Accelerating Cardiac MRI with Deep Learning

Thomas Fletcher

Introduction

Cardiac MRI Group at KCL

1. Sequence development
2. Clinicians scanning patients
3. Pre-clinical – imaging probes
4. **Deep Learning to accelerate reconstruction times**

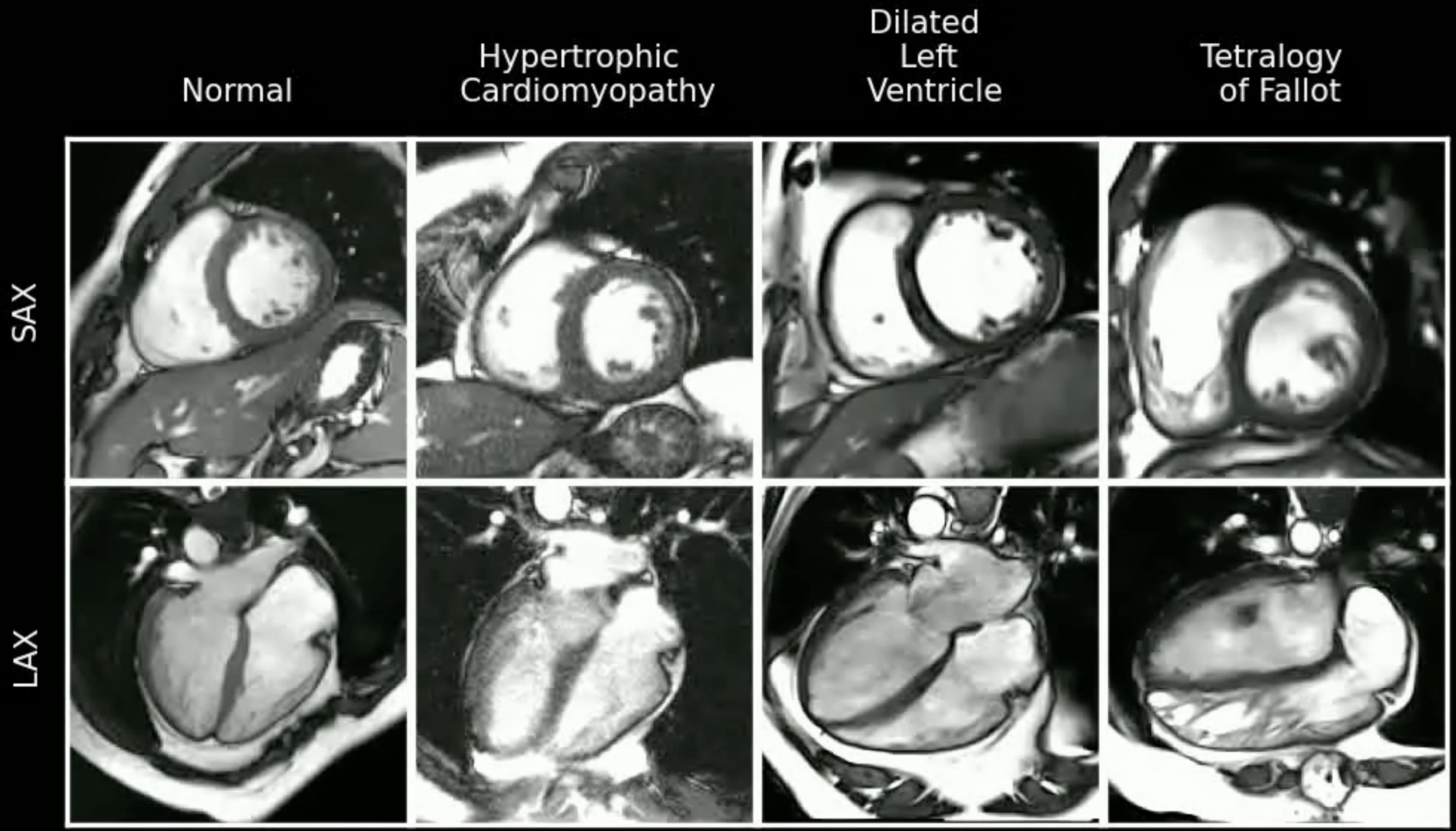
Based in St Thomas’ Hospital – access to MRI scanners and patients

Rapid Motion Estimation and Motion-Corrected End-to-End Deep Learning Reconstruction for 1 Heartbeat CINE

Thomas J. Fletcher[1], Lina Felsner[1], Andrew Phair[1], Gastão Cruz[2], Haikun Qi[3], René M. Botnar[1], Claudia Prieto[1]

1. School of Biomedical Engineering and Imaging Sciences, King's College London, London, UK
2. Department of Radiology, University of Michigan, Ann Arbor, USA
3. School of Biomedical Engineering, ShanghaiTech, University, Shanghai, China

Introduction - Cardiac CINE



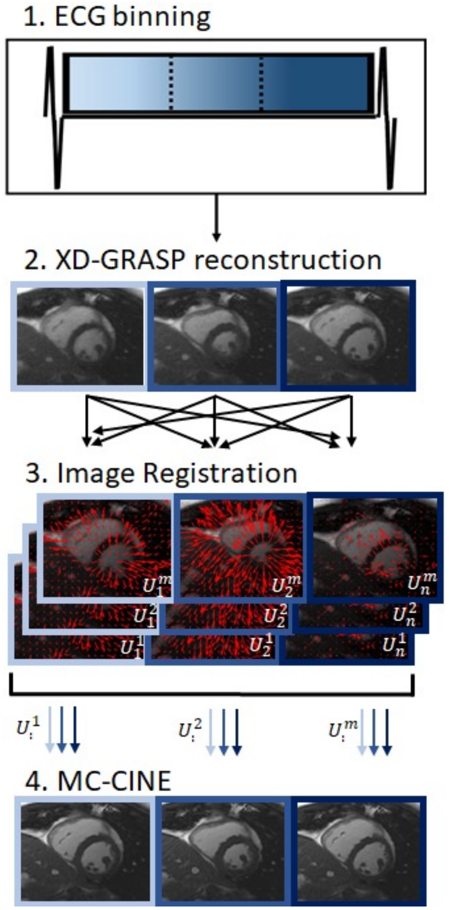
M&M2 Dataset, Martín-Isla et al.

1. Martín-Isla et al., IEEE Journal of Biomedical and Health Informatics (2023)

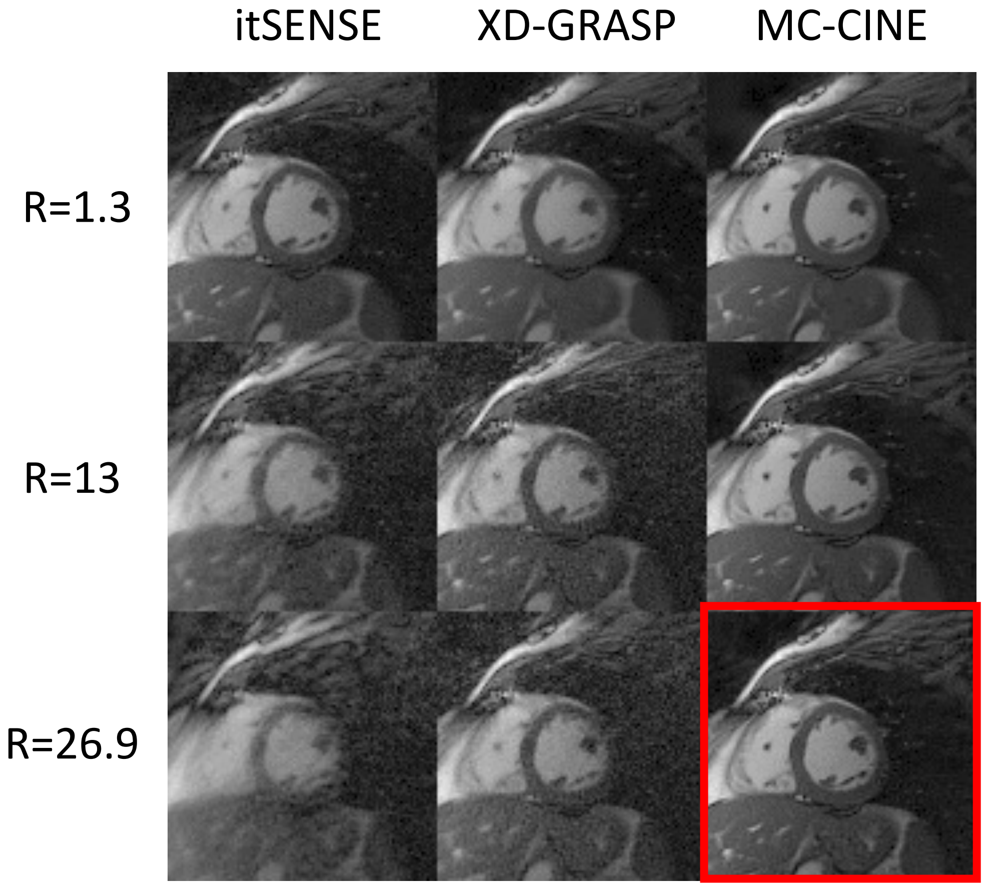
Introduction - MC-CINE[1]

Single-heartbeat cardiac cine imaging via jointly regularized nonrigid motion-corrected reconstruction

Gastao Cruz[1] | Kerstin Hammernik[2,3] | Thomas Kuestner[1,4] | Carlos Velasco[1] | Alina Hua[1] | Tevfik Fehmi Ismail[1] | Daniel Rueckert[2,3] | Rene Michael Botnar[1,5,6] | Claudia Prieto[1,5,6]



Cruz et al.



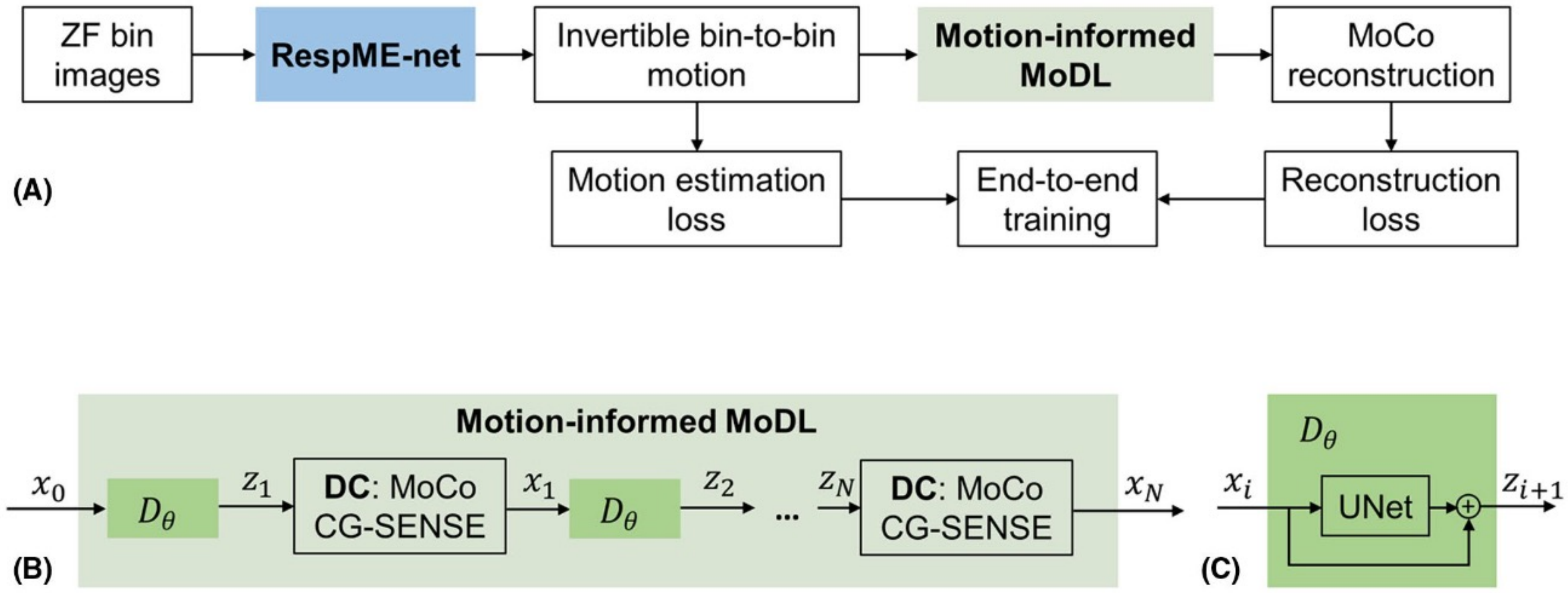
Cruz et al.

- CINE in 1 heartbeat
- Sharp, artifact-free
- Must estimate N^2 motion fields
- Motion-aligned patch-based reconstruction
- Slow reconstruction (4.5 hours per slice) for 1 second acquisition

Introduction – Non-rigid MoCo MoDL Reconstruction[2,3]

End-to-end deep learning nonrigid motion-corrected reconstruction for highly accelerated free-breathing coronary MRA

Haikun Qi[1,2] | Reza Hajhosseiny[1] | Gastao Cruz[1] | Thomas Kuestner[1,3] | Karl Kunze[1,4] | Radhouene Neji[1,4] | René Botnar[1,5] | Claudia Prieto[1,5]



- Unrolled End-to-End motion (respiratory) corrected reconstruction.
- Motion estimation network and reconstruction network trained together
- Respiratory motion only (4 motion bins)

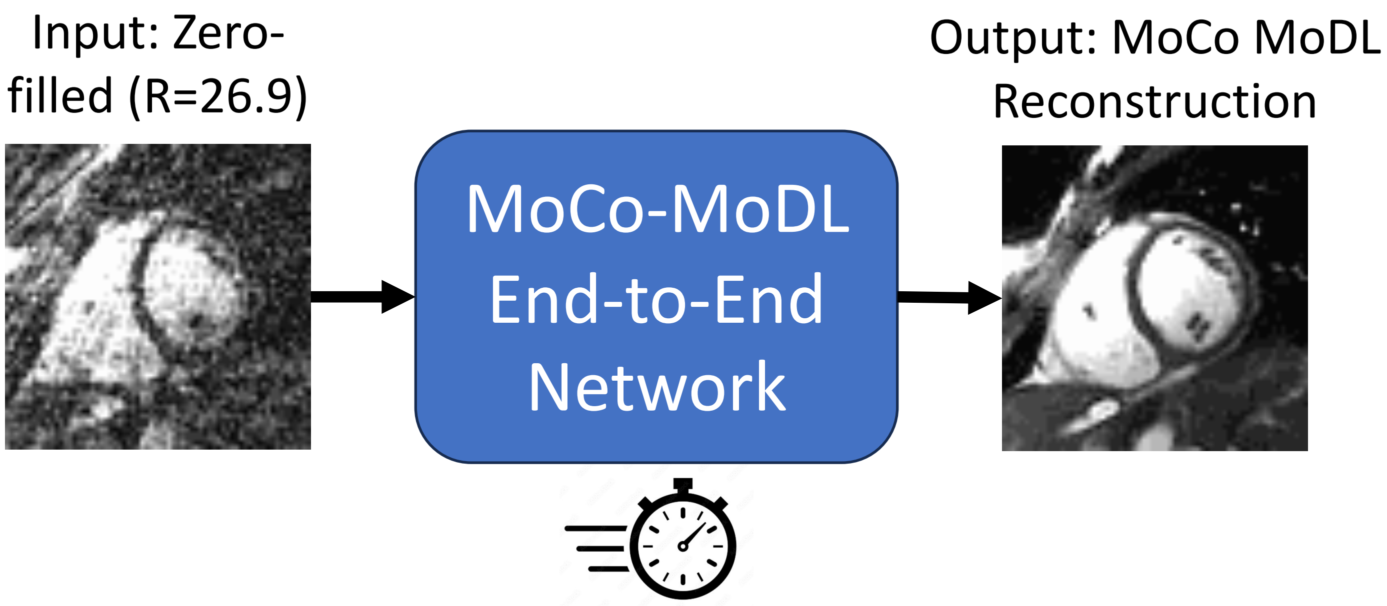
Introduction

- Conventional Cine → multiple breath-holds
  - **Slow (5-10 minutes)**[1], inefficient, can lead to mis-registration

- **MC-CINE[2] accurately reconstructs single-heartbeat CINE** with a motion-aligned patch-based reconstruction
  - However, **4.5-hour reconstruction per 2D slice**

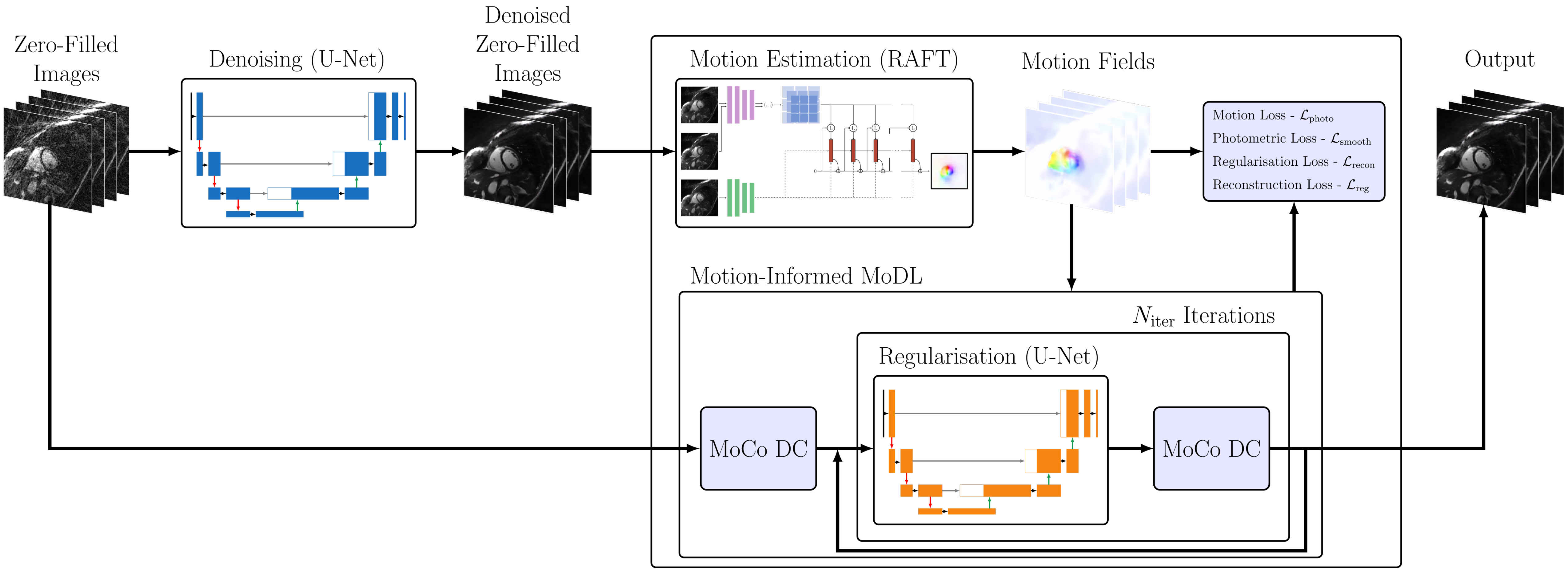
- Motion-corrected model-based deep learning approaches[3,4] can accelerate reconstruction times

Aim: Rapidly reconstruct single heartbeat CINE using end-to-end motion-corrected model-based deep learning reconstruction



1. Raman et al. JCMR (2022) 2. Cruz et al., NMR in Biomedicine (2023) 3. Aggarwal et al., IEEE transactions on medical imaging (2018) 4. Qi et al., MRM (2021)

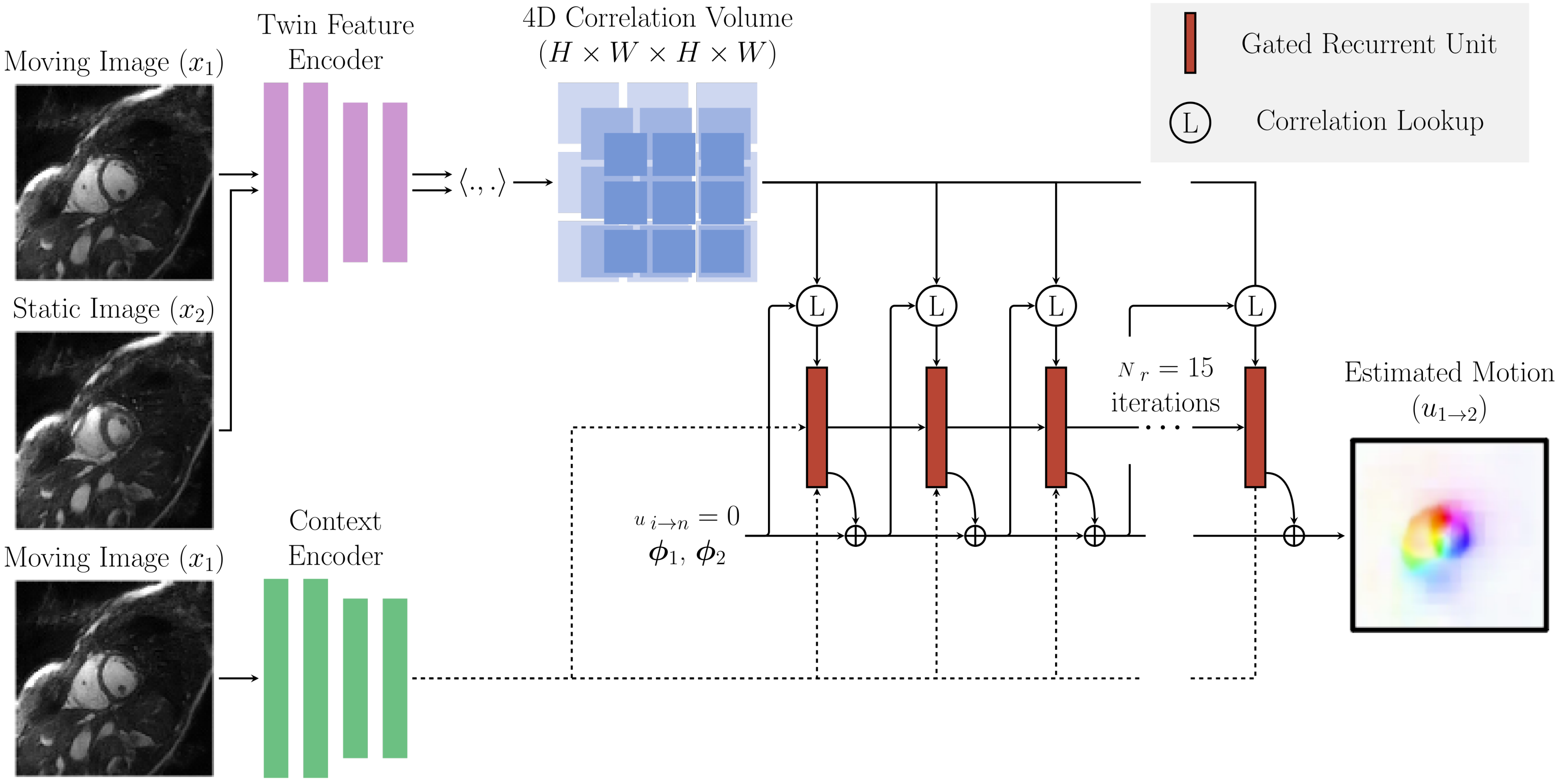
Methods - Network Overview and Training



- 10:2:2 split of subjects for training, validation and testing
- Train for 50 epochs (~200 hours, TensorFlow, 2x24GB NVIDIA Titan RTX)

Methods – Motion Estimation – RAFT[6] and SMURF[7]

- Feature Encoder and Context Encoder
- 4D correlation volume (HxWxHxW) → feature vectors
- Recurrent update block for flow
- Diffeomorphic Flow with scaling and squaring layer[8]
- Input Denoised ZF, Loss on MC-CINE



Methods – Deep Learning Iterative Motion-Corrected Reconstruction

KING'S College LONDON

Encoding Operator: $$E = AFCM$$

A: k-space sampling, F: Fourier Transform,
C: Coil Sensitivities M: Motion

MoCo-MoDL: $$\mathcal{L}(\boldsymbol{\rho}) = \|E\boldsymbol{\rho} - \boldsymbol{b}\|_2^2 + \lambda\|\boldsymbol{\rho} - \mathcal{D}_\theta(\boldsymbol{\rho})\|_1^2$$

Data Consistency
(Conjugate Gradient)

Regularisation
U-Net

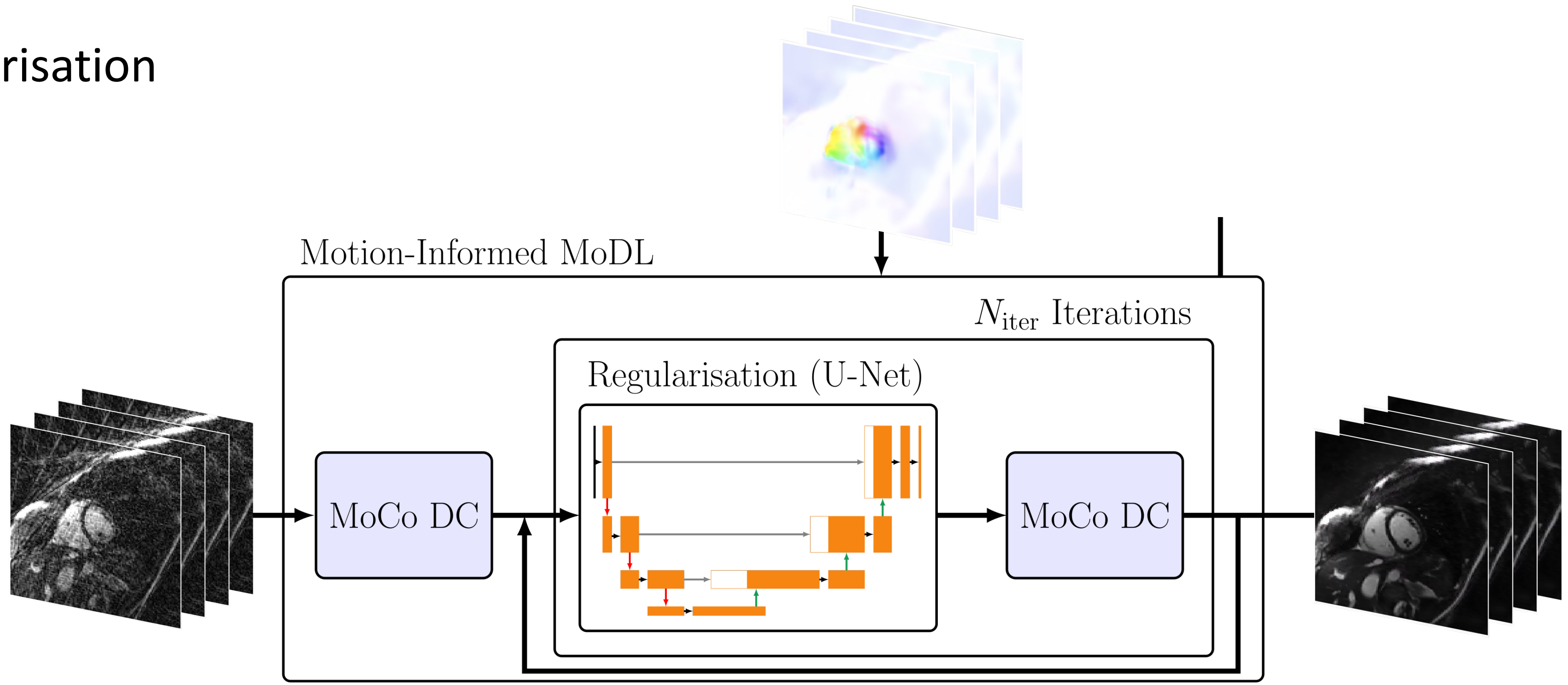
$$E^*E\boldsymbol{\rho} = E^*\boldsymbol{b} = M^*\boldsymbol{\rho}_{ZF}$$

Iterative Reconstruction
Radial Data
NUFFT → Toeplitz Embedding

Methods – Reconstruction Network

- Motion-corrected data consistency – conjugate gradient descent
- U-Net for regularisation
- 3 iterations

$$\mathcal{L}(\boldsymbol{\rho}) = \|E\boldsymbol{\rho} - \boldsymbol{b}\|_2^2 + \lambda\|\boldsymbol{\rho} - \mathcal{D}_\theta(\boldsymbol{\rho})\|_1^2$$



Methods - End-to-End Network Loss Functions

$$\mathcal{L}_{\text{photo}} = \sum_{i=1}^{30} \rho(W(x_{gt}^{i}, u_{i \to n}) - x_{gt}^{n})$$

$$\mathcal{L}_{\text{smooth}} = \sum_{i=1}^{N} \sum_{d \in x,y} ||\nabla_d u_{i \to n} \exp^{-\nabla_d x_{gt}^{i}}||$$

$$\rho(x) = \sqrt{x^2 + \epsilon^2}$$

Charbonnier Loss

$$\mathcal{L}_{\text{recon}/i,j} = \frac{1}{W_{i,j} H_{i,j}} \sum_{x=1}^{W_{i,j}} \sum_{y=1}^{H_{i,j}} (\phi_{i,j}(x_{gt})_{x,y} - \phi_{i,j}(x_{recon}))^2$$

$\phi_{i,j}$ Are VGG19 Feature maps

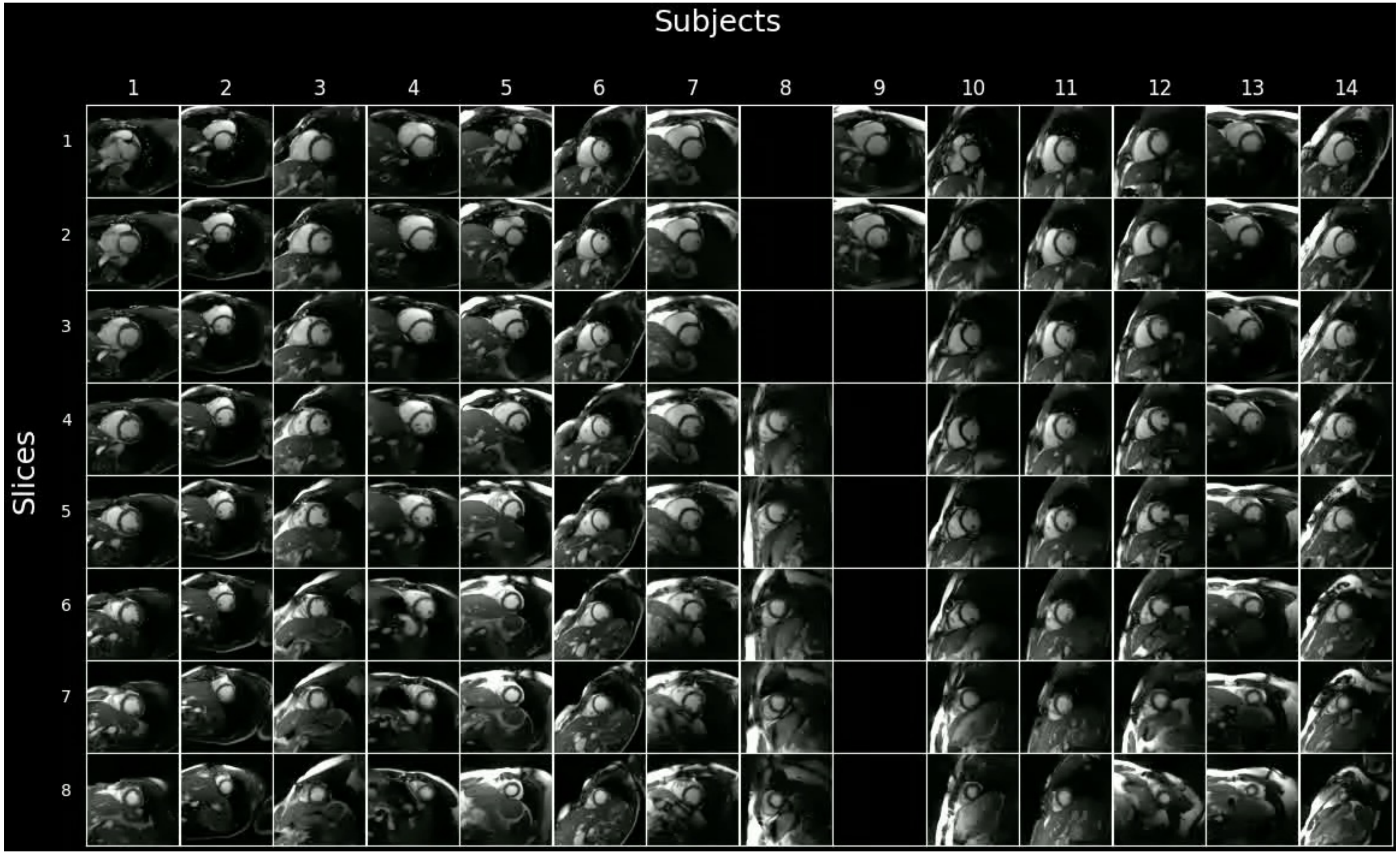
$$\mathcal{L}_{\text{total}} = \lambda_1 \mathcal{L}_{\text{photo}} + \lambda_2 \mathcal{L}_{\text{smooth}} + \lambda_3 \mathcal{L}_{\text{recon}} + \lambda_4 \mathcal{L}_{\text{reg}}$$

Methods - Prospectively Acquired Data

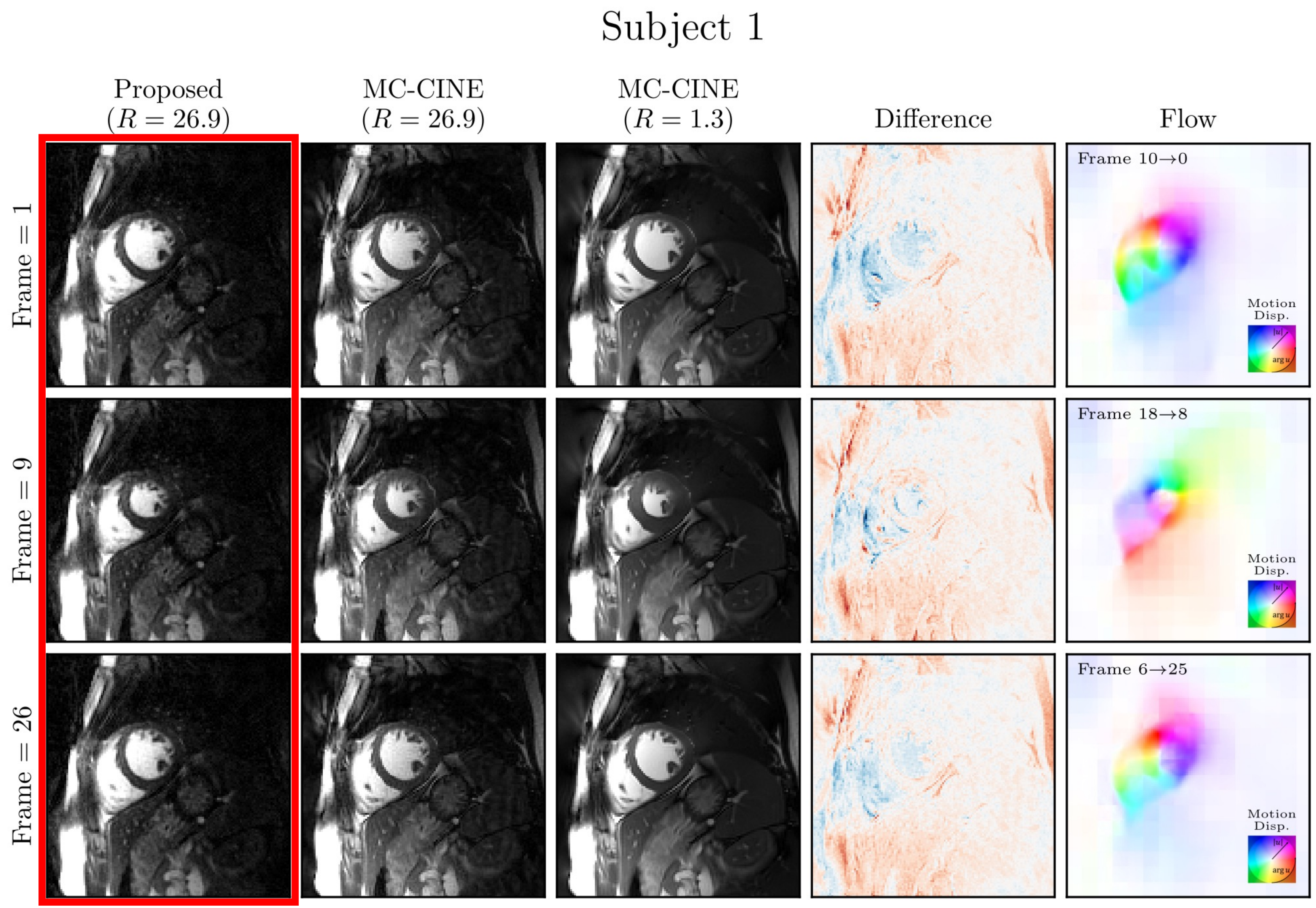
- Prospectively acquired with a gold-angle radial trajectory
- **Acceleration R=26.9 (1-heartbeat)**
- 14 healthy subjects (8 slices per volunteer, 103 CINEs)
- 1.5 T (Philips, Ingenia).

Main imaging parameters:

- FoV=256x256 mm^2
- 8 mm slice thickness
- resolution=2x2mm^2
- TE/TR=1.16/2.3 ms
- b-SSFP readout
- Radial tiny golden angle of 23.6°
- Flip angle 60°
- 448 radial spokes acquired
- ~1 second acquisition



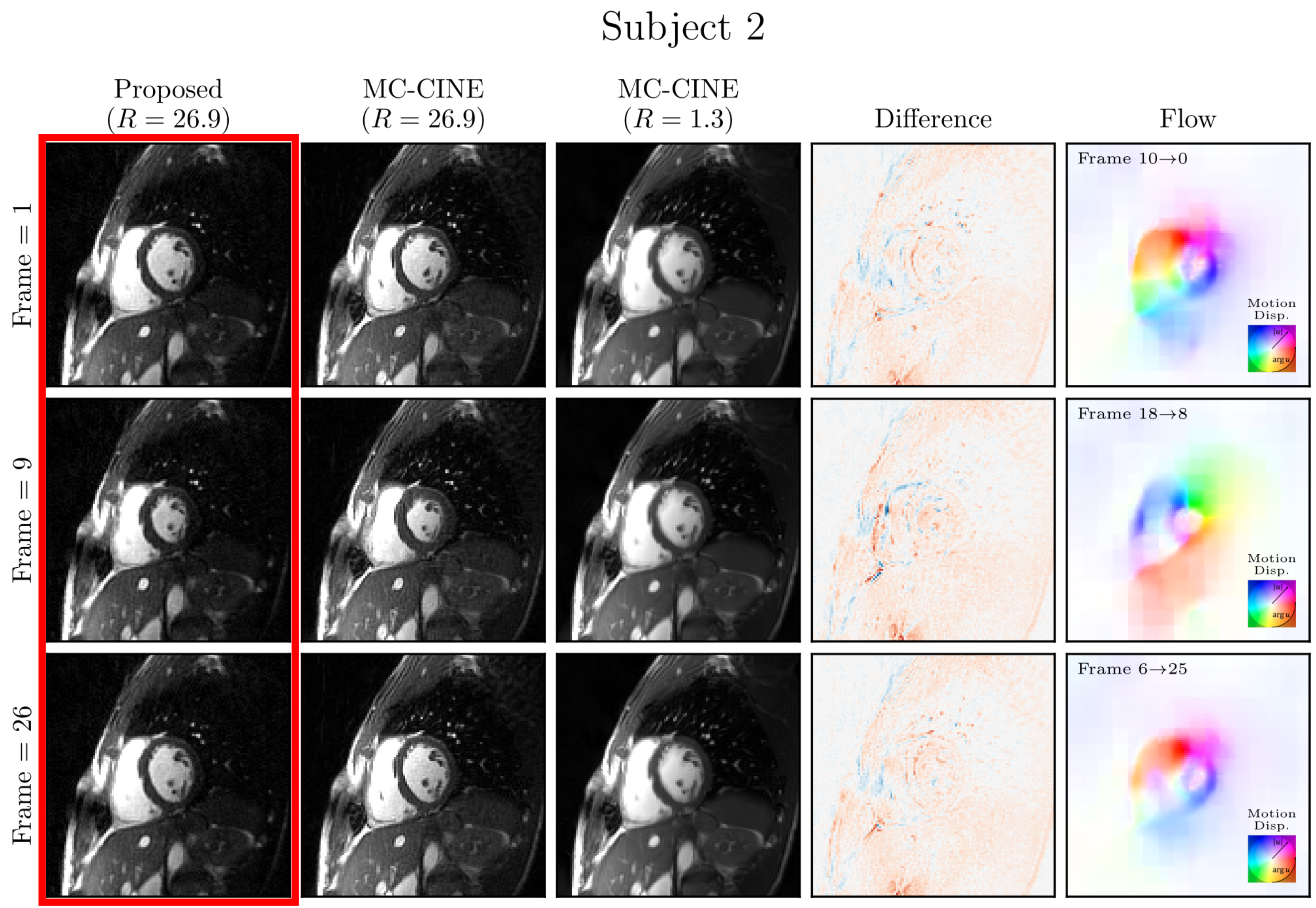
Results – Mid-Short-Axis Images, Subject 1



SSIM ~ 0.8

~ 40 seconds (400x faster than SOTA)

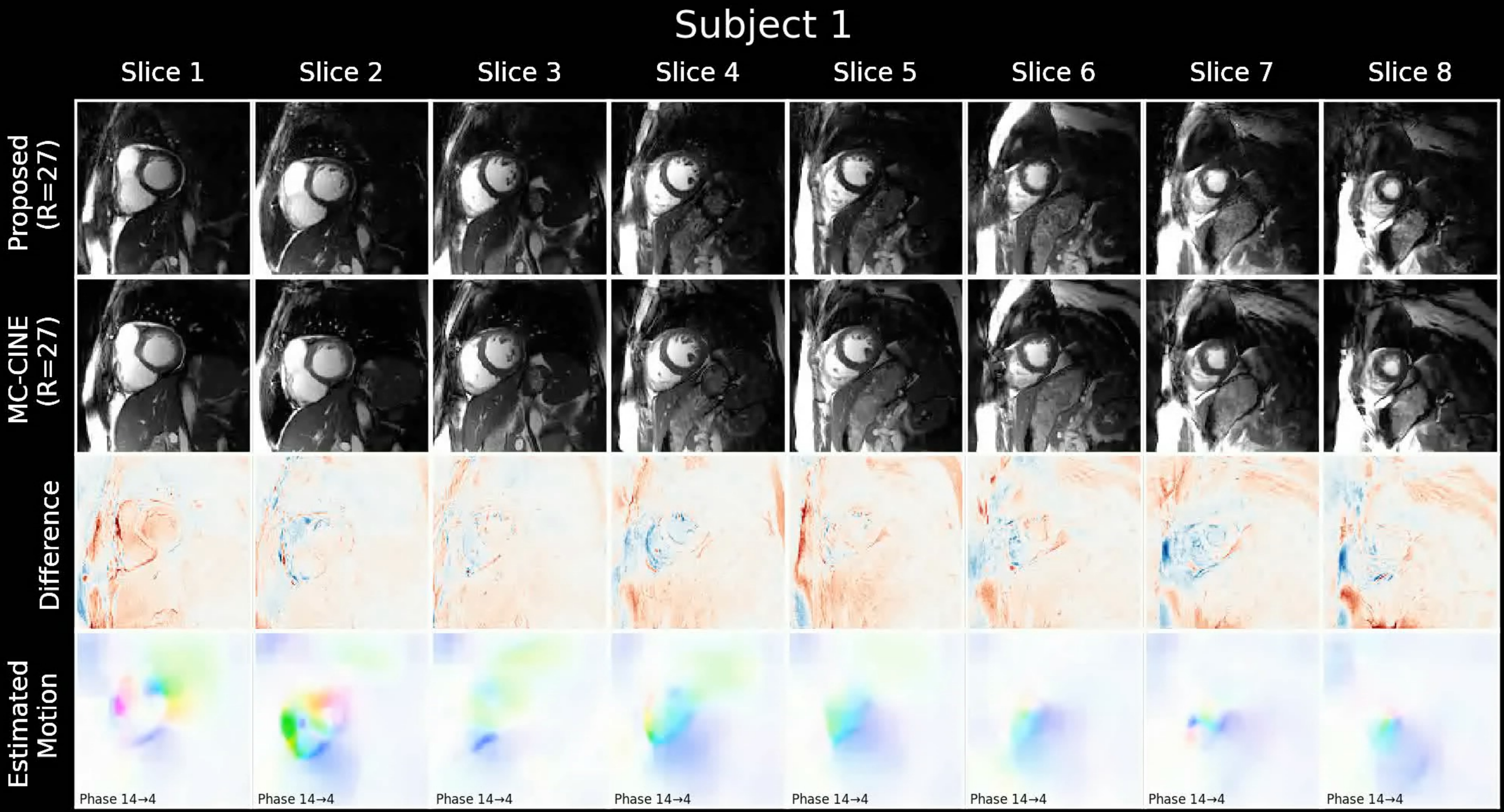
Results – Mid-Short-Axis Images, Subject 2



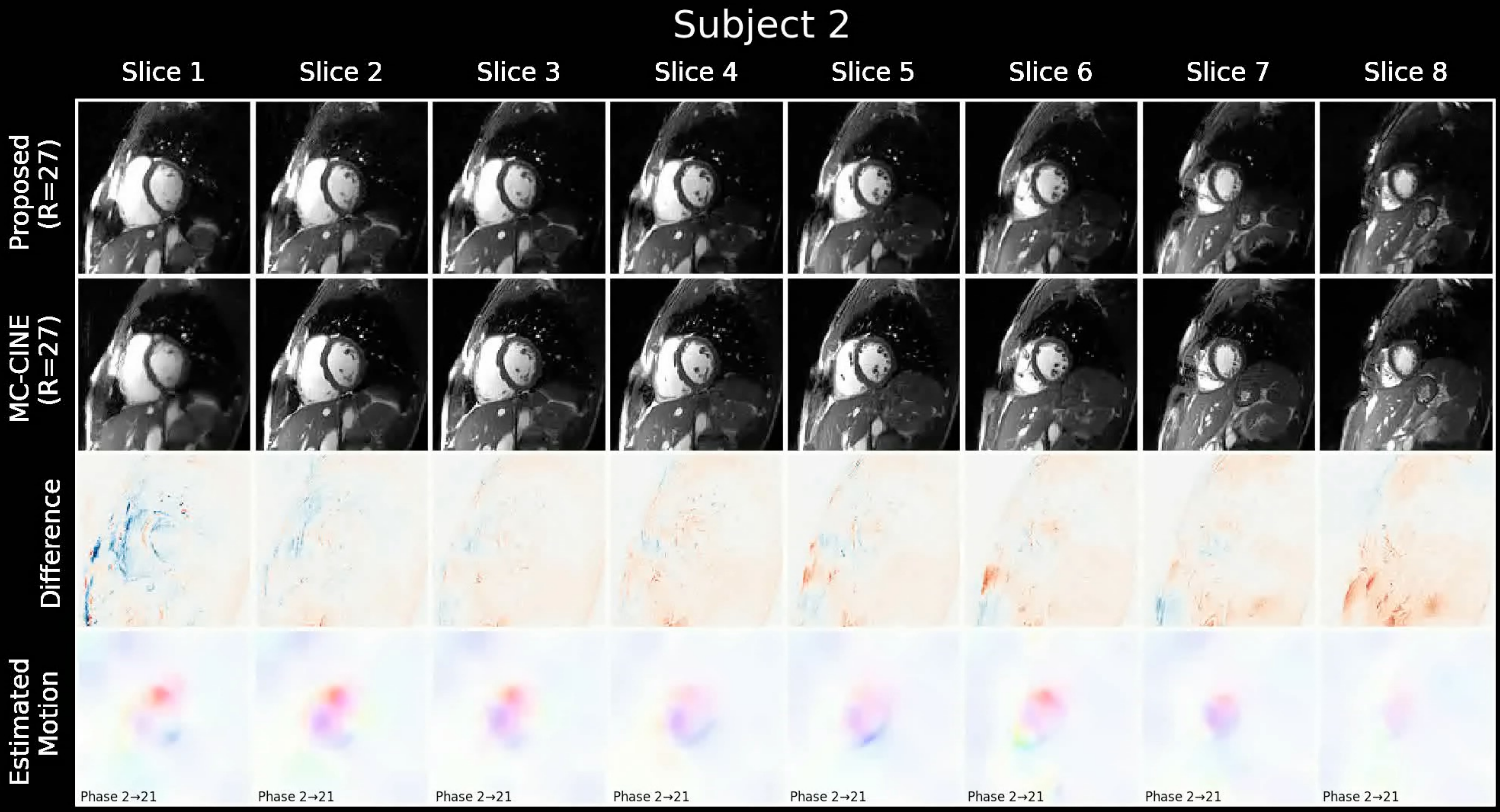
SSIM ~ 0.8

~ 40 seconds (400x faster than SOTA)

Results – Short-Axis CINEs - Subject 1



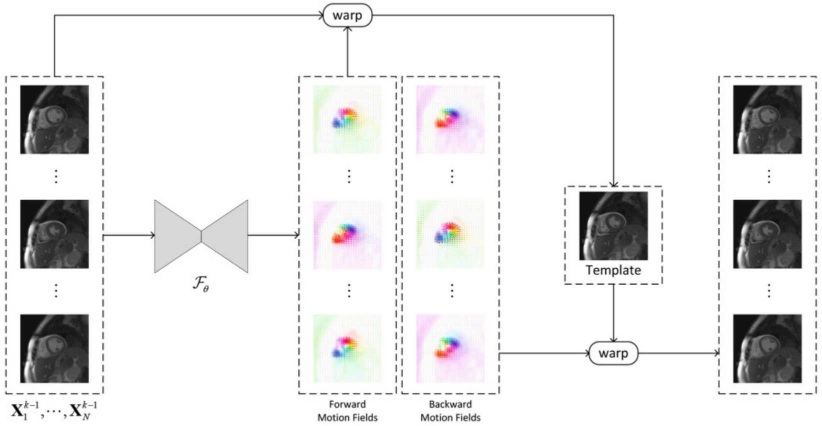
Results – Short-Axis CINEs - Subject 2



Discussion – Similar Work

Yang et al. (2022) - **End-to-End Deep Learning of Non-rigid Groupwise Registration and Reconstruction of Dynamic MRI**

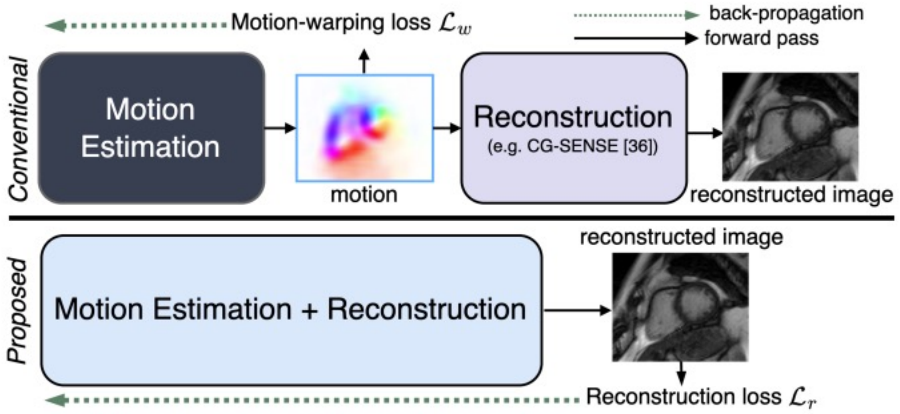
- Group-wise motion estimation
- Retrospectively undersampled data up to R=16



Yang et al.

Pan et al. (2023) - **Reconstruction-driven motion estimation for motion-compensated MR CINE imaging**

- Treats problem as single optimization
- Use neighbouring K frames
- No denoising network in iterative reconstruction
- Retrospectively undersampled data up to R=20



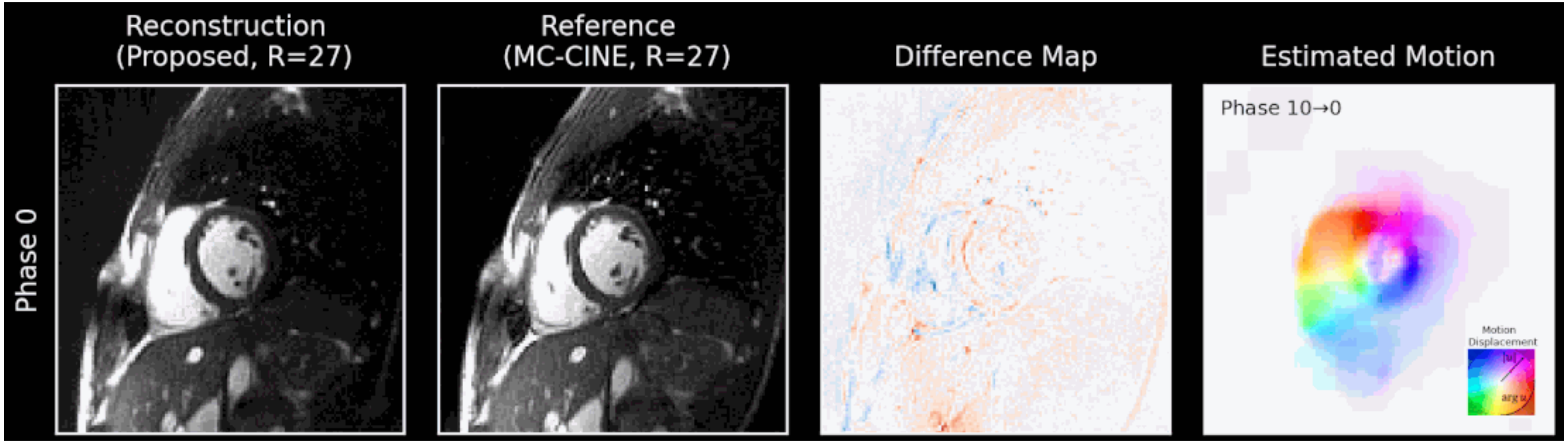
Pan et al.

Conclusion

1. Proposed an end-to-end deep learning framework combining motion estimation and motion-corrected reconstruction for single-heartbeat CINE

2. Network accurately reconstructs CINEs in ~40 seconds (400x faster than state-of-the art)

3. Future work will apply this to data covering the whole left ventricle in a single breath-hold

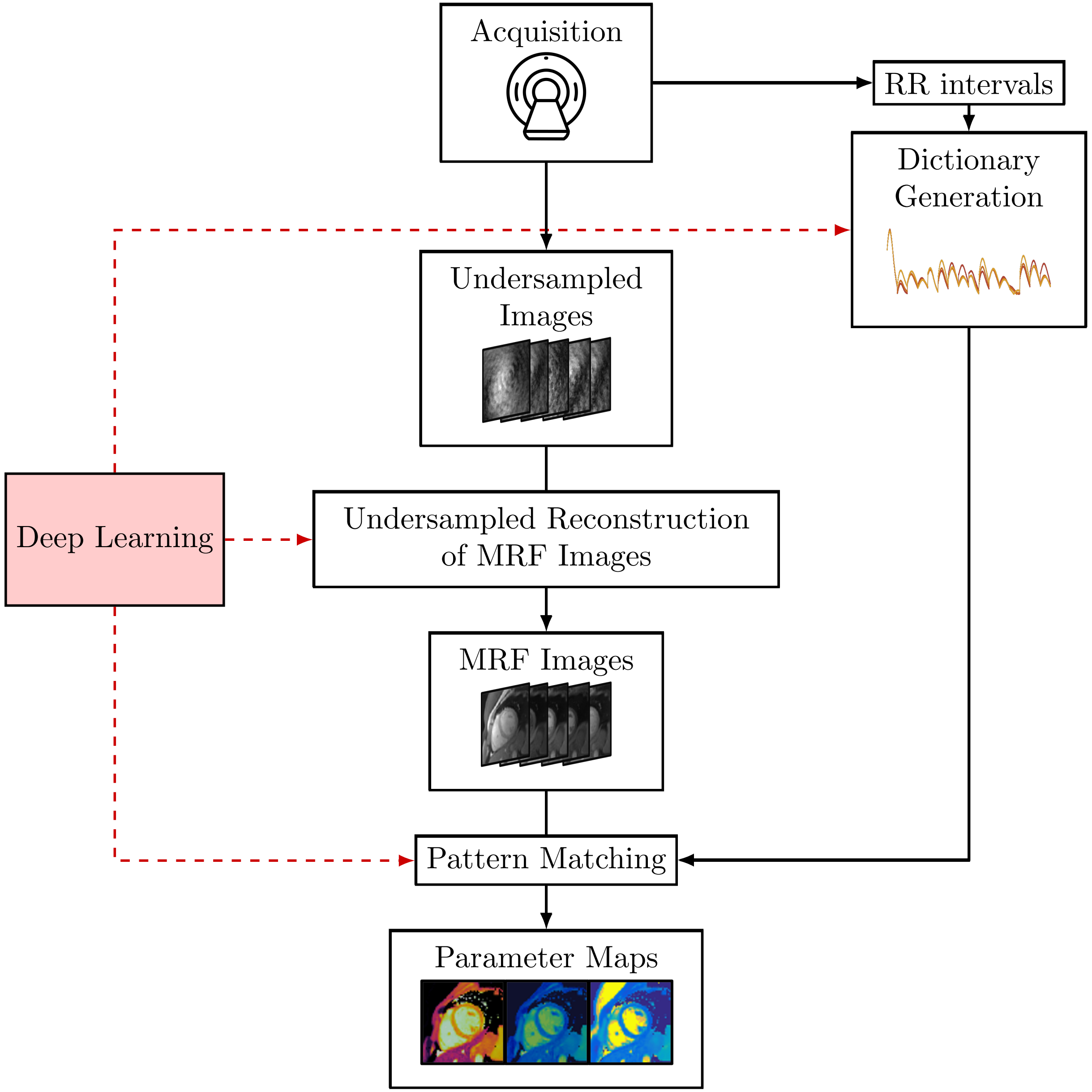


Invertible Neural Networks for Cardiac MRF

Cardiac MRF Challenges

- Cardiac MRF[1,2] acquires multiple co-registered parameter maps in a single breath-held ECG-triggered acquisition
- Subject-specific dictionaries must be simulated
- Conventionally, an exhaustive search of the dictionary is performed to generate parameter maps
- Deep learning can be used for both dictionary[3] and map[4,5] generation

- Aim: Dictionary-free invertible neural network to speed up cardiac MRF map generation, directly from undersampled images for a T1, T2, T1ρ sequence[6]



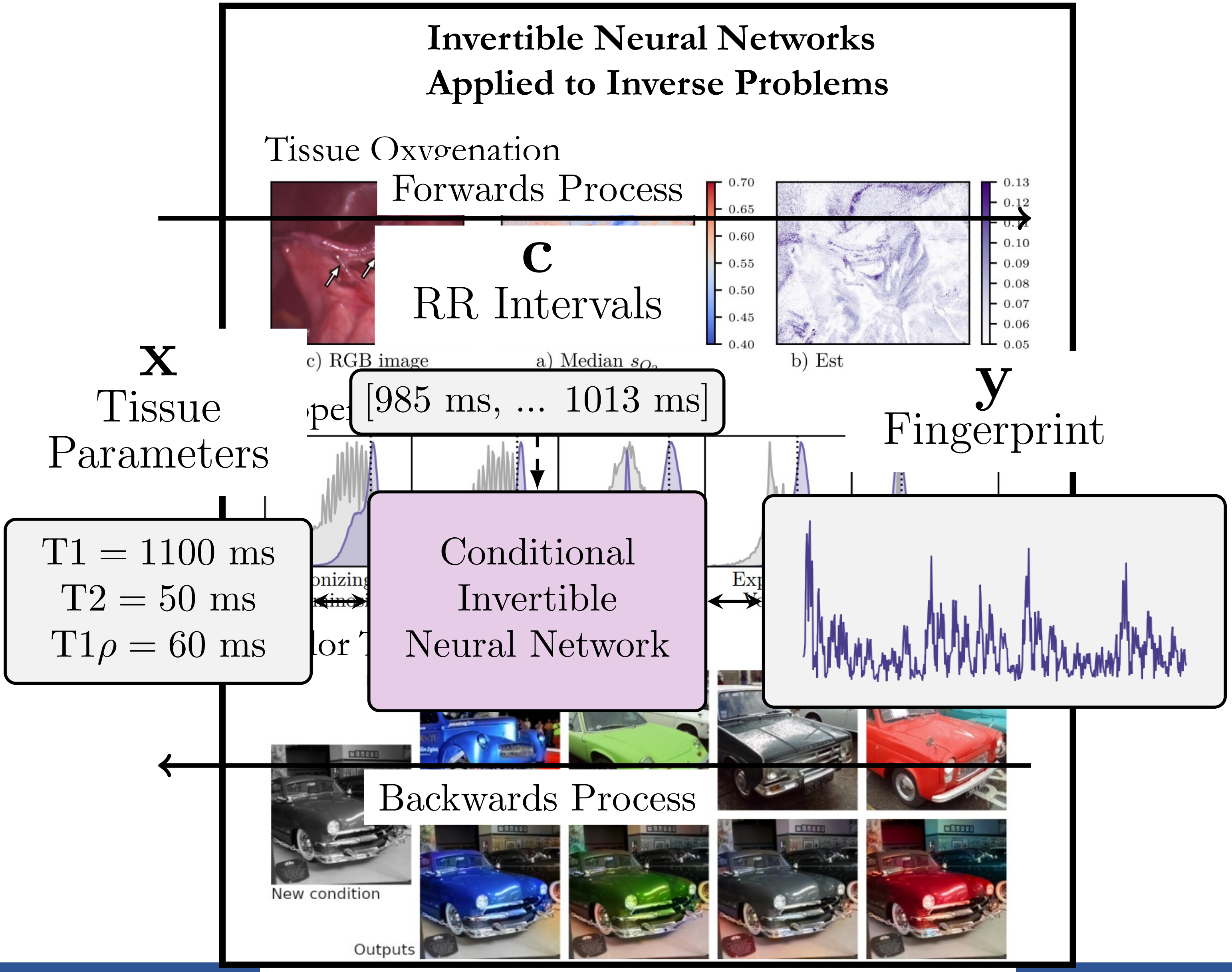
Invertible Neural Networks

- Inverse problems such as cardiac MRF are ill-posed

- One fingerprint could correspond to multiple sets of parameters and a network will average across these to give a single solution.

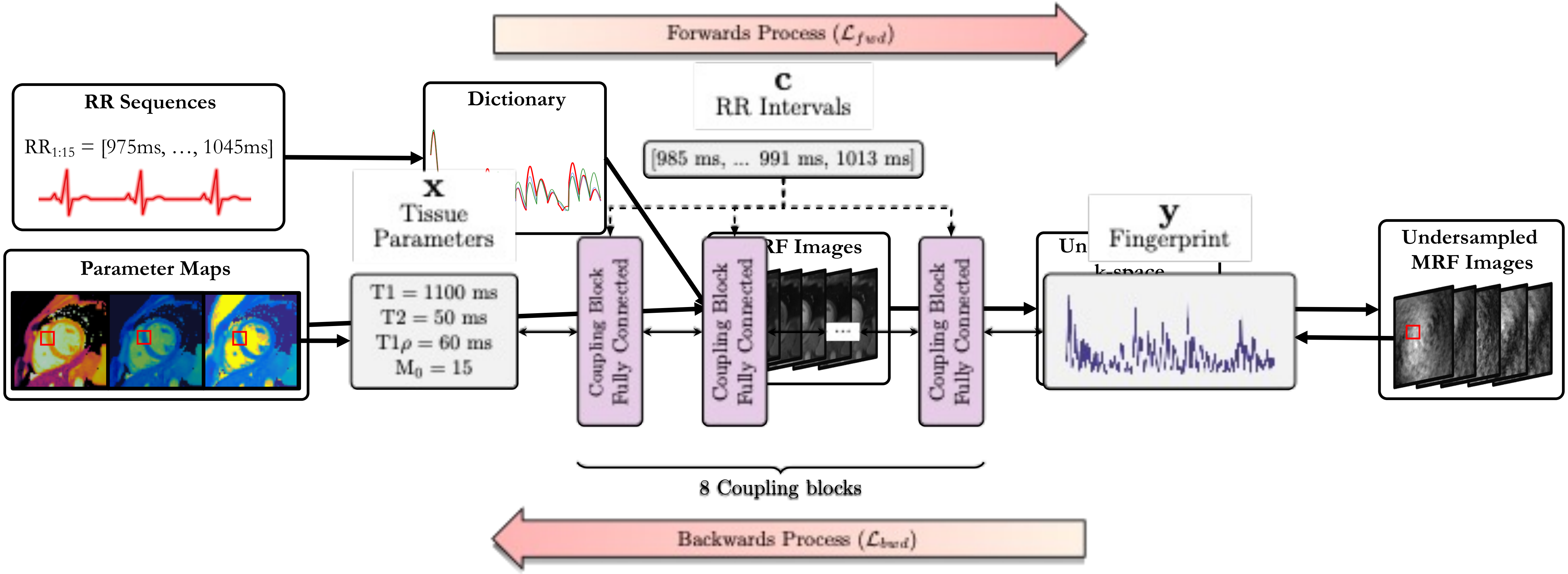
- Invertible Neural Networks (INNs)[7] use the well-defined forwards process and learn to disentangle ambiguous cases for the backwards process.

- INNs outperform competing networks for a wide range of inverse problems in natural science[7], including MRF[8]



Training

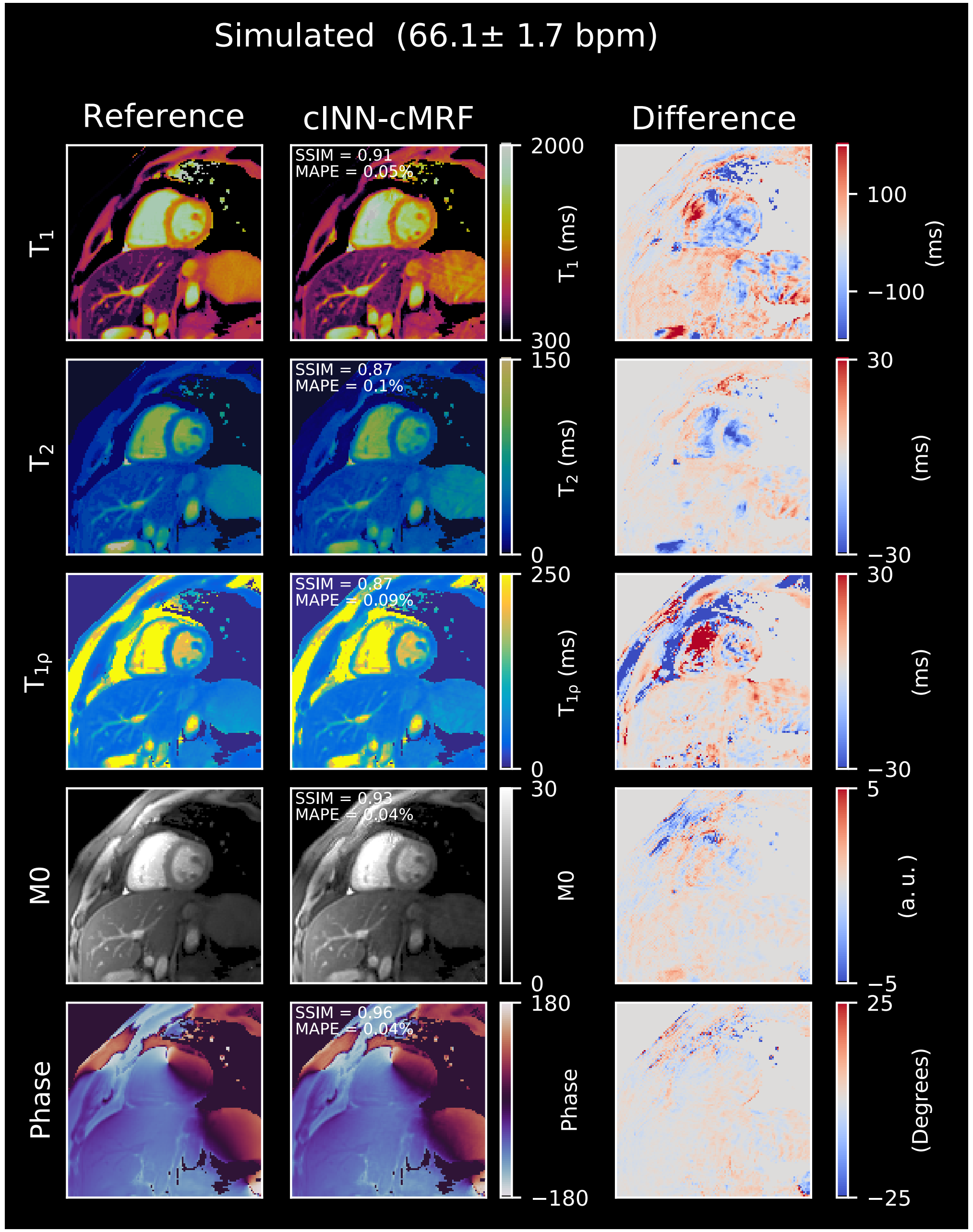
- Reconstructed maps and RR sequences from patients are used to simulate undersampled images for a wide variety of cardiac rhythms



$$\mathcal{L}_{total} = \mathcal{L}_{fwd} + \lambda_2 \cdot \mathcal{L}_{bwd}$$

Experiments

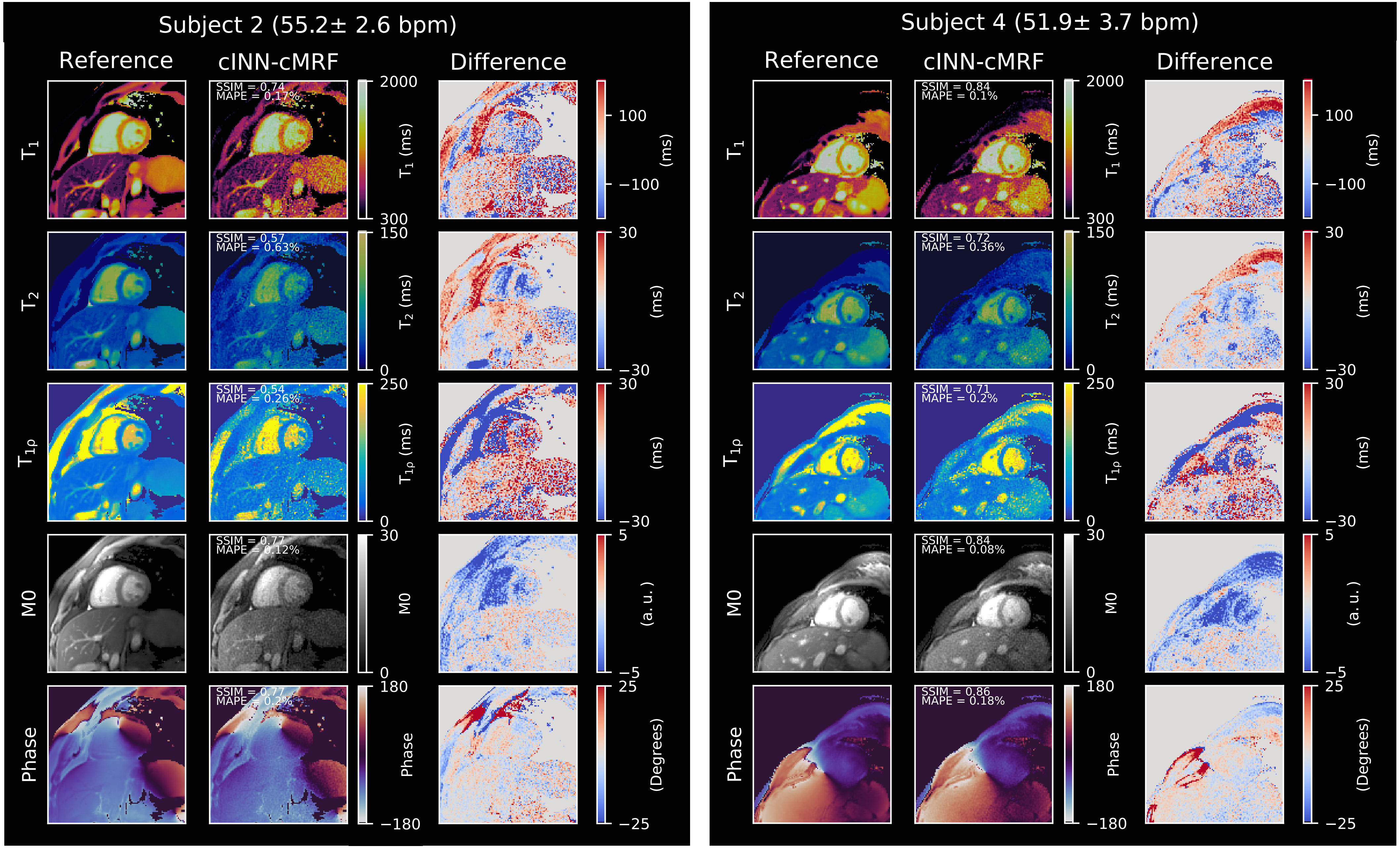
- Use >1000 RR sequences for 10 sets of cardiac MRF maps to simulate >15 million unique fingerprints
- Experiment 1 – Simulated data. Evaluate cINN-cMRF on undersampled simulated data unseen during training
- Experiment 2 – *in-vivo* data. Evaluate cINN-cMRF on undersampled *in-vivo* data for a map not seen during training or validation
- Compare to maps reconstructed with low rank inversion and iterative reconstruction.



Results – *in-vivo*

- Good quality maps obtained on unseen *in-vivo* data in 3.2 seconds without a dictionary

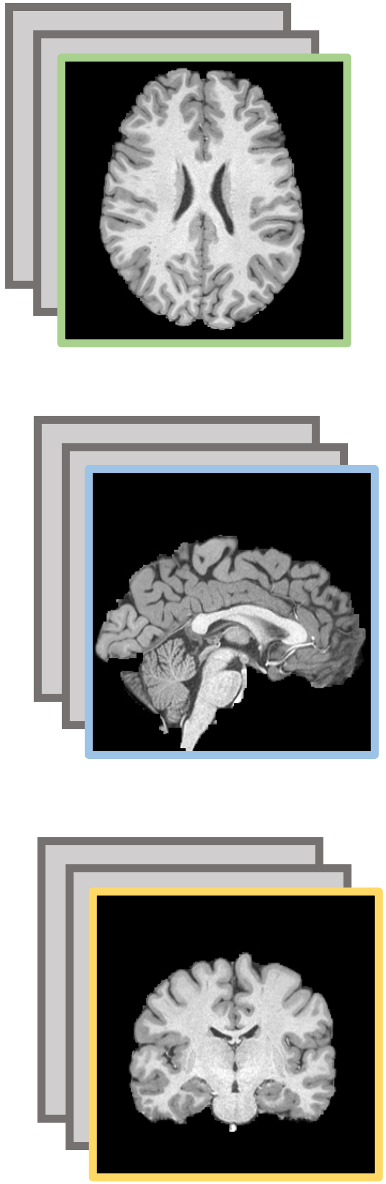
- Mean relative errors for myocardium of ~5-10%



Motion-Robust and Efficient fMRI

Motion-Robust and Efficient fMRI

IMPERIAL



Aim: Reconstruct 3D+t fMRI volume from motion-corrupted slices