Adaptive Correspondence Scoring for Unsupervised Medical Image Registration

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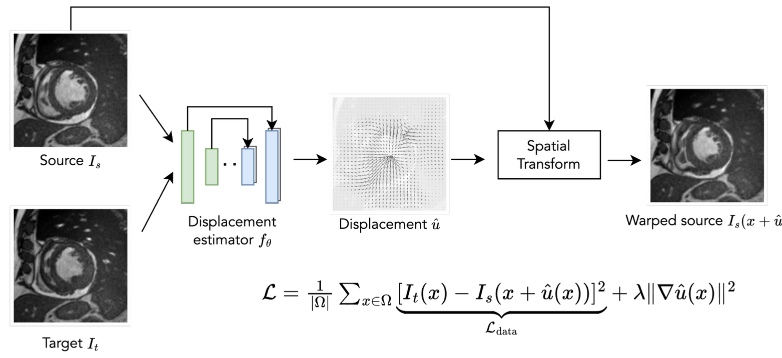
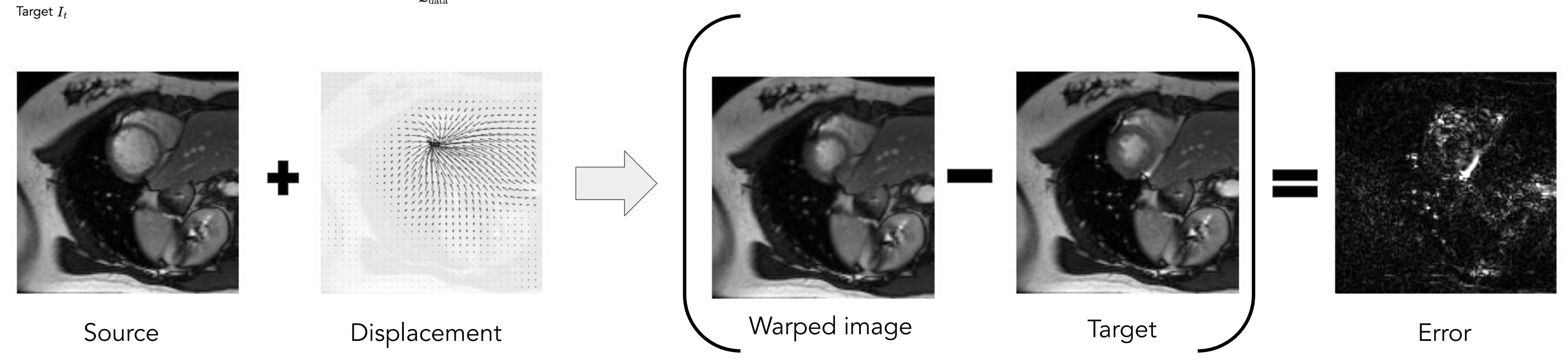
Project page

Paper

Introduction

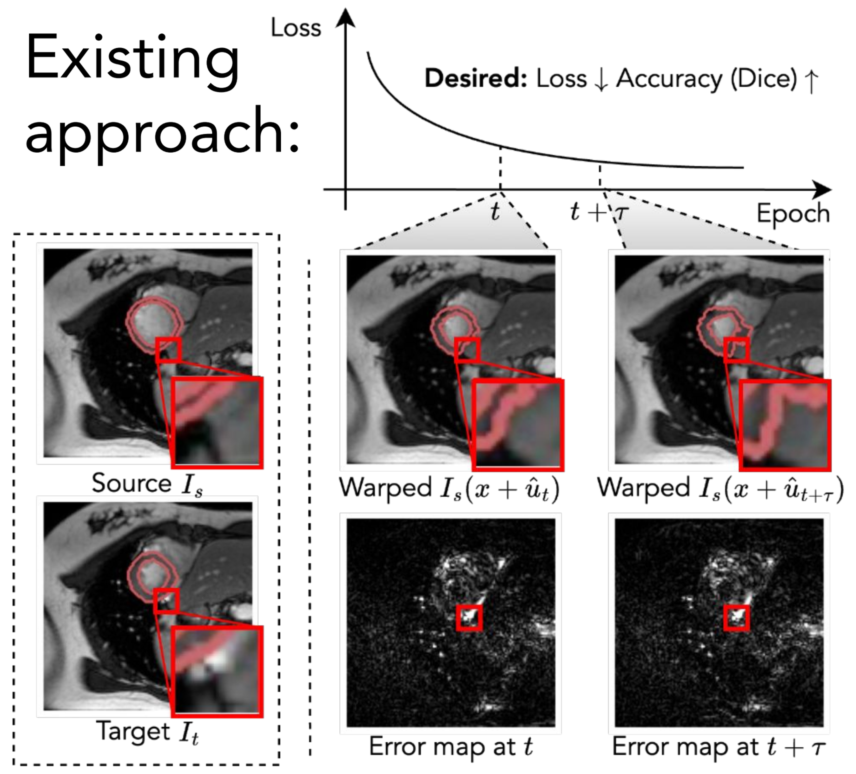


- Unsupervised registration aims to align two images without any labels.
- It enables accurate tracking of changes, label propagation, improved diagnosis, and enhanced treatment planning.



- Even with the "perfect" displacement, the error between the warped and target is still non-zero.

Motivation



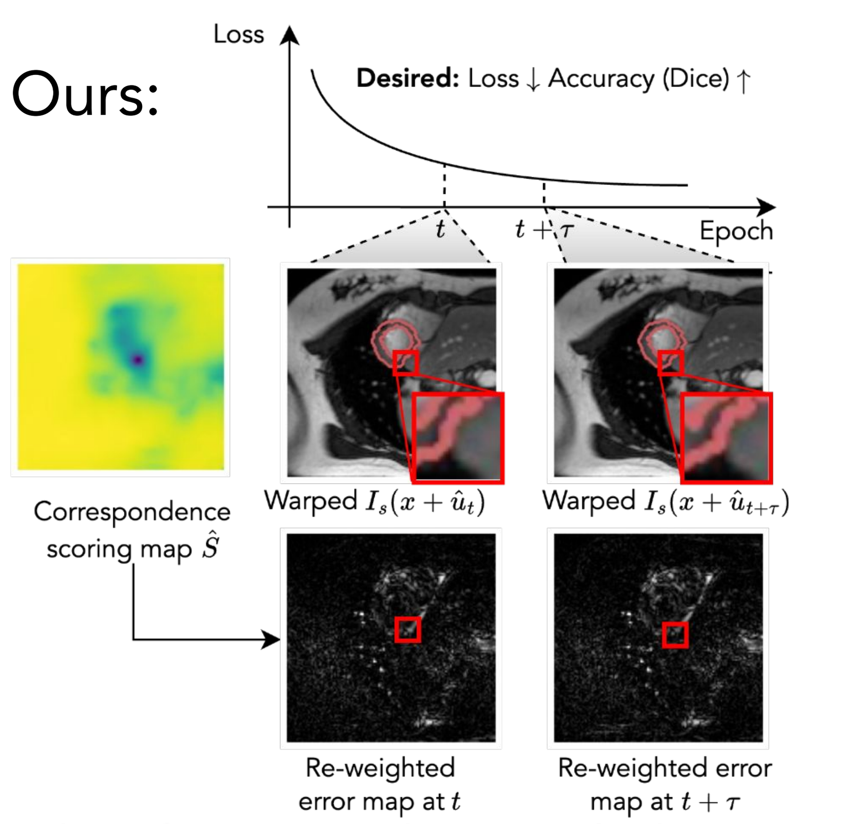
Irreconcilable penalties due to absence of correspondence

⇓

Intensity constancy assumption violated

⇓

Loss ↓ Accuracy (Dice) ↓



Identify regions that may lack correspondence

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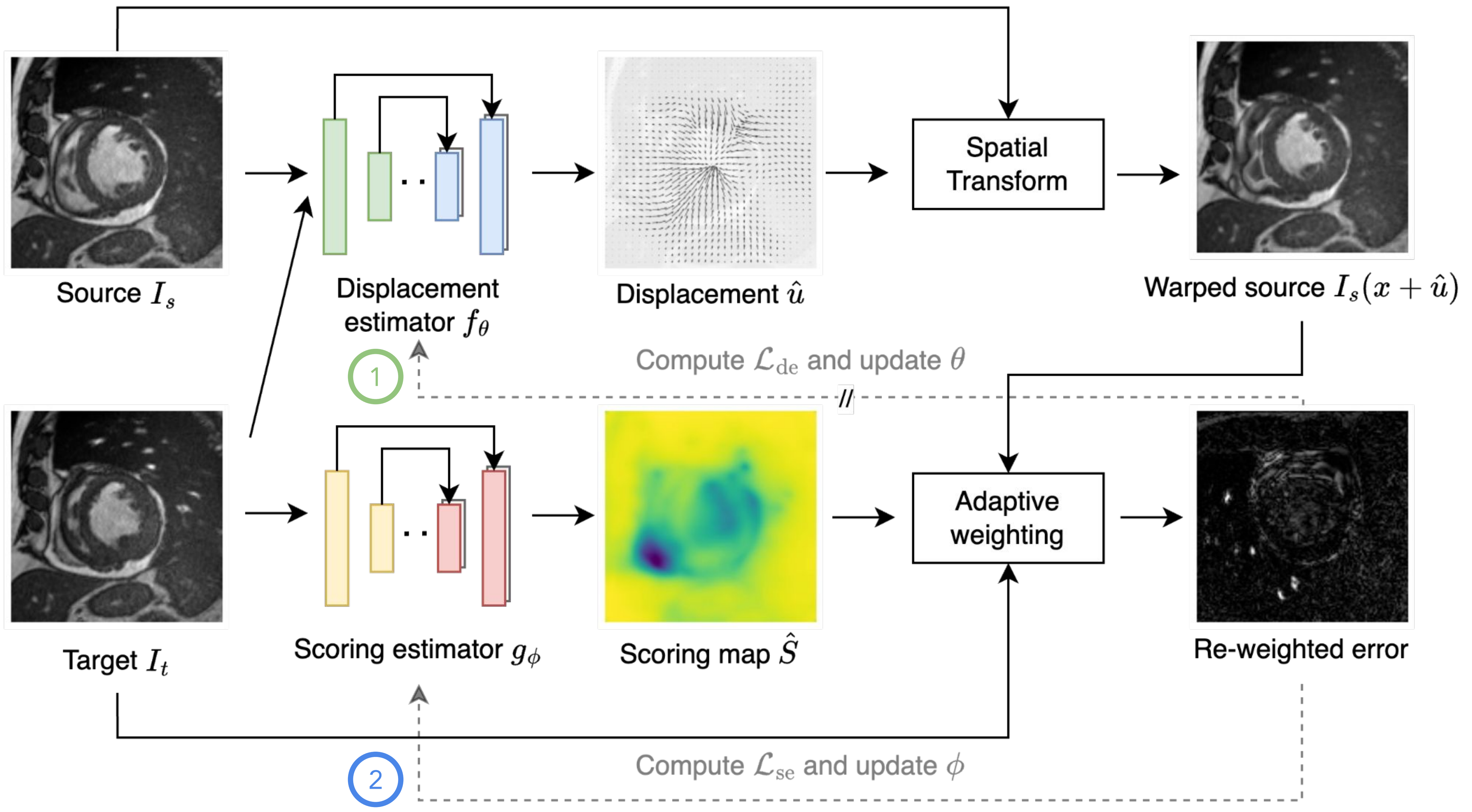
Re-weight loss with correspondence scoring to regularize outliers

⇓

Loss ↓ Accuracy (Dice) ↑

Methods



Our approach can be plugged-and-played into existing frameworks with no extra cost during inference.

**Note: The displacement and scoring estimators are optimized in separate alternating steps 1 and 2

Displacement estimator loss: $\mathcal{L}_{\text{de}} = \frac{1}{|\Omega|}\sum_{x\in\Omega}\lfloor\hat{S}(x)\rfloor[I_t(x) - I_s(x+\hat{u}(x))]^2 + \lambda\|\nabla\hat{u}(x)\|^2$

Scoring estimator loss: $\mathcal{L}_{\text{se}} = \mathcal{L}_{\text{ucs}} + \alpha\mathcal{L}_{\text{reg}} + \beta\mathcal{L}_{\text{smooth}}$

$\mathcal{L}_{\text{ucs}}$:Unsupervised correspondence scoring

$$\mathcal{L}_{\text{ucs}} = \frac{1}{|\Omega|}\sum_{x\in\Omega}\hat{S}(x)[I_t(x) - I_s(x + \lfloor\hat{u}(x)\rfloor)]$$

- Encourage the estimator to assign a lower score to regions with higher error residuals.

$\mathcal{L}_{\text{reg}}$:Scoring estimator regularization

$$\mathcal{L}_{\text{reg}} = \frac{1}{|\Omega|}\sum_{x\in\Omega}[1 - \hat{S}(x)]^2$$

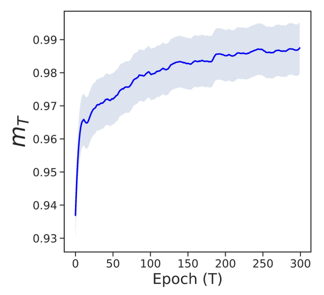
- Regularize the scoring map to avoid the trivial solution of all zeros.

$\mathcal{L}_{\text{smooth}}$:Momentum-guided smoothness

Mean residual: $\mu_T = \frac{1}{|\Omega|}\sum_{x\in\Omega}[I_t(x) - I_s(x + \lfloor\hat{u}_T(x)\rfloor)]^2$

Momentum: $b_T = \cos\frac{\pi}{2}\mu_T; m_T = \gamma m_{T-1} + (1-\gamma)b_T$

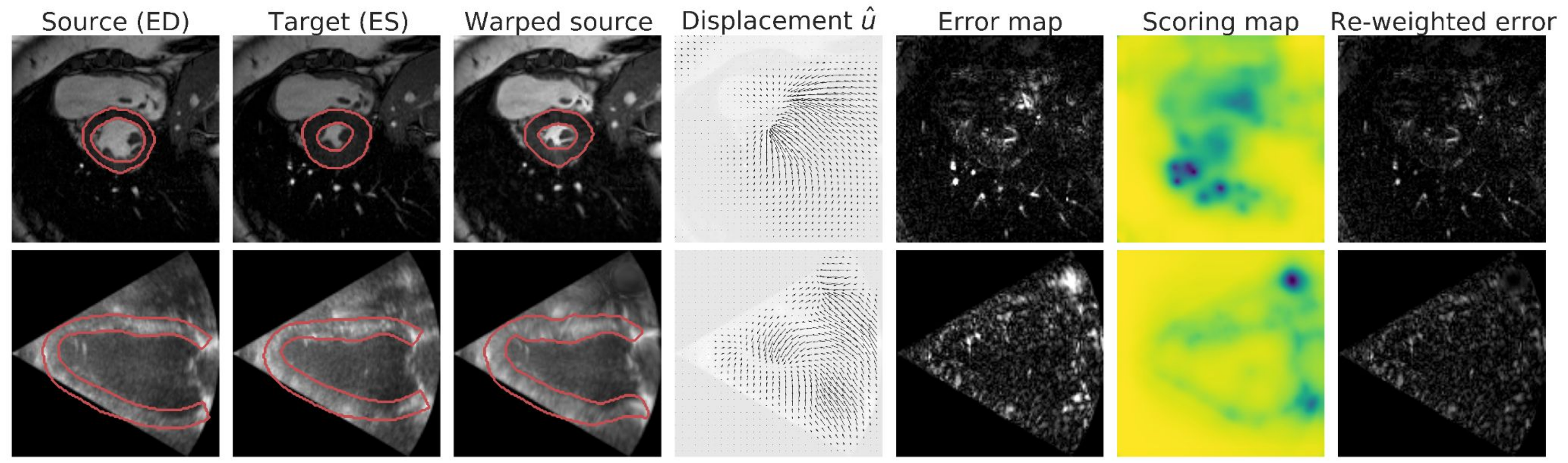
$$\mathcal{L}_{\text{smooth}} = m_T\frac{1}{|\Omega|}\sum_{x\in\Omega}\|\nabla\hat{S}(x)\|^2$$



- We treat residuals as a proxy for time
- We use momentum-guided adaptive regularization to encourage exploration during early steps and exploitation during later steps

Results

Scoring map visualization



Quantitative evaluation

		ACDC			CAMUS		
		DSC ↑	HD ↓	ASD ↓	DSC ↑	HD ↓	ASD ↓
	Undeformed	47.98	7.91	2.32	66.77	10.87	2.61
	Elastix	77.26	4.95	1.28	80.18	10.02	1.81
CNN	Voxelmorph	79.48	4.79	1.27	81.50	8.72	1.74
CNN	NLL	76.49	5.46	1.45	75.24	11.05	2.20
CNN	β-NLL	78.74	5.07	1.33	79.75	9.39	1.93
CNN	AdaFrame	66.38	5.80	1.67	77.88	10.54	1.93
CNN	AdaReg	78.75	5.13	1.33	79.31	9.78	1.88
CNN	AdaCS (Ours)	**80.50**	**4.69**	**1.23**	**81.74**	**8.55**	**1.72**
Transformer	Transmorph	76.94	5.51	1.30	79.24	10.30	**1.79**
Transformer	NLL	73.12	7.22	**1.27**	75.08	11.60	**1.79**
Transformer	β-NLL	75.74	6.12	1.29	77.39	10.99	1.86
Transformer	AdaFrame	67.95	5.72	1.59	78.06	9.86	1.91
Transformer	AdaReg	76.22	5.68	1.29	78.12	10.62	1.84
Transformer	AdaCS (Ours)	**78.39**	**5.40**	1.32	**79.64**	**9.85**	**1.79**
Diffusion	Diffusemorph	67.38	5.80	1.67	75.23	**9.80**	2.07
Diffusion	NLL	66.24	5.84	1.73	74.78	10.62	2.15
Diffusion	β-NLL	66.31	5.93	1.74	73.27	9.85	2.25
Diffusion	AdaFrame	59.78	6.46	1.93	75.04	10.41	2.10
Diffusion	AdaReg	69.41	6.25	1.78	74.36	10.66	2.21
Diffusion	AdaCS (Ours)	**72.09**	**5.35**	**1.53**	**77.65**	9.82	**1.99**

Smoothness

	ACDC			CAMUS		
	DSC ↑	$\lvert J_{\hat{u}}\rvert \le 0$ ↓	T_{train}	DSC ↑	$\lvert J_{\hat{u}}\rvert \le 0$ ↓	T_{train}
Voxelmorph	79.48 ± 9.23	0.29	0.26	81.50 ± 5.58	0.60	0.26
AdaCS (Ours)	**80.50 ± 8.58**	0.22	0.43	**81.74 ± 5.36**	0.30	0.43
Transmorph	76.94 ± 8.93	0.76	0.60	79.24 ± 6.06	1.41	0.59
AdaCS (Ours)	**78.39 ± 9.06**	0.57	0.87	**79.64 ± 6.37**	0.70	0.70
Diffusemorph	67.38 ± 15.65	0.05	1.08	75.23 ± 8.71	0.05	1.06
AdaCS (Ours)	**72.09 ± 13.60**	0.06	1.86	**77.65 ± 7.64**	0.08	1.91

Ablation

	Loss		ACDC			CAMUS		
	$\mathcal{L}_{\text{reg}}$	$\mathcal{L}_{\text{smooth}}$	DSC ↑	HD ↓	ASD ↓	DSC ↑	HD ↓	ASD ↓
vxm	✓	✗	80.24	**4.64**	1.23	81.58	8.89	1.74
vxm	✓	✓	**80.50**	4.69	**1.23**	**81.74**	**8.55**	**1.72**
tsm	✓	✗	77.84	5.41	1.33	79.58	10.17	1.81
tsm	✓	✓	**78.39**	**5.40**	**1.32**	**79.64**	**9.85**	**1.79**
dfm	✓	✗	71.62	5.56	1.58	77.32	9.71	2.00
dfm	✓	✓	**72.09**	**5.35**	**1.53**	**77.65**	**9.82**	**1.99**

Comparison with robust losses

		ACDC			CAMUS		
		DSC ↑	HD ↓	ASD ↓	DSC ↑	HD ↓	ASD ↓
vxm	NCC	78.55	4.94	1.29	77.01	10.23	1.89
vxm	MI	78.04	5.25	1.35	78.18	9.83	1.99
vxm	TBL	79.31	**4.64**	**1.23**	81.18	8.91	**1.72**
vxm	MAE	78.27	5.36	1.43	78.59	10.23	1.97
vxm	MSE	79.48	4.79	1.27	81.50	8.72	1.74
vxm	AdaCS	**80.50**	4.69	**1.23**	**81.74**	**8.55**	**1.72**
tsm	NCC	73.77	6.64	1.12	73.03	11.87	**1.70**
tsm	MI	73.57	6.57	**1.11**	74.83	11.94	1.83
tsm	TBL	78.23	**5.11**	1.27	79.12	**9.75**	1.84
tsm	MAE	74.30	6.36	1.28	75.96	11.35	1.89
tsm	MSE	76.94	5.51	1.30	79.24	10.30	1.79
tsm	AdaCS	**78.39**	5.40	1.32	**79.64**	9.85	1.79
dfm	NCC	70.25	**5.29**	1.58	75.67	10.75	2.06
dfm	MI	71.16	5.40	1.56	76.19	10.09	2.16
dfm	TBL	69.12	5.73	1.63	76.05	**9.54**	2.06
dfm	MAE	66.30	5.75	1.71	77.30	10.36	2.09
dfm	MSE	67.38	5.80	1.67	75.23	9.80	2.07
dfm	AdaCS	**72.09**	5.35	**1.53**	**77.65**	9.82	**1.99**

Our proposed approach consistently outperforms baselines in various architectures and datasets and produces reasonably smooth displacement.

Application - cardiac strain analysis

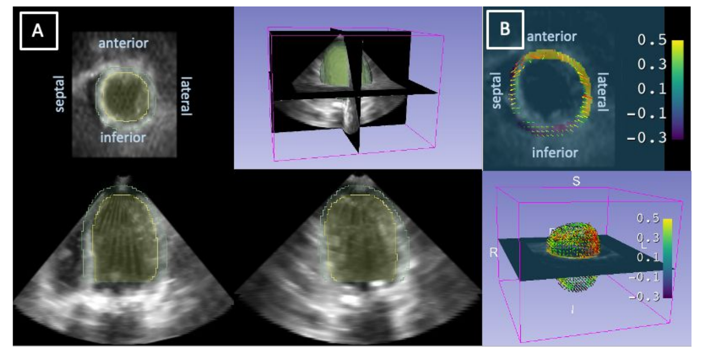


Figure: A) Segmented clinical echo (rest); B) Rest radial strain overlayed with estimated displacement revealing akinetic septal and inferior walls.

We produce regional cardiac strain map that can be used to identify myocardial infarction.

Paper: https://arxiv.org/abs/2312.00837

Code: https://github.com/Voldemort108X/AdaCS

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