https://github.com/Voldemort108X/AdaCS

Yale

EUROPEAN CONFERENCE ON COMPUTER VISION

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Project page

Adaptive Correspondence Scoring for Unsupervised Medical Image Registration

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Yale University

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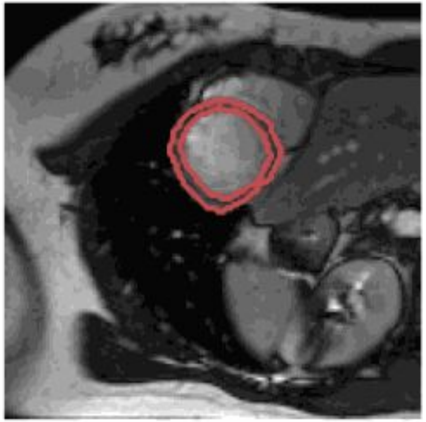
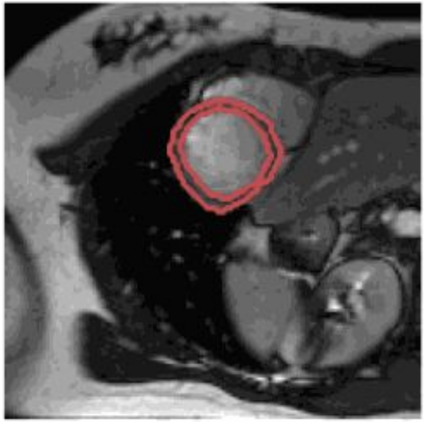
Tracking Anatomies Over Time



MRI video with only
ED label

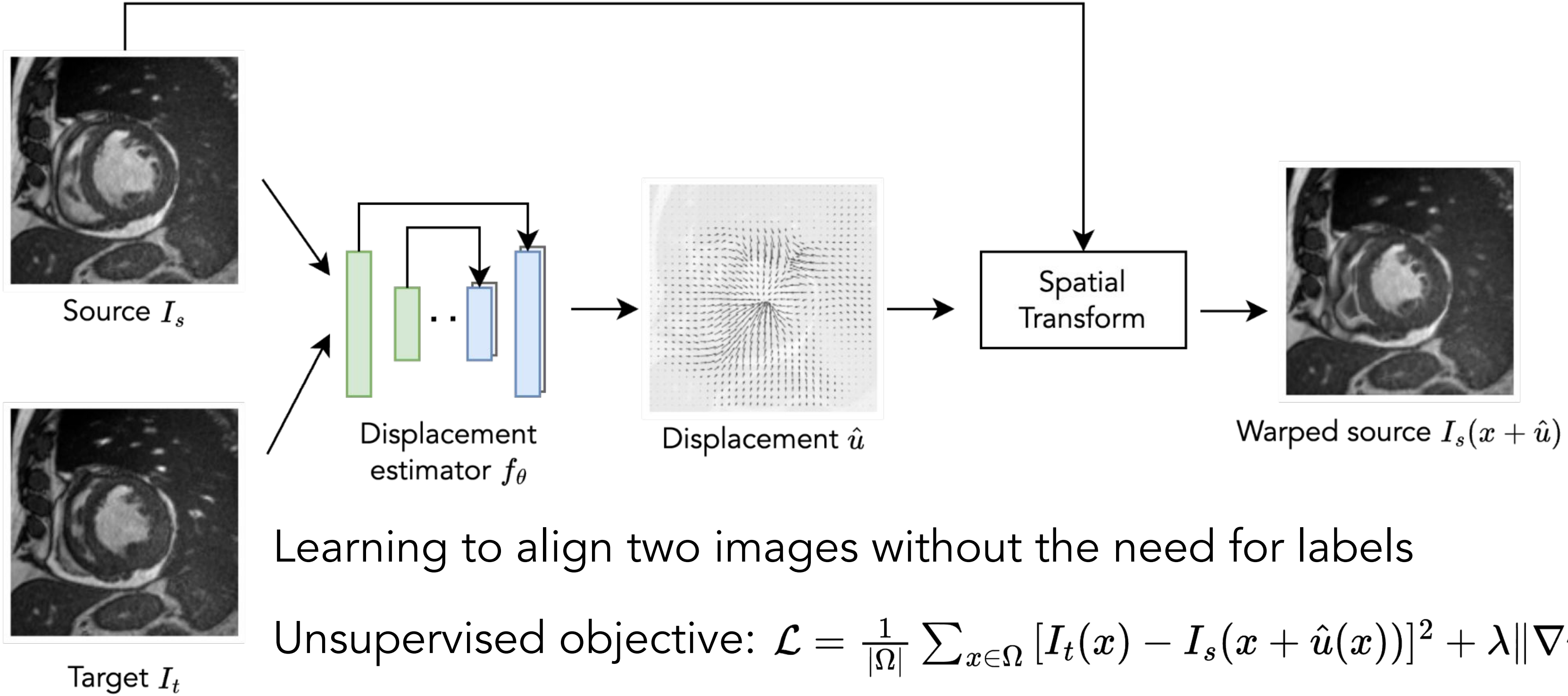
Estimated displacement



MRI video with
propagated labels

Unsupervised image registration enables accurate tracking of changes, label propagation, improved diagnosis, and enhanced treatment planning.

Unsupervised Image Registration



Learning to align two images without the need for labels

Unsupervised objective: $\mathcal{L} = \frac{1}{|\Omega|}\sum_{x\in\Omega}\left[I_t(x) - I_s(x+\hat{u}(x))\right]^2 + \lambda\|\nabla\hat{u}(x)\|^2$

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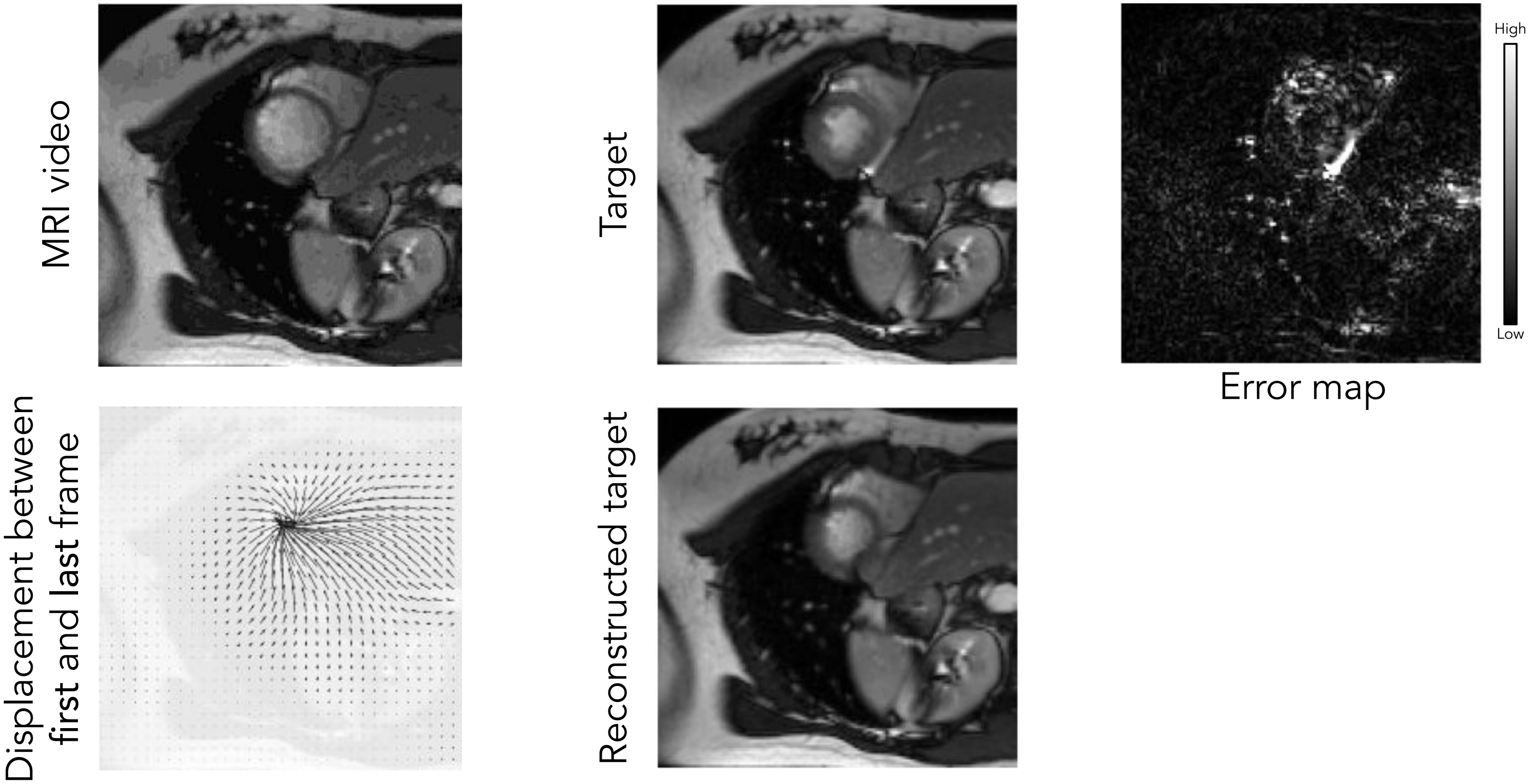
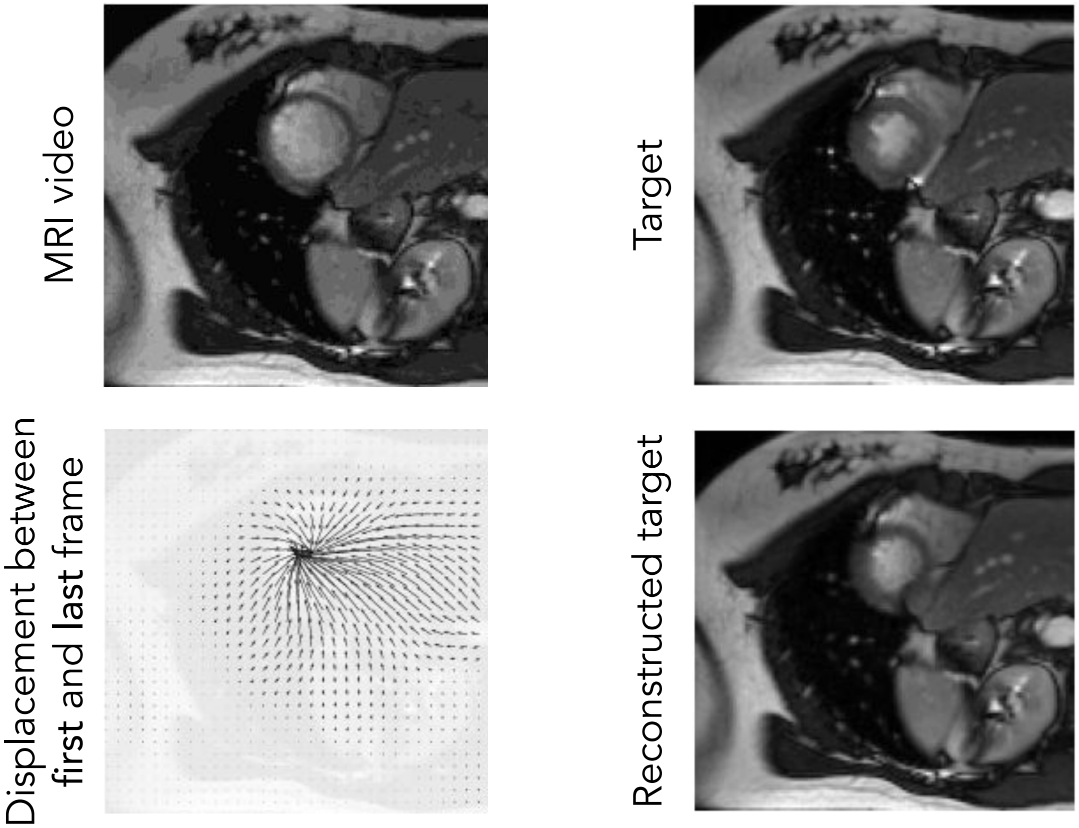
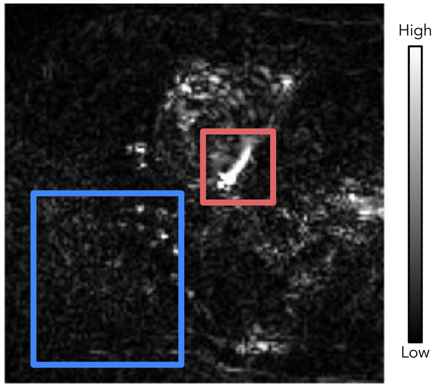
Violations of Basic Assumptions



Violations of Basic Assumptions





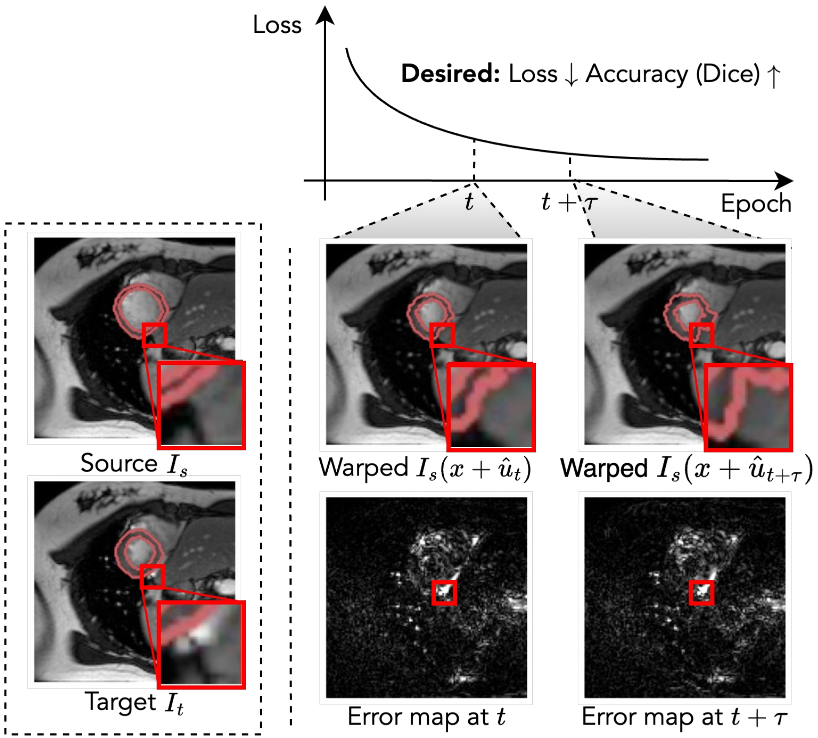
Error map

Occlusions

Heteroscedastic noise

… and many others

A Closer Look



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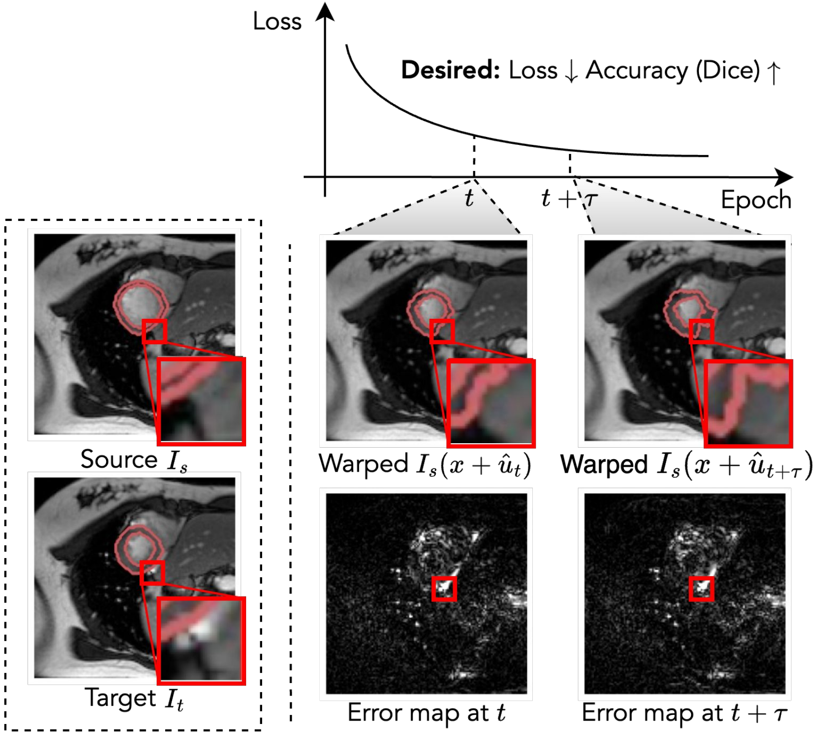
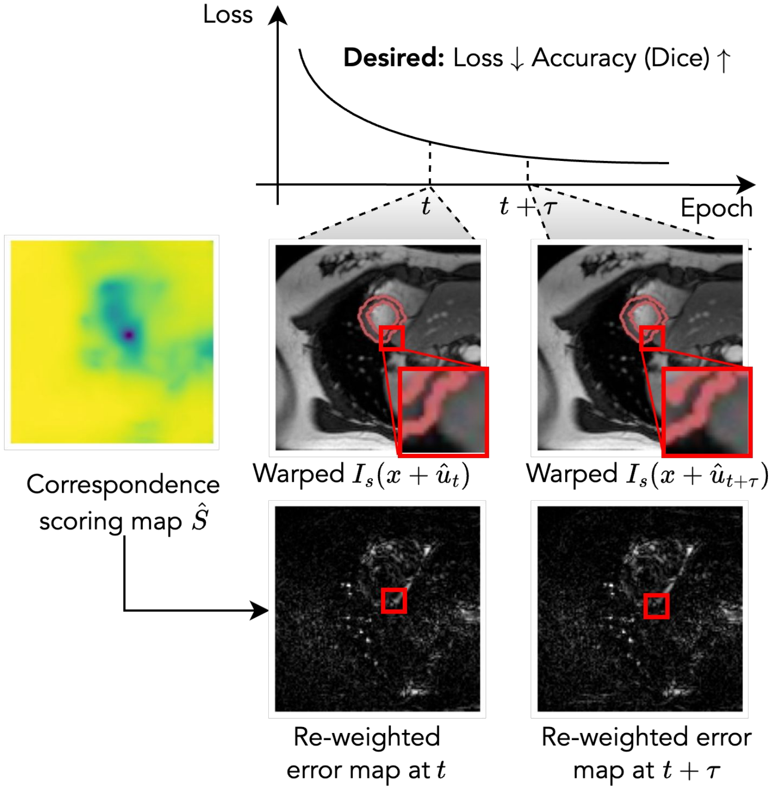
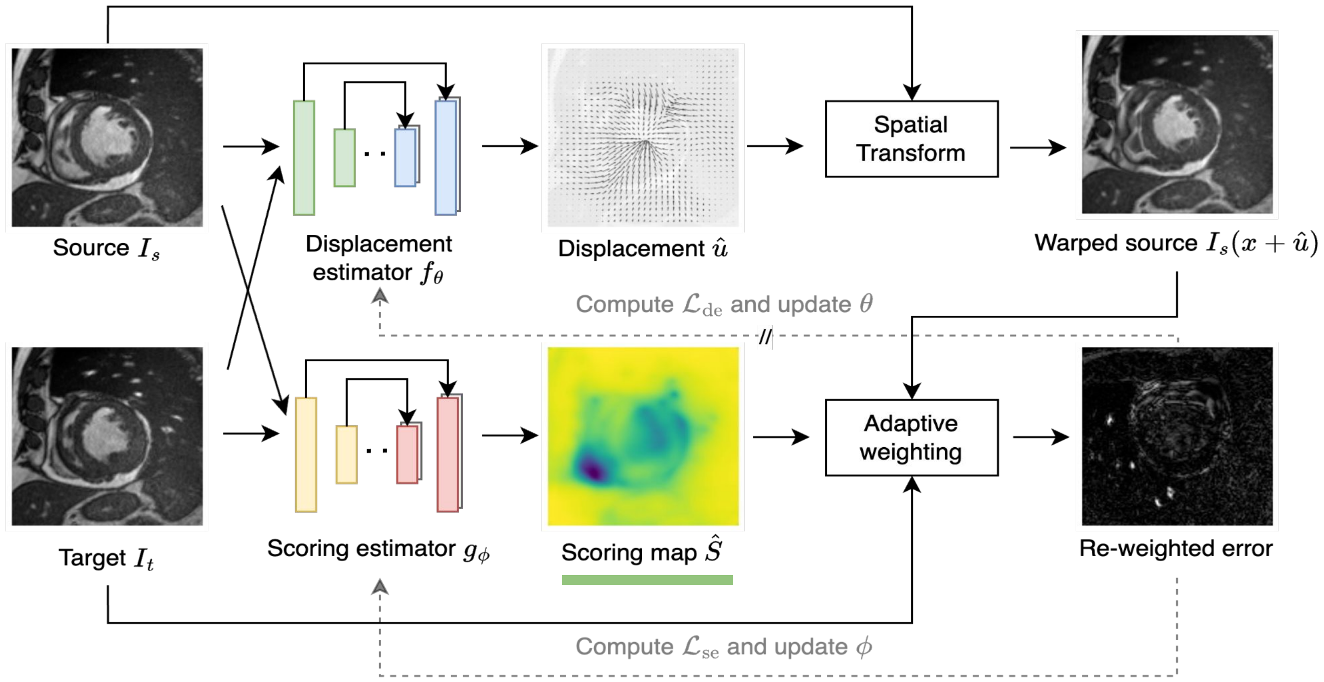
A Closer Look



Our approach:



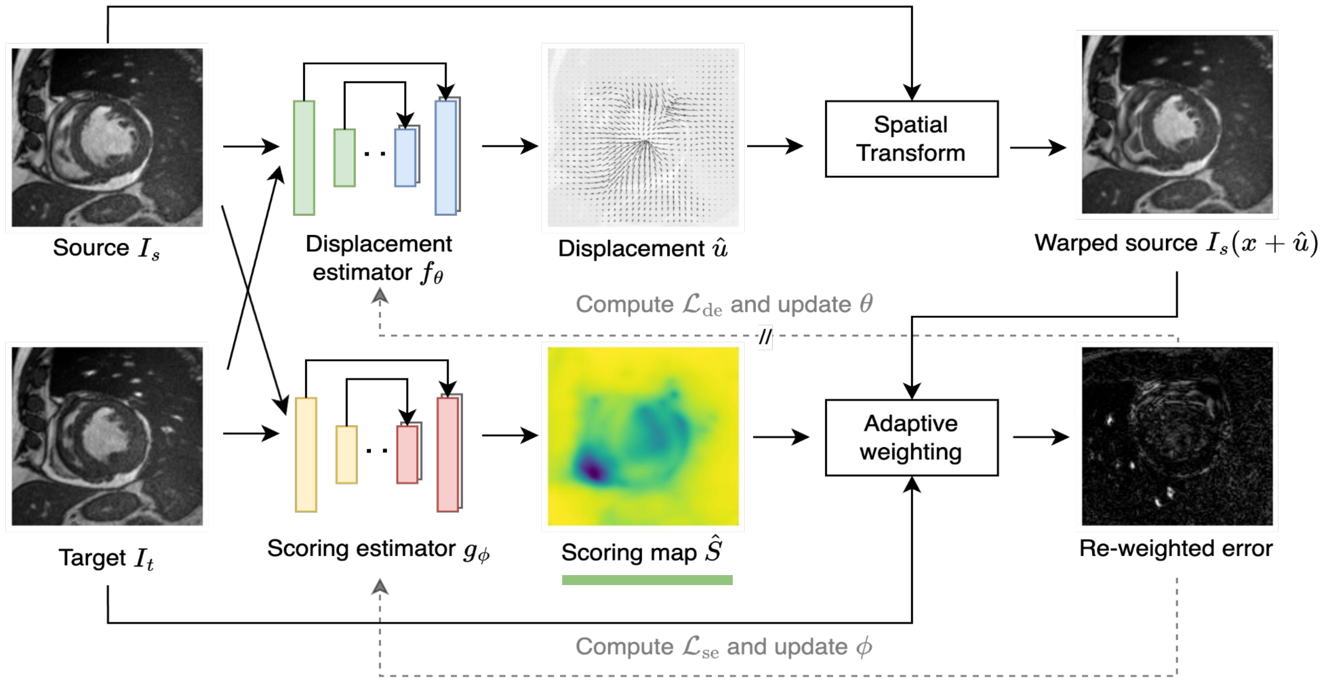
Method



But there is a trivial solution…

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

Method



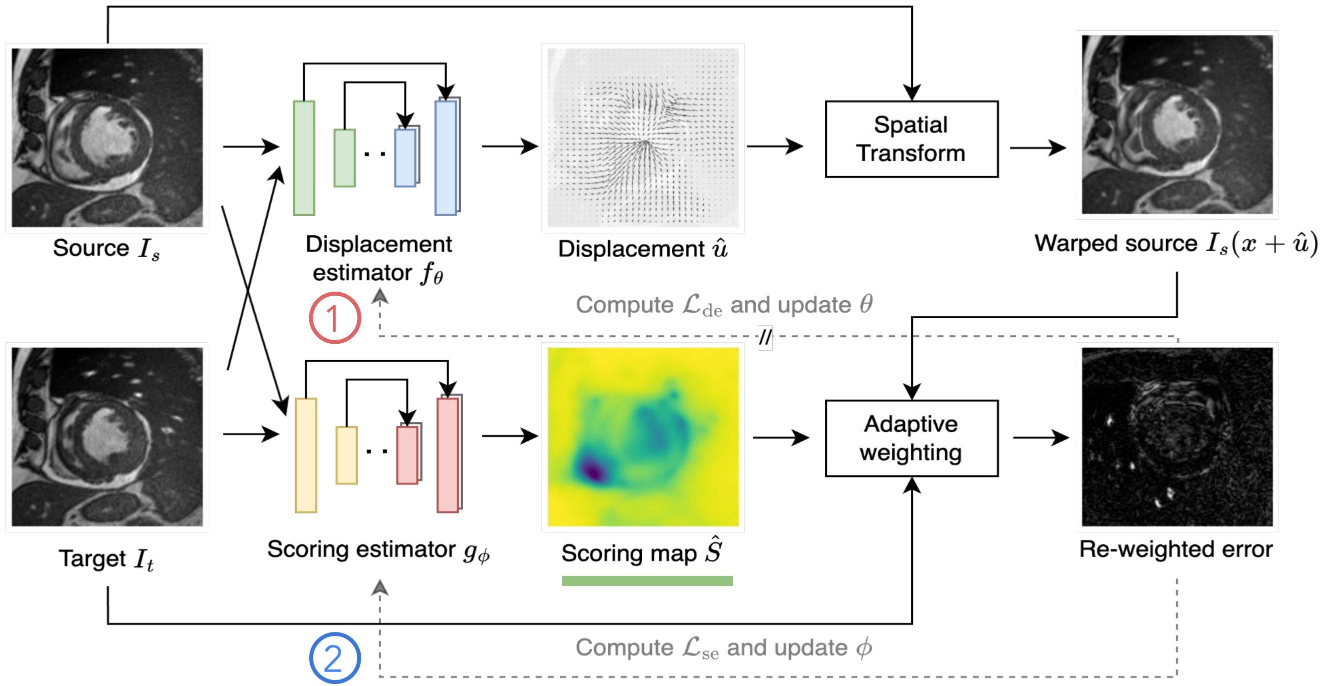
Avoid trivial solution:

$$\frac{1}{|\Omega|} \sum_{x \in \Omega} [1 - \hat{S}(x)]^2$$

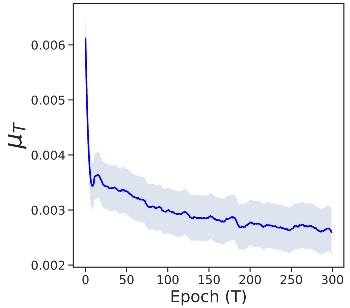
Scores correspond to surfaces that are locally smooth:

$$\frac{1}{|\Omega|} \sum_{x \in \Omega} \|\nabla \hat{S}(x)\|^2$$

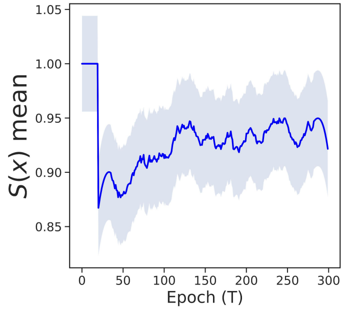
Method



Average residuals:



Average scores:



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

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

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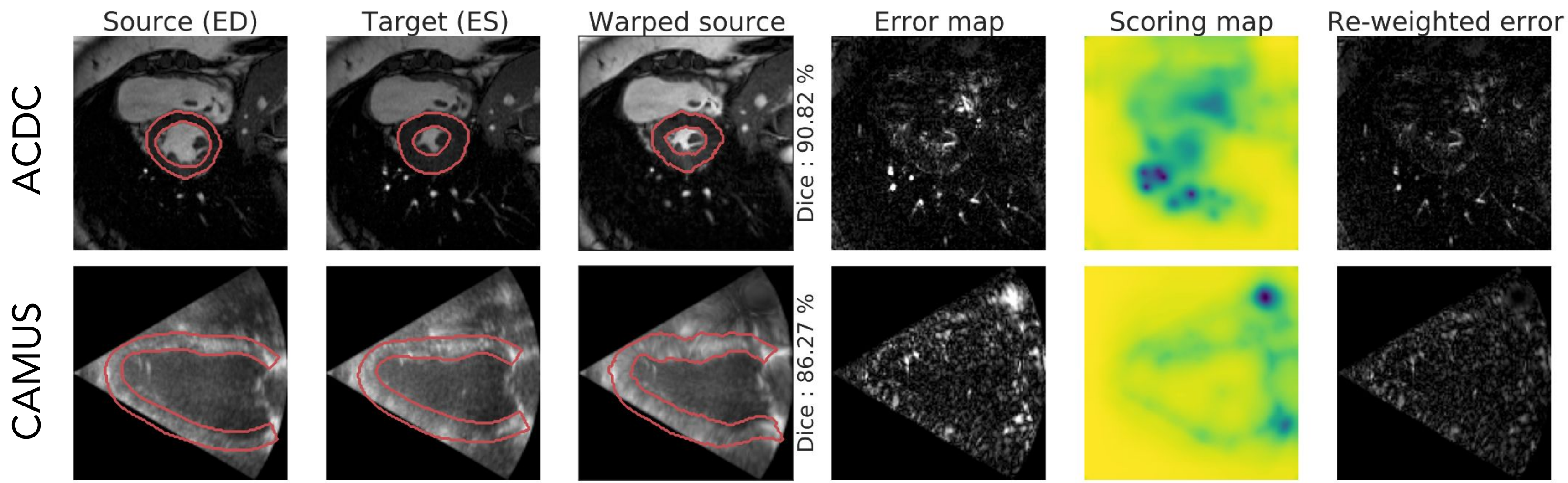
Results on ACDC and CAMUS



Our estimated scoring map identifies spurious error residuals and prevents parameter drift during training.

Results on ACDC and CAMUS

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
	NLL	76.49	5.46	1.45	75.24	11.05	2.20
	β-NLL	78.74	5.07	1.33	79.75	9.39	1.93
	AdaFrame	66.38	5.80	1.67	77.88	10.54	1.93
	AdaReg	78.75	5.13	1.33	79.31	9.78	1.88
	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**
	NLL	73.12	7.22	**1.27**	75.08	11.60	**1.79**
	β-NLL	75.74	6.12	1.29	77.39	10.99	1.86
	AdaFrame	67.95	5.72	1.59	78.06	9.86	1.91
	AdaReg	76.22	5.68	1.29	78.12	10.62	1.84
	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
	NLL	66.24	5.84	1.73	74.78	10.62	2.15
	β-NLL	66.31	5.93	1.74	73.27	9.85	2.25
	AdaFrame	59.78	6.46	1.93	75.04	10.41	2.10
	AdaReg	69.41	6.25	1.78	74.36	10.66	2.21
	AdaCS (Ours)	**72.09**	**5.35**	**1.53**	**77.65**	9.82	**1.99**

Comparison to robust losses

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

Smoothness

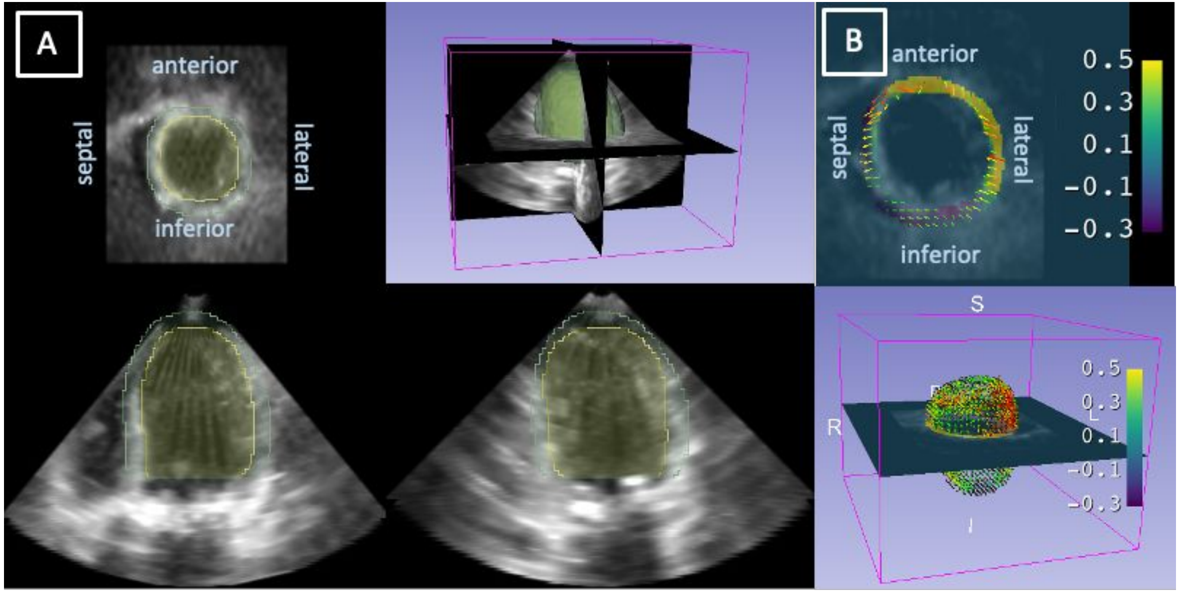
	ACDC			CAMUS		
	DSC ↑	$\lvert J_{\hat{u}} \rvert \leq 0$ ↓	T_{train}	DSC ↑	$\lvert J_{\hat{u}} \rvert \leq 0$ ↓	T_{train}
Voxelmorph	79.48 ± 9.23	0.29	0.26	81.50 ± 5.58	0.60	0.26
AdaCS (Ours)	**80.50 ± 8.58**	0.22	0.43	**81.74 ± 5.36**	0.30	0.43
Transmorph	76.94 ± 8.93	0.76	0.60	79.24 ± 6.06	1.41	0.59
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
	✓	✓	**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
	✓	✓	**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
	✓	✓	**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



(A) Segmented clinical echo (rest)

(B) Rest radial strain overlayed with estimated displacement revealing akinetic septal and inferior walls

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Conclusion

Xiaoran Zhang

https://xiaoranzhang.com/

- We identify the limitation of the widely used unsupervised training objective

- We address this by proposing an adaptive correspondence scoring framework during training

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

Project page

Paper

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