Learning to reconstruct accelerated dynamic MRI without ground-truth

Andrew Wang[1], Mike Davies[1]

[1] Institute for Imaging, Data and Communications, School of Engineering, University of Edinburgh

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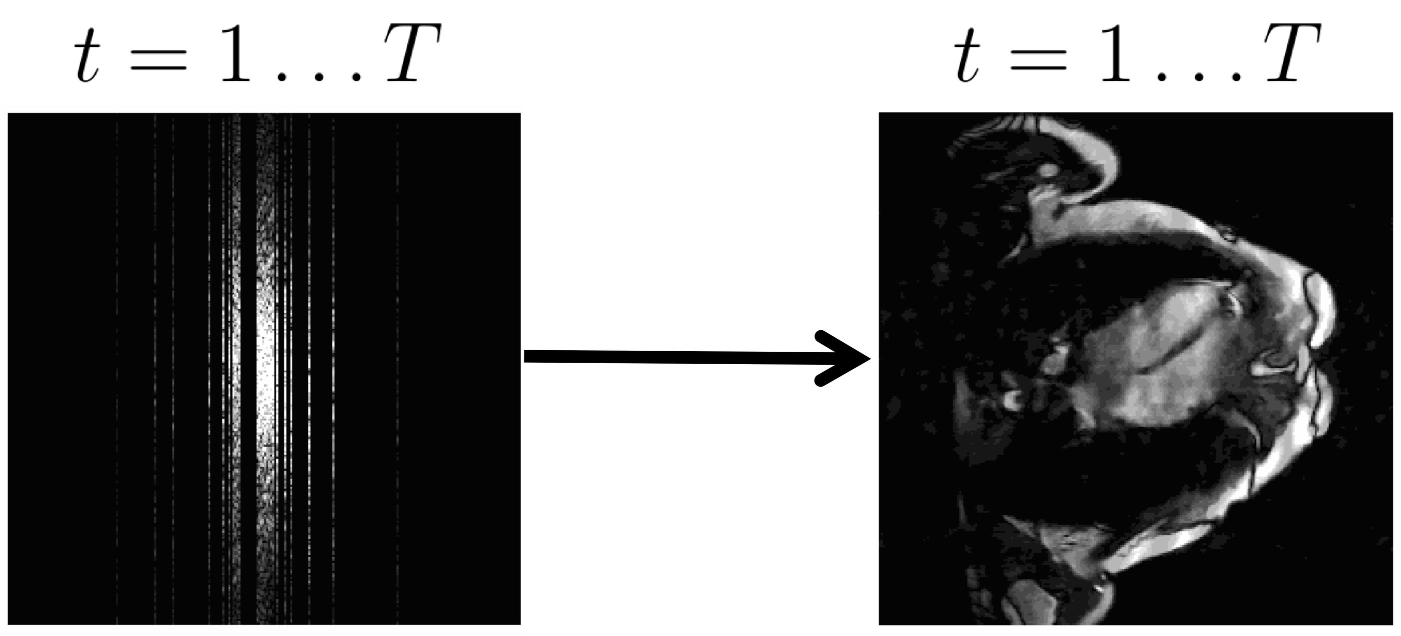
Introduction

We want to reconstruct dynamic MRI sequences **x** from undersampled k-space measurements **y** w/o ground truth:

$$\mathbf{y}_t = \mathbf{A}_t \mathbf{x}_t + \epsilon$$

$$\mathbf{A}_t = \mathbf{M}_t \mathbf{F}$$

$$\mathbf{y}_t \in \mathbb{R}^m, \mathbf{x}_t \in \mathbb{R}^n, m \ll n$$



$$y \longrightarrow \boxed{f_\theta} \longrightarrow \hat{x}$$

Applications: real-time cardiac imaging, free-breathing motion, vocal tract…

Challenge: ground truth fully spatiotemporally sampled sequences impossible to truly obtain.

Classical paradigm: cine imaging (assumes periodicity)

Supervised learning: use cine as GT – data crime! Can never learn true motion or arrhythmias.

Background

Supervised learning *(CineNet, diffusion models etc.)*:

$$\mathcal{L}_{\text{sup}} = \|\hat{\mathbf{x}} - \mathbf{x}_{\text{GT}}\|_2^2$$

Unsupervised with measurement consistency (MC):

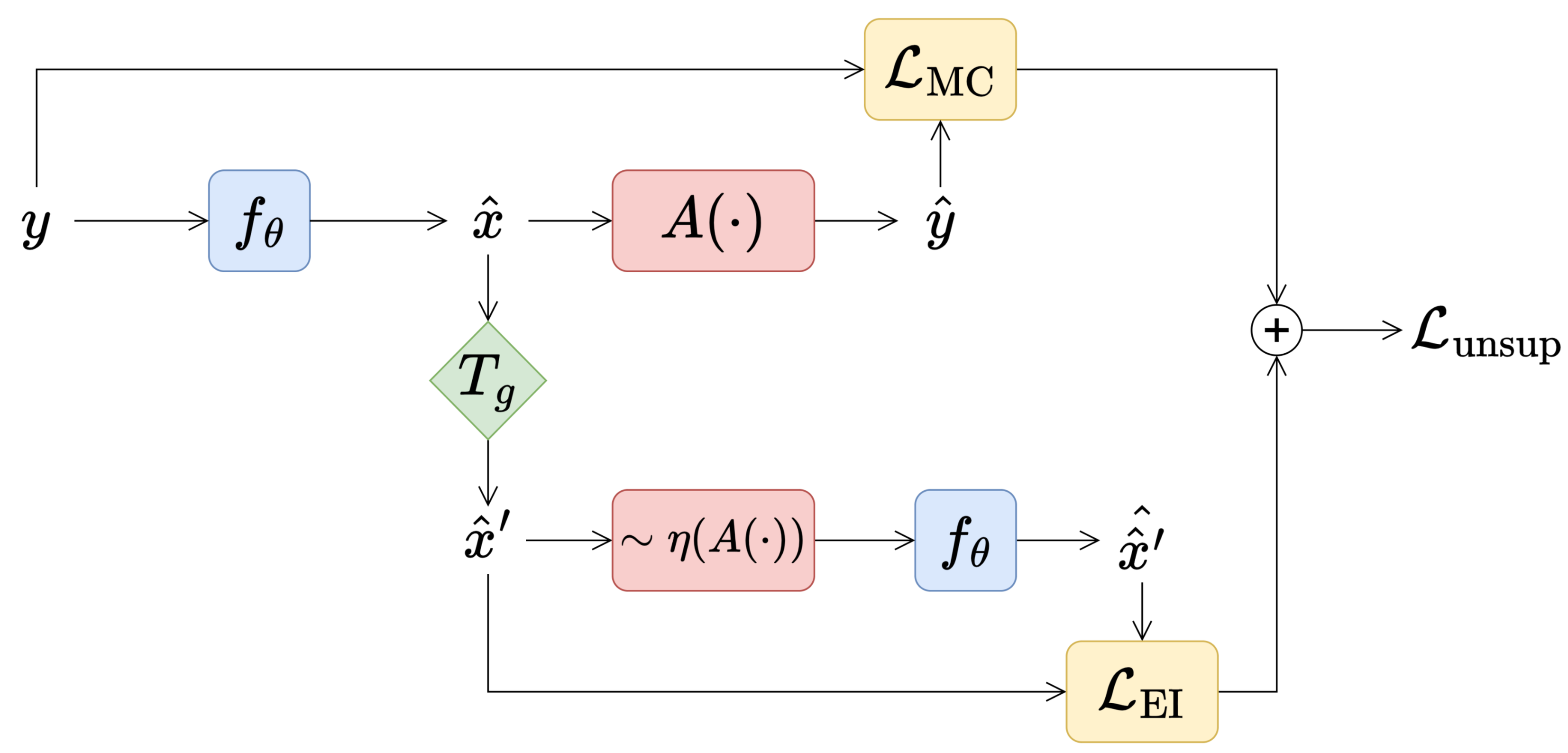
$$\mathcal{L}_{\text{MC}} = \|\mathbf{A}\hat{\mathbf{x}} - \mathbf{y}\|_2^2$$

Unsupervised with Equivariant Imaging (EI) [1]:

$$\forall \mathbf{x} \in \mathcal{X}, g \in G \quad \mathbf{T}_g \mathbf{x} \in \mathcal{X}$$

$$f(\mathbf{A}\mathbf{T}_g \mathbf{x}) = \mathbf{T}_g f(\mathbf{A}\mathbf{x})$$

$$\mathcal{L}_{\text{EI}} = \mathcal{L}_{\text{MC}} + \|\mathbf{T}_g \hat{\mathbf{x}} - f_\theta(\mathbf{A}\mathbf{T}_g \hat{\mathbf{x}})\|_2^2$$

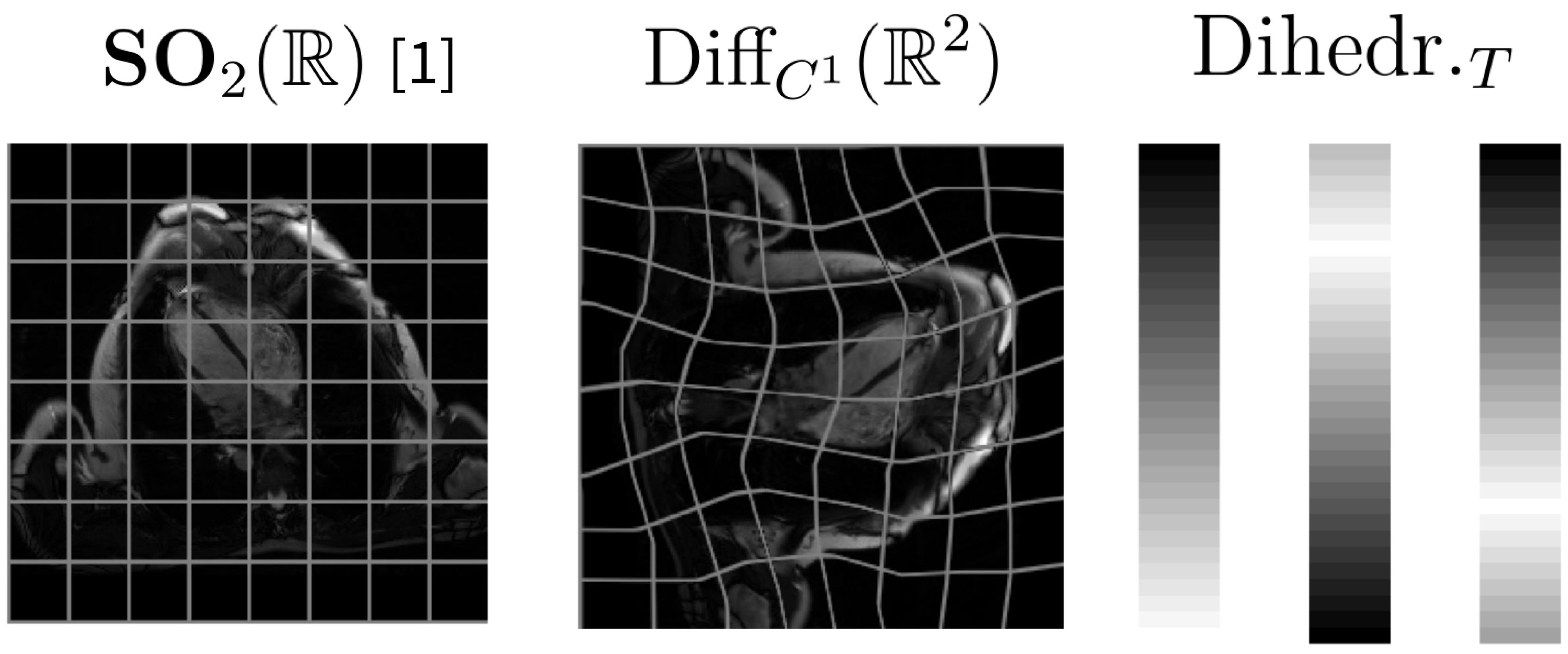


Project page, code & videos

DeepInverse library

Dynamic Diffeomorphic Equivariant Imaging

DDEI: naturally assume that the unknown image set of MRI image sequences is invariant to groups G:



Implementation: continuous piecewise-affine-based diffeomorphisms [2]; **DeepInverse** library (see above)

Results

Experiment: 8x retrospective Cartesian undersampling, CMRxRecon 2023 challenge dataset [3], f_θ = CRNN [4]

Competitors: SSDU methods [5] $\mathcal{L}(\mathbf{M}_2\mathbf{A}f_\theta(\mathbf{M}_1\mathbf{y}, \mathbf{M}_1\mathbf{A}), \mathbf{M}_2\mathbf{y})$

	Loss	PSNR	SSIM
baselines	ZF	28.0±0	0.683±0
	MC	28.0±0	0.683±0
Competitors	t-SSDU [5]	18.8±0	0.509±0
	t-SSDU*	29.6±0	0.691±0
SO(2) only [1]	EI-$\mathcal{R}$otate [1]	30.8±0	0.793±0
	DDEI (ours)	**33.9**±0	**0.880**±0
	(Oracle sup)	35.8±0	0.888±0

Future work

- Train from raw, real k-space with true irregular motion?
- How to evaluate without ground truth?

References

[1] D. Chen, J. Tachella, M. Davies, *Equivariant Imaging: Learning Beyond the Range Space*, ICCV 2021

[2] O. Freifeld et al., *Transformations based on continuous piecewise-affine velocity fields*, TPAMI 2017

[3] C. Wang, J. Lyu, S. Wang et al., *CMRxRecon [...]*, Scientific Data, 2024

[4] C. Qin et al., *Convolutional recurrent neural networks […]*, TMI 2018

[5] Acar et al., *Self-supervised Dynamic MRI Reconstruction*, MLMIR 2021

Andrew Wang

andrew.wang@ed.ac.uk