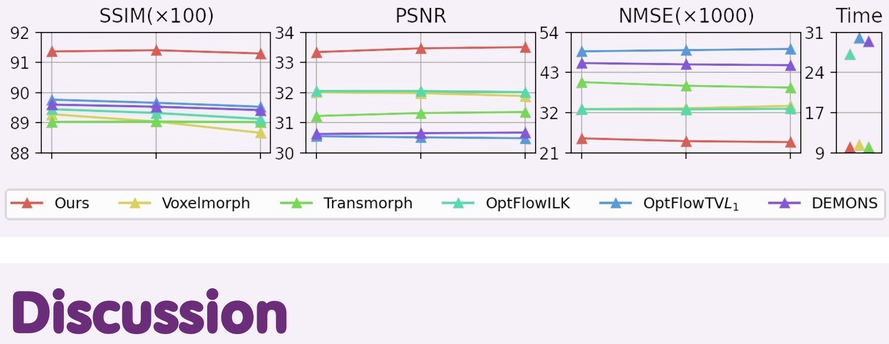



## Results

- Metrics computed after warping reconstructed moving frames to the reference.
- Ground-truth deformation fields are unavailable.

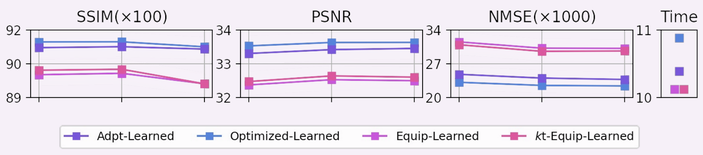
### Registration component

**The proposed lightweight 2D U-Net achieves the best registration accuracy.**



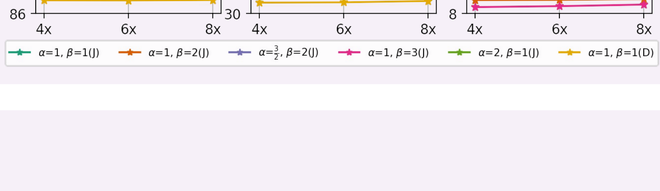

### Adaptive sampling

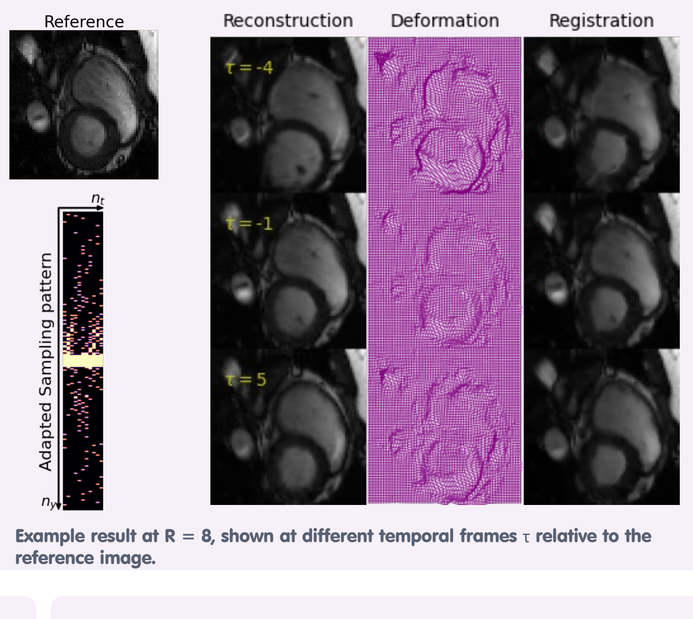
**Patient-specific sampling improves registered-image similarity over fixed, non-adaptive patterns.**




### Joint training

- Joint optimization improves registration over decoupled training.
- Giving reconstruction and registration equal weight provides the most balance.




Example result at R = 8, shown at different temporal frames $\tau$ relative to the reference image.

## Discussion

### Take-away

- End-to-end co-design and joint training of sampling, reconstruction, and registration improves motion estimation from undersampled dynamic MRI.
- Results quantify similarity after warping, so they reflect both reconstruction and registration quality.

### Limitations

- The current implementation estimates in-plane motion slice by slice.
- Similarity after warping reflects both reconstruction and registration quality rather than a direct deformation-field error.
- Fully-sampled data required for end-to-end training.

### References

[1] Yiasemis et al. End-to-End Co-Optimization of Adaptive k-space Sampling and Reconstruction for Dynamic MRI. MIDL, 2026.
[2] Yiasemis et al. vSHARP: variable splitting half-quadratic ADMM for reconstruction of inverse problems. Magnetic Resonance Imaging, 2024.
[3] Jaderberg et al.. Spatial transformer networks. Advances in neural information processing systems 28, 2015.
[4] Wang et al. CMRxRecon: an open cardiac MRI dataset for accelerated reconstruction. 2023.

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Code & weights

Pre-print