GradICON: Approximate Diffeomorphisms via Gradient Inverse Consistency

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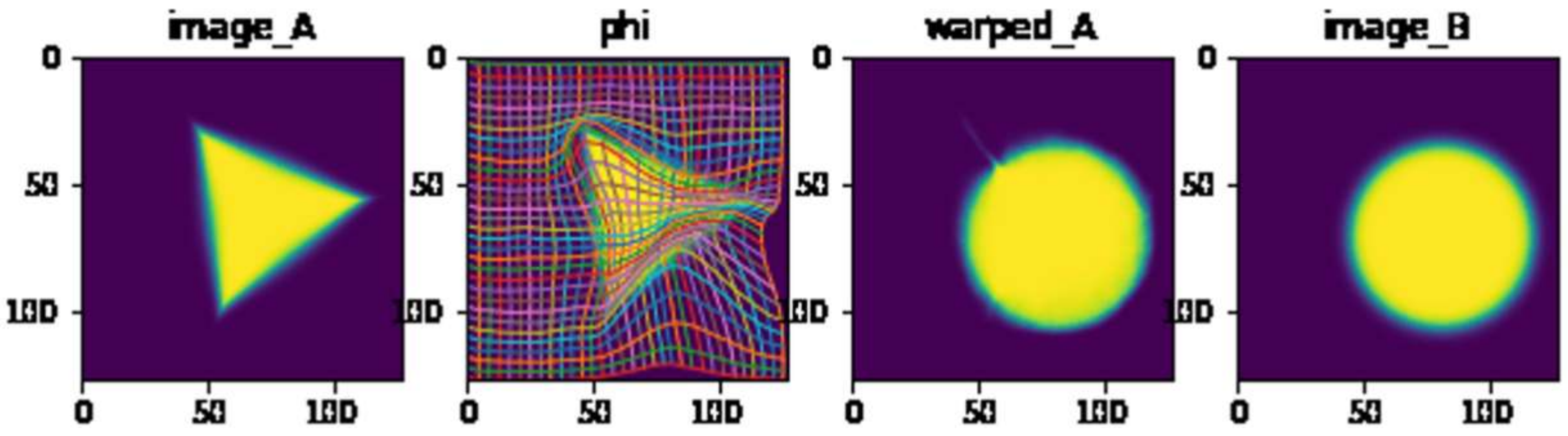
Summary

- Medical Image Registration
  - Finding Physically plausible spatial transformation between two images



Physically Plausible Transformation – One to one mapping without folding.

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Summary

When using displacement vector field (DVF)

~~Bending Energy~~ $\cancel{\mathcal{L}_{\text{reg}} = \sum_i ||\nabla^2((\Phi^{AB} - \text{Id})_i)||_F^2}$

~~Diffusion~~ $\cancel{\mathcal{L}_{\text{reg}} = ||\nabla(\Phi^{AB} - \text{Id})||_F^2}$

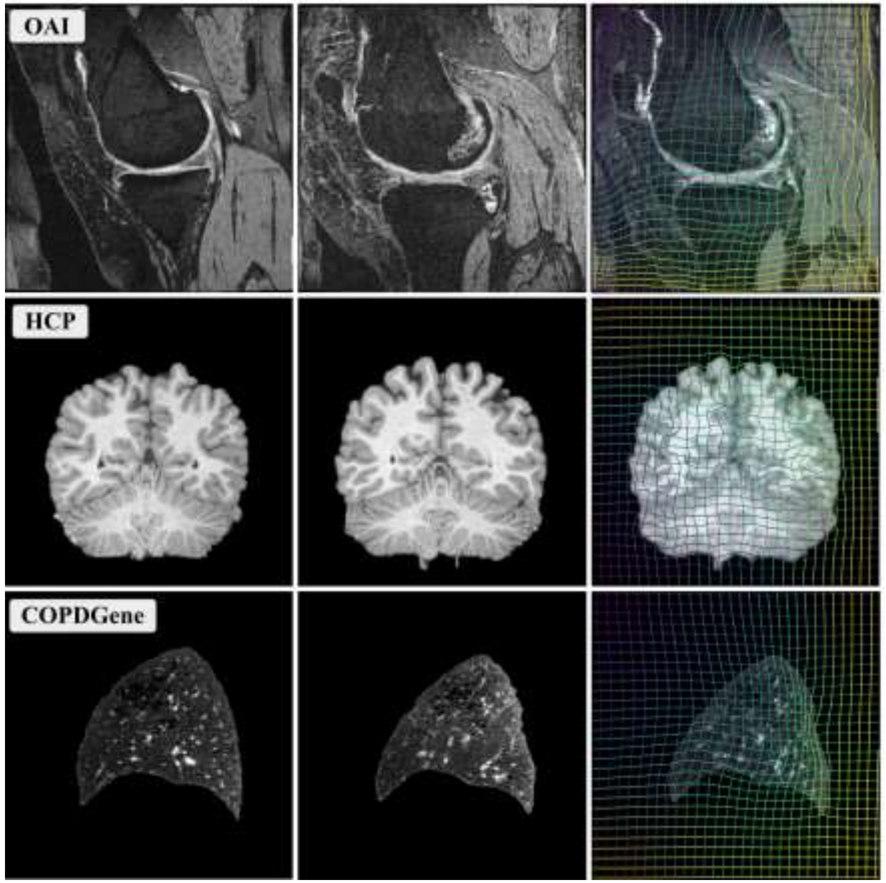
$$\mathcal{L}_{\text{reg}}^{\texttt{GradICON}} = \left\| \nabla \left[\Phi_\theta^{AB} \circ \Phi_\theta^{BA} \right] - \mathbf{I} \right\|_F^2$$

Gradient Inverse Consistency

Summary

Using Gradient Inverse Consistency as an implicit transformation regularizer results in

- Spatially regular maps
- Better registration accuracy on knee, brain and Lung registration tasks



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Background – Medical Image Registration

- Given a paired I^A and I^B, a registration neural network

$$\Phi^{AB} = \Phi[I^A, I^B]$$

aims to predict the transformation between I^A and I^B. We train such a neural network via

$$\theta^* = \arg\min_{\theta} \frac{1}{N} \sum_{i=1}^{N} \mathcal{L}_{\text{sim}} \left(I_i^A \circ \Phi_{\theta,i}^{AB}, I_i^B \right) + \lambda \mathcal{L}_{\text{reg}} (\Phi_{\theta,i}^{AB})$$

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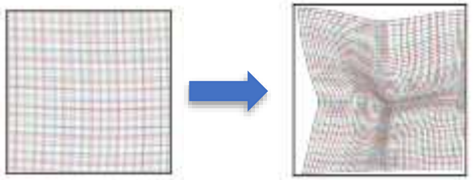
Previous Work

Displacement Vector Field (DVF) $\Phi^{AB} = Id + D$



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Limit large and complex deformation when trying to minimize them in the loss function.

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Previous Work

- ICON proposed and proved that inverse consistency on the map yields regularized transformation map

$$\mathcal{L}_{\text{inv}} = \left\|\Phi^{AB}_{\theta\varepsilon} \circ \Phi^{BA}_{\theta\varepsilon} - \mathrm{Id}\right\|_2^2 + \left\|\Phi^{BA}_{\theta\varepsilon} \circ \Phi^{AB}_{\theta\varepsilon} - \mathrm{Id}\right\|_2^2$$

But it has difficulty reduce percentage of folding to zero, especially when the resolution gets greater.

Gradient Inverse Consistency

$$\mathcal{L}_{\text{reg}}^{\texttt{GradICON}} = \left\| \nabla \left[\Phi_\theta^{AB} \circ \Phi_\theta^{BA} \right] - \mathbf{I} \right\|_F^2$$

- In theory, it is an implicit H^1 type regularization. (see paper)
- Empirically, we observe that it
  - converges faster
  - is less sensitive to varying lambda λ
- Thus, we can learn registration networks with the same architecture, same learning rate and same lambda across registration tasks (inter-patient and intra-patient).

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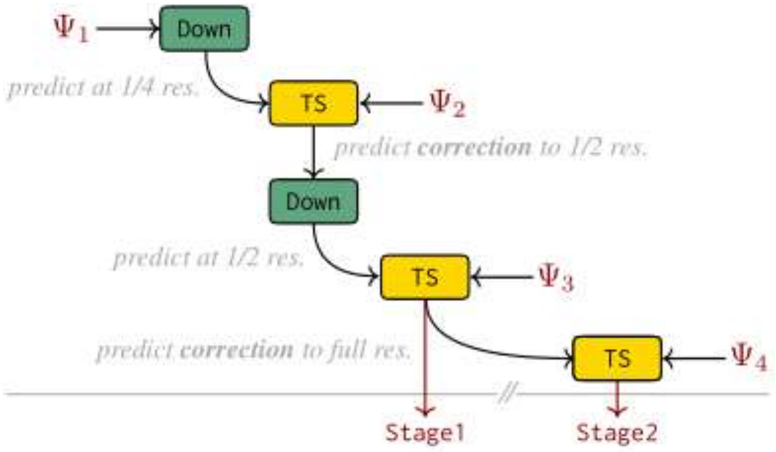
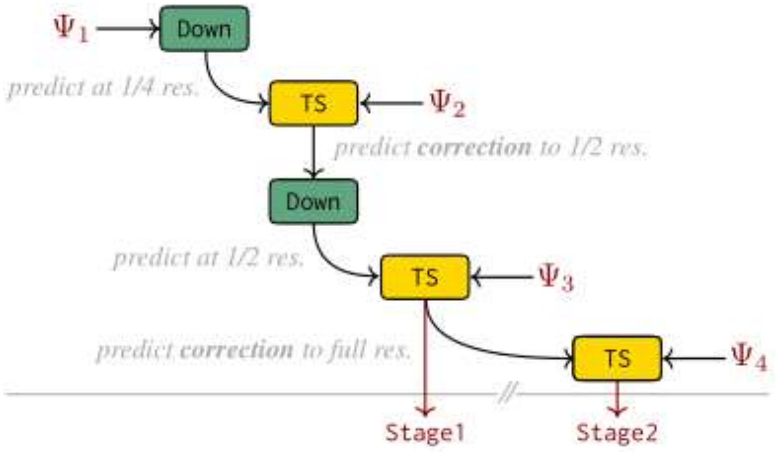
Mang, Andreas, and George Biros. "Constrained H^1-regularization schemes for diffeomorphic image registration." *SIAM journal on imaging sciences* 9.3 (2016): 1154-1194.

GradICON



A multi-step and multi-resolution network structure

GradICON



A multi-step and multi-resolution network structure

$$\begin{aligned}\mathcal{L} =& \mathcal{L}_{\text{sim}}(I^A \circ \Phi[I^A, I^B], I^B) + \\ & \mathcal{L}_{\text{sim}}(I^B \circ \Phi[I^B, I^A], I^A) + \\ & + \lambda \|\nabla(\Phi[I^A, I^B] \circ \Phi[I^B, I^A]) - \mathbf{I}\|_F^2\end{aligned}$$

Experiments

- Comparison to other regularizers
- Empirical convergence analysis
- Applications on three datasets
  - A knee MRI dataset of the Osteoarthritis Initiative (OAI)
  - The Human Connectome Project's collection of Young Adult brain MRIs (HCP)
  - A CT inhale/exhale lung dataset from COPDGene.

Better Trading off between Similarity and Regularity

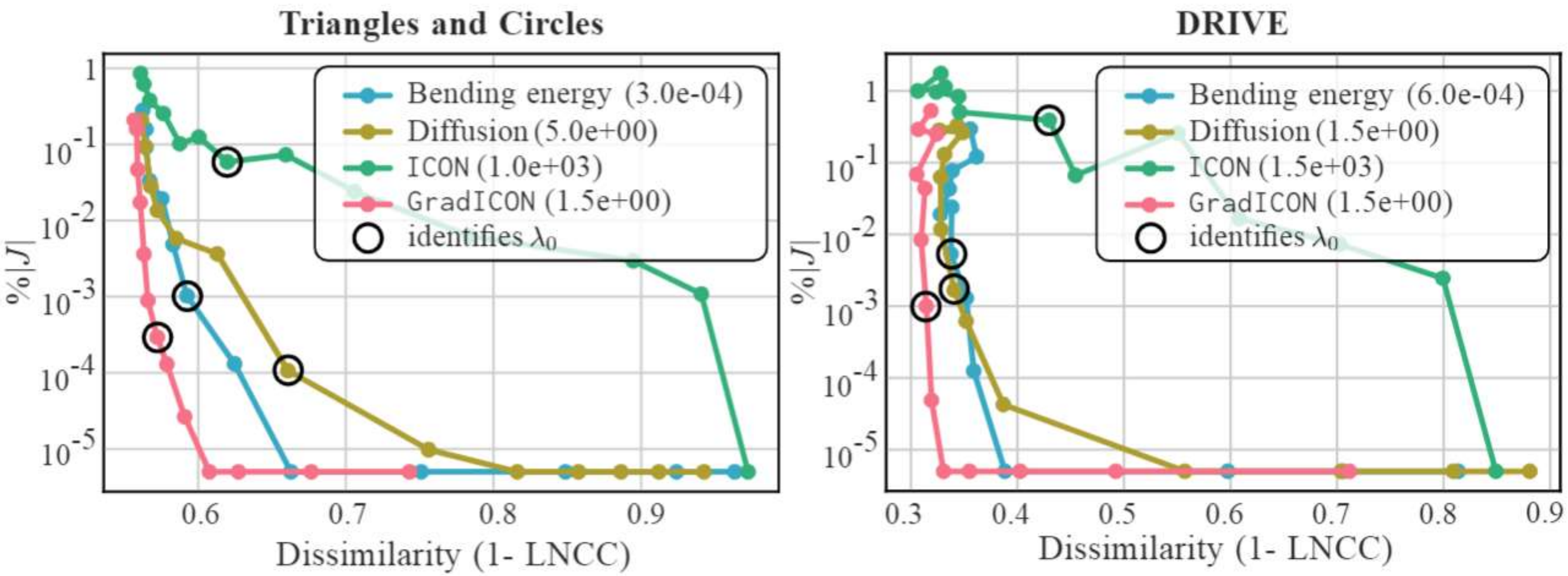


Figure 3. GradICON *vs.* other regularization techniques.

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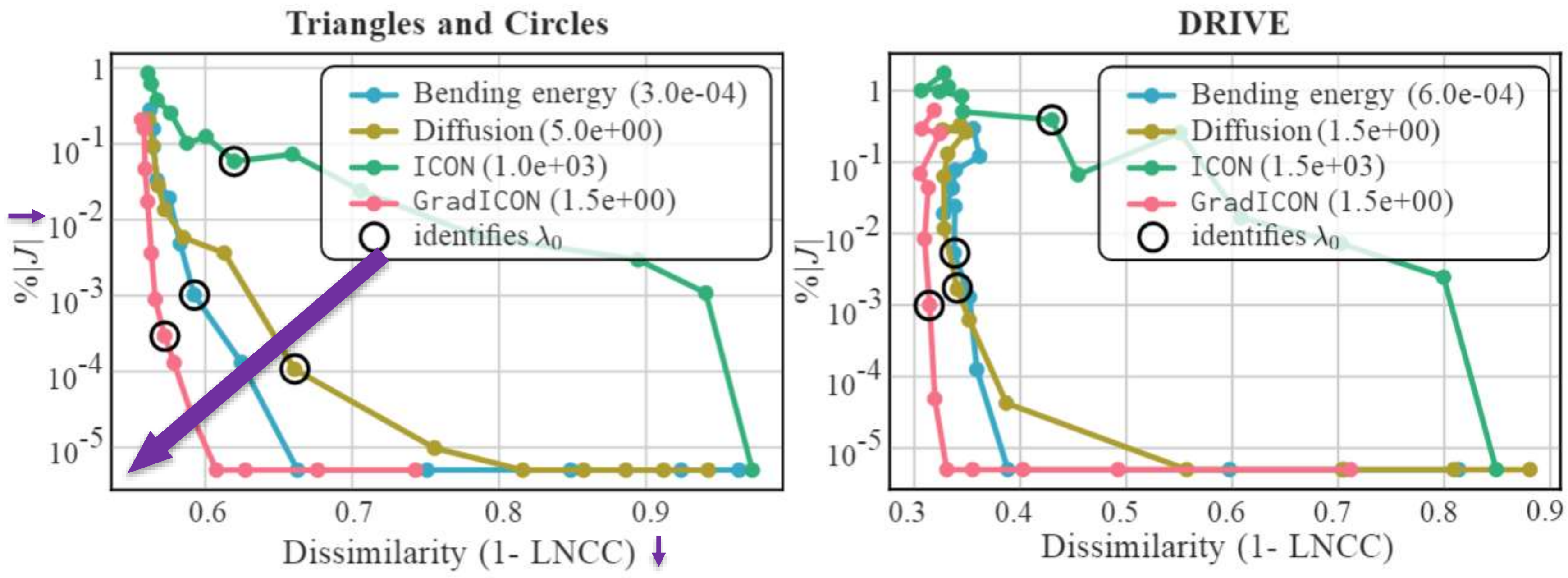

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Converge Faster than ICON

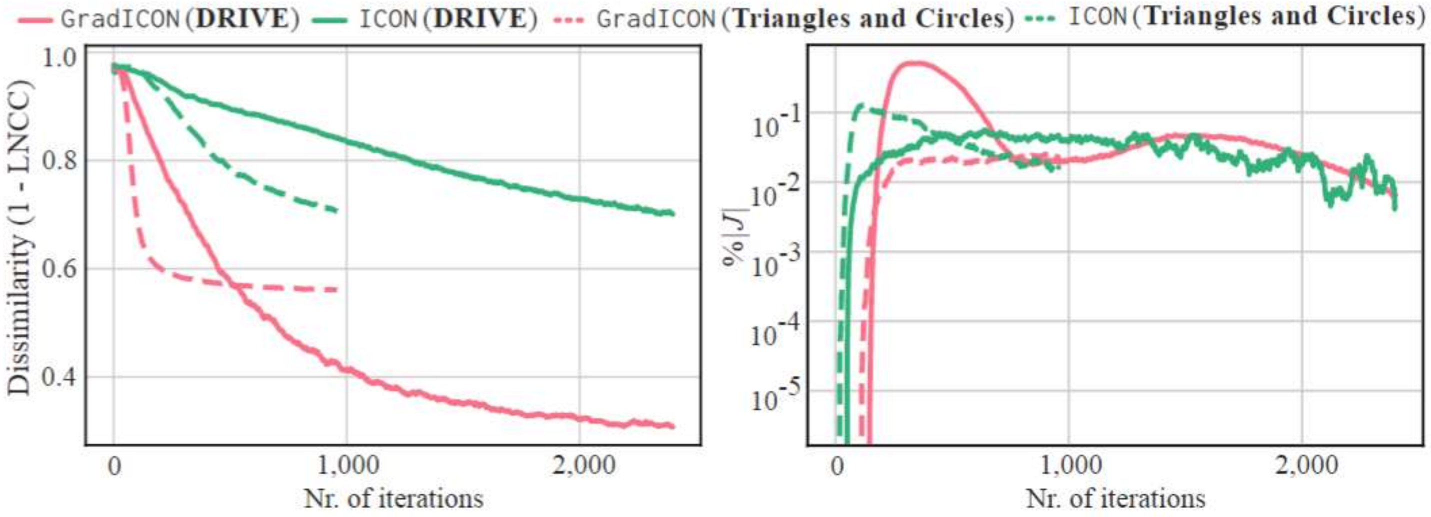

Figure 4. Comparison of the convergence speed (*left*), visualized as 1-LNCC (*i.e.*, dissimilarity), for ICON and GradICON when λ is set to produce a similar level of map regularity (*right*).

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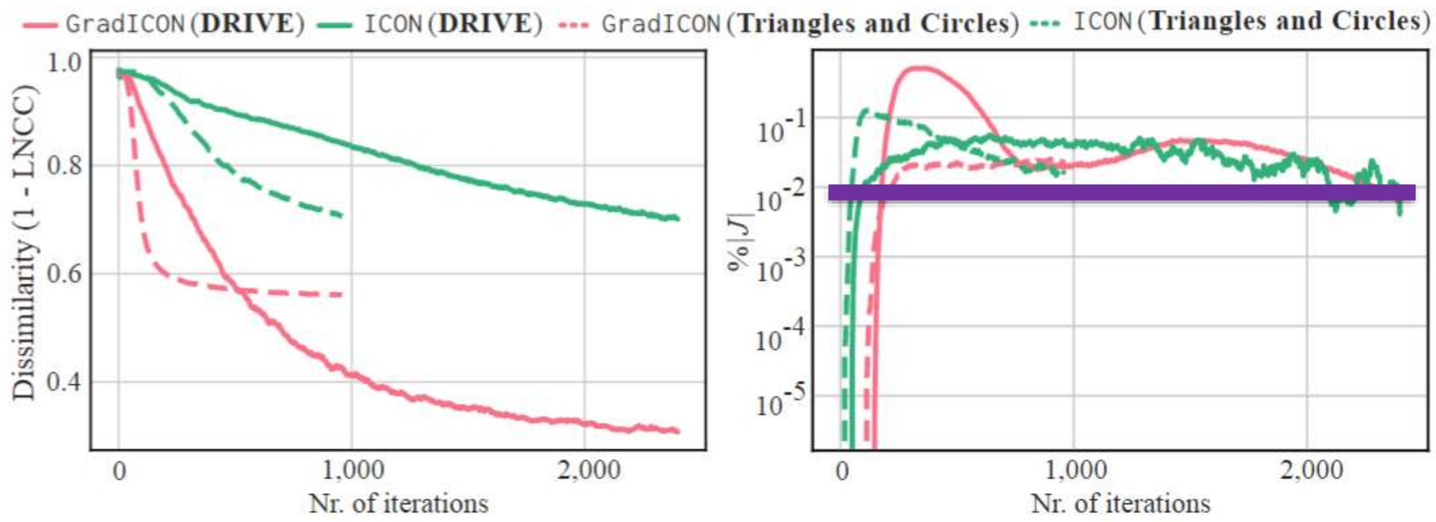

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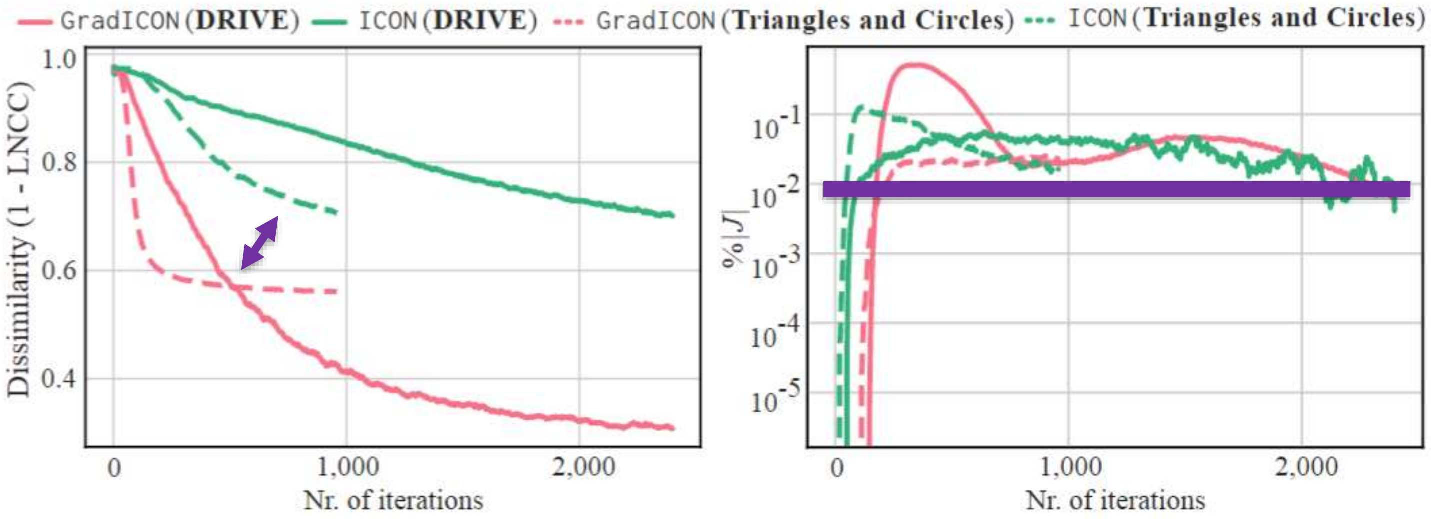

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Ours (*std. protocol*)	DVF	GradICON	LNCC	[illegible]	[illegible]	
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		HCP				
Initial				45.2		
FreeSurfer-Affine* [48]	A	—	TB	58.5	0.0000	
SyN* [3]	A,VF	Gaussian	MI	**68.9**	0.0000	
sm-shapes* [31]	A,SVF	Diff.	DICE	72.5	0.2886	
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GraphRegNet [26]	DV	—	MSE	1.34	—	
PLOSL [66]	DVF	Diff.	TVD+VMD	[illegible]	[illegible]	
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	DVF	GradICON	LNCC	**0.96†**	0.0002	

Inter-patient

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Table 3. Full comparison on **OAI**, **HCP** and **DirLab**. † and ‡ indicate results from our standard training protocol, with (†) and without (‡) instance optimization (Sec. 4.2). Only when GradICON is trained with MSE, we set λ = 0.2. *Top* and *bottom* table parts denote non-learning and learning-based methods, resp. For **DirLab**, results are shown in the common *inspiration→expiration* direction. Results marked with * are obtained using code from the official repository; no * indicates values from literature. A: affine pre-registration, BE: bending energy, MI: mutual information, DV: displacement vector of sparse key points, TV: total variation, Curv: curvature regularizer, VCC: volume change control, NGF: normalized gradient flow, TVD: sum of squared tissue volume difference, VMD: sum of squared vesselness measure difference, Diff: diffusion, VF: velocity field, SVF: stationary VF, DVF: displacement vector field, $PLOSL_{50}$: 50 iterations of instance optimization with PLOSL.

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	DVF	GradICON	LNCC	**0.96**‡	0.0002	

Table 3. Full comparison on **OAI**, **HCP** and **DirLab**. † and ‡ indicate results from our standard training protocol, with (†) and without (‡) instance optimization (Sec. 4.2). Only when GradICON is trained with MSE, we set $\lambda = 0.2$. *Top* and *bottom* table parts denote non-learning and learning-based methods, resp. For **DirLab**, results are shown in the common *inspiration→expiration* direction. Results marked with * are obtained using code from the official repository; no * indicates values from literature. A: affine pre-registration, BE: bending energy, MI: mutual information, DV: displacement vector of sparse key points, TV: total variation, Curv: curvature regularizer, VCC: volume change control, NGF: normalized gradient flow, TVD: sum of squared tissue volume difference, VMD: sum of squared vesselness measure difference, Diff: diffusion, VF: velocity field, SVF: stationary VF, DVF: displacement vector field, $PLOSL_{50}$: 50 iterations of instance optimization with PLOSL.

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SOTA on Knee, Brain and Lung

- GradICON achieves SOTA results on inter-patient registration and intra-patient registration tasks.
- GradICON achieves best performance on knee and lung registration and on par with the SOTA method(need Affine pre-registration) on brain registration.
- GradICON does not need affine pre-alignment even for large deformation.
- GradICON creates very small portion of foldings.
- In the table, GradICON is trained with the same network structure, same lambda and same learning rate for all three tasks.

Method	Trans.	$\mathcal{L}_{reg}$	$\mathcal{L}_{sim}$	DICE ↑	%|J| ↓	Reported by
			OAI			
Initial				7.6		
Demons [62]	A,DVF	Gaussian	MSE	63.5	0.0006	[52]
SyN [3]	A,VF	Gaussian	LNCC	65.7	0.0000	[52]
NiftyReg [43]	A,B-Spline	BE	NMI	59.7	0.0000	[52]
NiftyReg [43]	A,B-Spline	BE	LNCC	**67.9**	0.0068	[52]
vSVF-opt [52]	A,vSVF	m-Gauss	LNCC	67.4	0.0000	
VM [4]	SVF	Diff.	MSE	46.1	0.0028	[52]
VM [4]	A,SVF	Diff.	MSE	66.1	0.0013	[52]
AVSM [52]	A,vSVF	m-Gauss	LNCC	68.4	0.0005	
ICON* [23]	DVF	ICON	MSE	65.1	0.0040	
Ours (MSE, λ=0.2)	DVF	GradICON	MSE	69.5	0.0000	
Ours (MSE, λ=0.2, Opt.)	DVF	GradICON	MSE	70.5	0.0001	
Ours *(std. protocol)*	DVF	GradICON	LNCC	70.1†	0.0261	
	DVF	GradICON	LNCC	**71.2‡**	0.0042	
			HCP			
Initial				45.2		
FreeSurfer-Affine* [48]	A	—	TB	58.5	0.0000	
SyN* [3]	A,VF	Gaussian	MI	**68.9**	0.0000	
sm-shapes* [31]	A,SVF	Diff.	DICE	72.5	0.2886	
sm-brains* [31]	A,SVF	Diff.	DICE	72.4	0.0318	
Ours *(std. protocol)*	DVF	GradICON	LNCC	71.1†	0.0009	
	DVF	GradICON	LNCC	**72.5‡**	0.0003	
			DirLab			
Method	**Trans.**	$\mathcal{L}_{reg}$	$\mathcal{L}_{sim}$	**mTRE ↓** [mm]	%|J| ↓	
Initial				23.36		
SyN [3]	A,VF	Gaussian	LNCC	1.79	—	[26]
Elastix [38]	A,B-Spline	BE	MSE	1.32	—	[26]
NiftyReg [43]	A,B-Spline	BE	MI	2.19	—	[26]
PTVReg [65]	DVF	TV	LNCC	0.96	—	
RRN [28]	DVF	TV	LNCC	**0.83**	—	
VM* [4]	A,SVF	Diff.	NCC	9.88	0	
LapIRN* [45]	SVF	Diff.	NCC	2.92	0	
LapIRN* [45]	DVF	Diff.	NCC	4.24	0.0105	
Hering et al. [30]	DVF	Curv+VCC	DICE+KP+NGF	2.00	0.0600	
GraphRegNet [26]	DV	—	MSE	1.34	—	
PLOSL [66]	DVF	Diff.	TVD+VMD	3.84	0	
$PLOSL_{50}$ [66]	DVF	Diff.	TVD+VMD	1.53	0	
ICON* [23]	DVF	ICON	LNCC	7.04	0.3792	
Ours *(std. protocol)*	DVF	GradICON	LNCC	1.26†	0.0003	
	DVF	GradICON	LNCC	**0.96†**	0.0002	

Table 3. Full comparison on **OAI**, **HCP** and **DirLab**. † and ‡ indicate results from our standard training protocol, with (†) and without (‡) instance optimization (Sec. 4.2). Only when GradICON is trained with MSE, we set λ = 0.2. *Top* and *bottom* table parts denote non-learning and learning-based methods, resp. For **DirLab**, results are shown in the common *inspiration→expiration* direction. Results marked with * are obtained using code from the official repository; no * indicates values from literature. A: affine pre-registration, BE: bending energy, MI: mutual information, DV: displacement vector of sparse key points, TV: total variation, Curv: curvature regularizer, VCC: volume change control, NGF: normalized gradient flow, TVD: sum of squared tissue volume difference, VMD: sum of squared vesselness measure difference, Diff: diffusion, VF: velocity field, SVF: stationary VF, DVF: displacement vector field, $PLOSL_{50}$: 50 iterations of instance optimization with PLOSL.

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Summary

- We develop Gradient Inverse Consistency, a versatile regularizer for learning-based image registration that relies on penalizing the Jacobian of the inverse consistency constraint and results, empirically and theoretically, in spatially well-regularized transformation maps.

- We demonstrate SOTA performance of models trained with GradICON on three large medical datasets with a unified training protocal.

Thank you!

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Github https://github.com/uncbiag/ICON

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