Registration and Segmentation

A Mutual Promotion Paradigm of Correspondence and Perception in Medical Images

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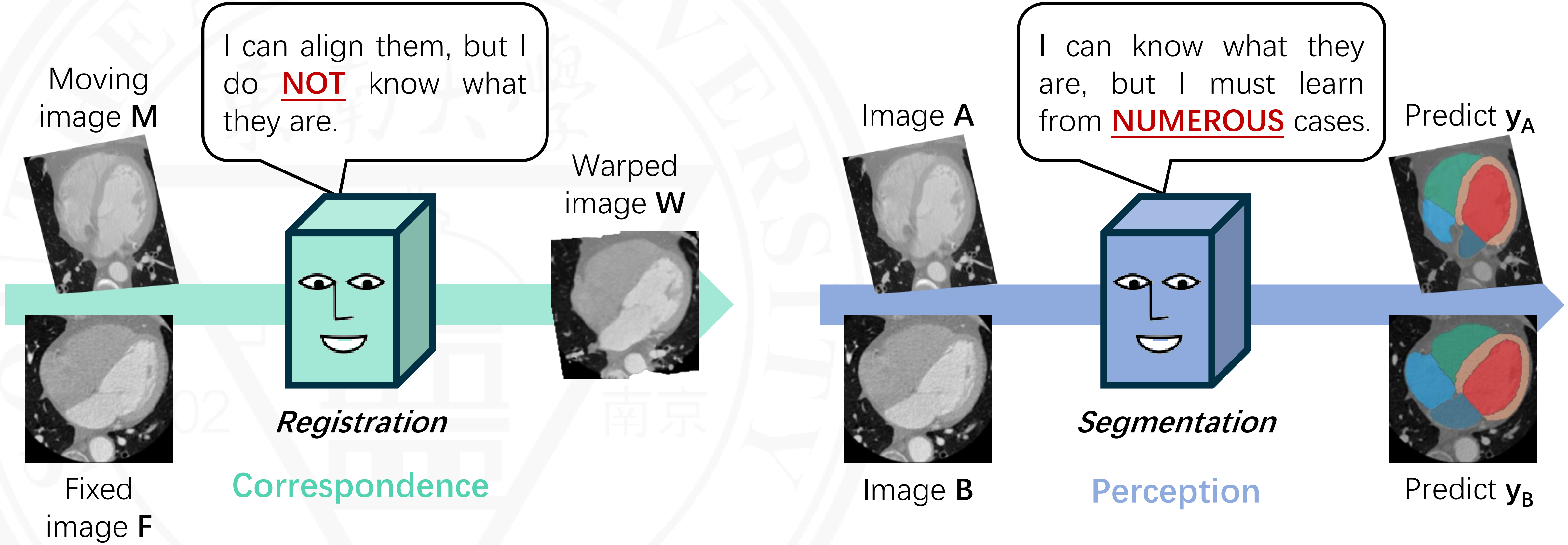
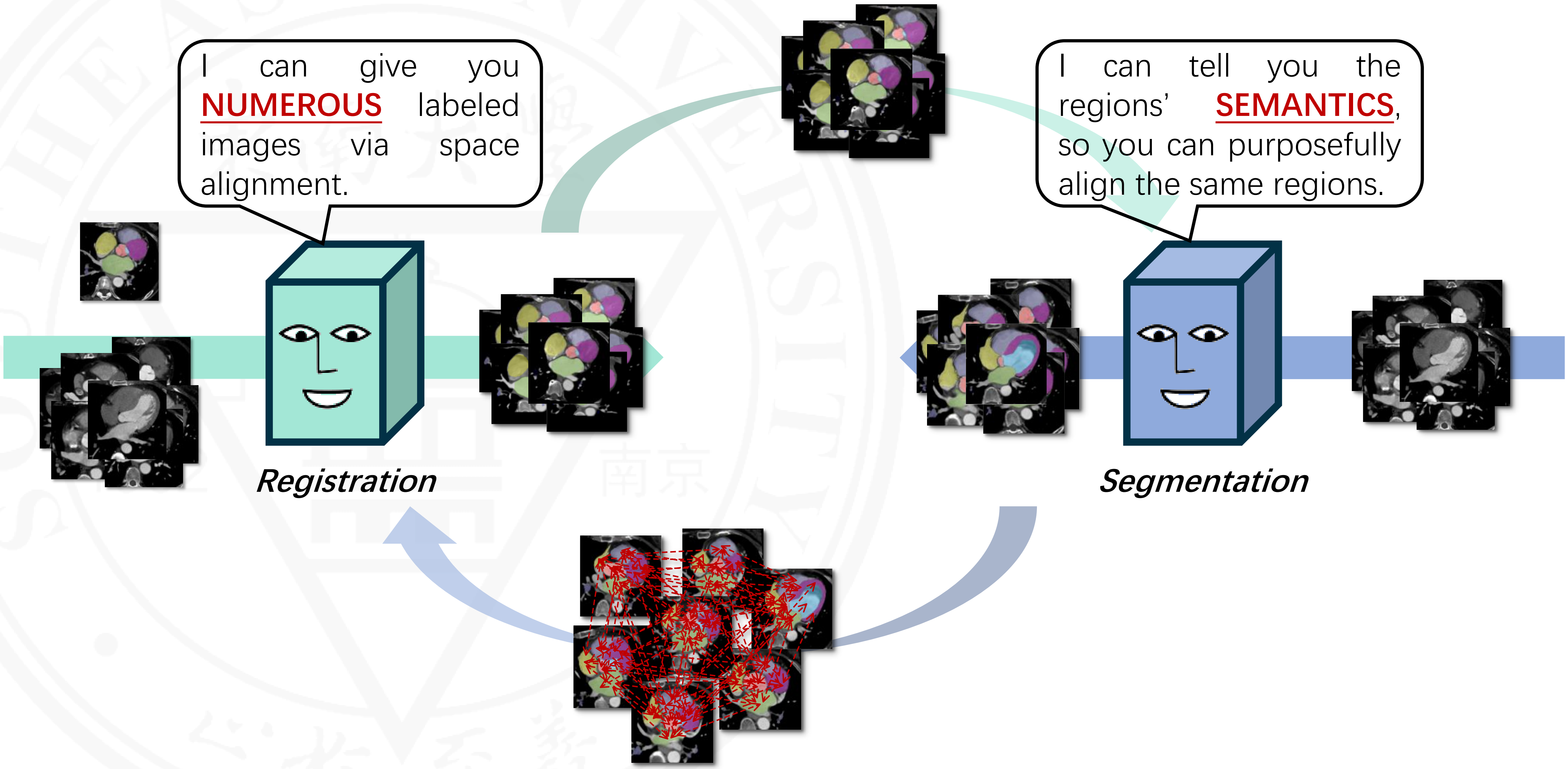
Deep learning(DL)-Registration *V.S.* DL-Segmentation

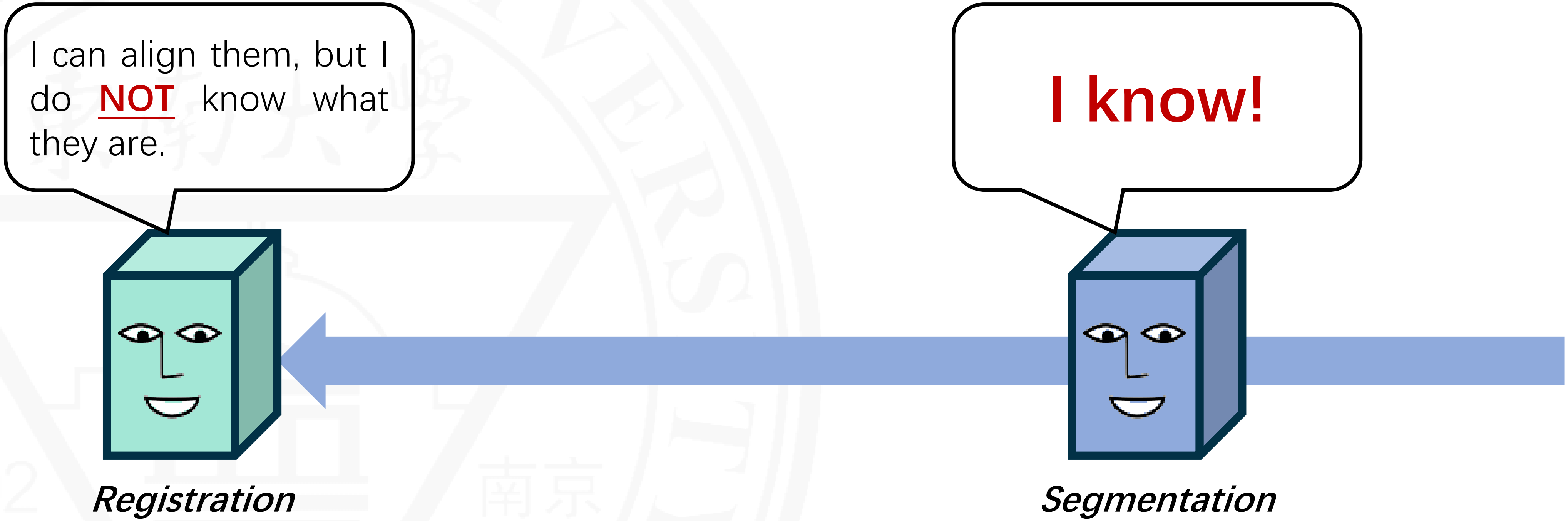


Complementary of registration and segmentation



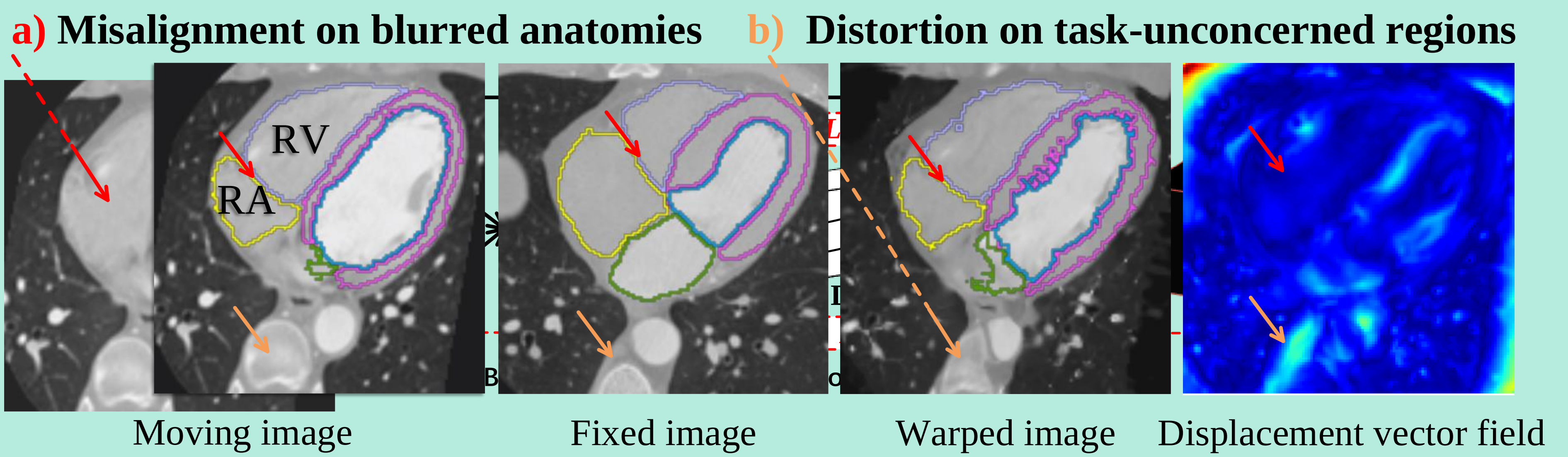
Y. He, et. al. Deep Complementary Joint Model for Complex Scene Registration and Few-shot Segmentation on Medical Images. In 16th ECCV 2020, Vol. 1, pp. 770–786.

I: Learning segmentation to improve registration

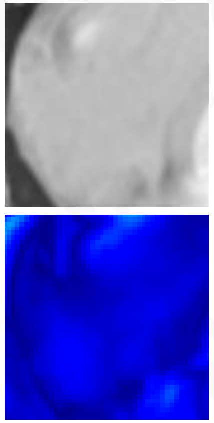


Y. He, et al., "Few-shot Learning for Deformable Medical Image Registration with Perception-Correspondence Decoupling and Reverse Teaching," in IEEE J-BHI 2021, doi: 10.1109/JBHI.2021.3095409.

I: Learning segmentation to improve registration (Without perception)

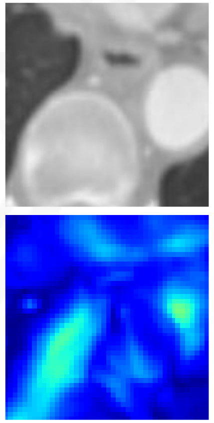


Task-dependent but low-significant regions



Without perception, registration is unable to perceive the low-significant regions for correspondence.

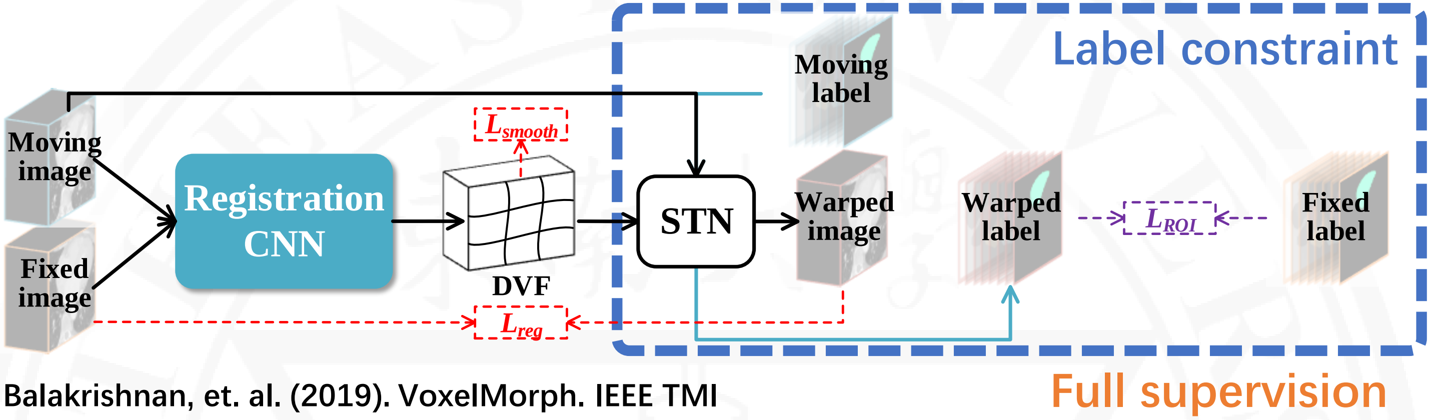
Task-independent but significant regions



Without perception, registration seeks the alignment of all anatomies, making the ROIs have to compromise with them.

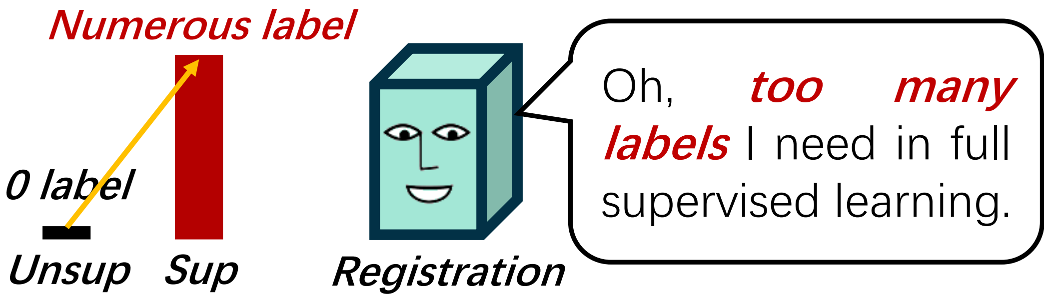
Y. He, et al., "Few-shot Learning for Deformable Medical Image Registration with Perception-Correspondence Decoupling and Reverse Teaching," in IEEE J-BHI 2021, doi: 10.1109/JBHI.2021.3095409.

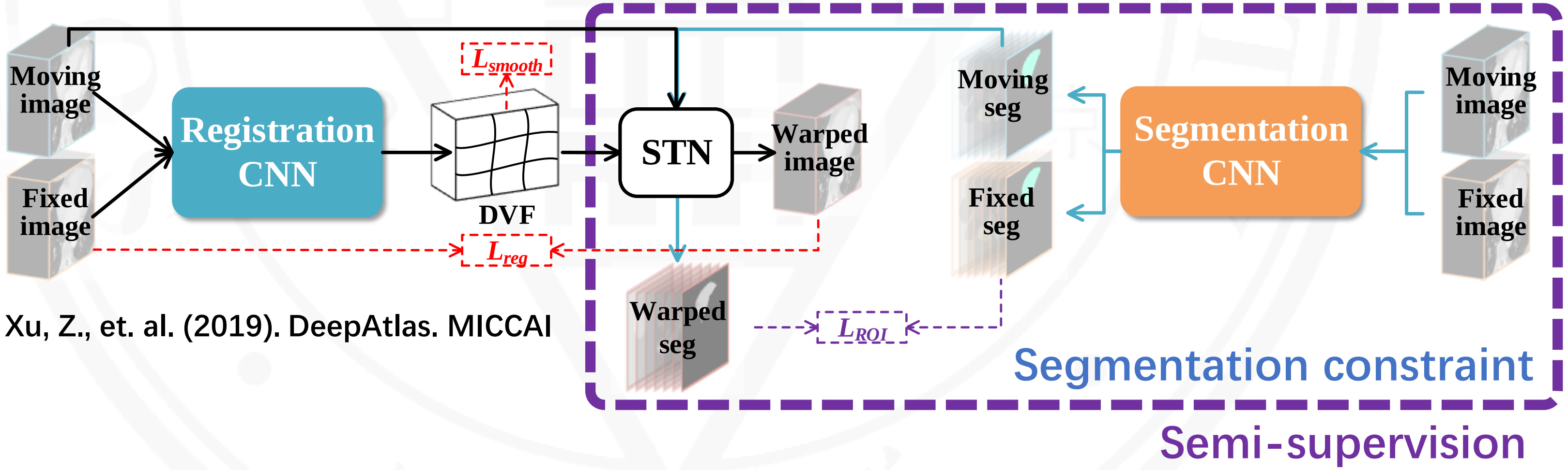
I: Learning segmentation to improve registration (Embedding perception)



Balakrishnan, et. al. (2019). VoxelMorph. IEEE TMI

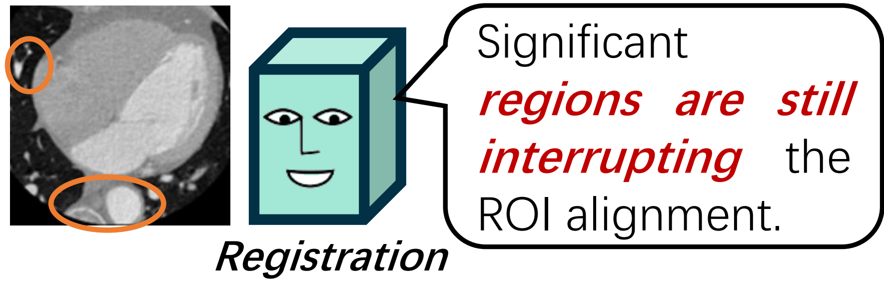
Bring the limitation of label amount
Still limited by significant background





Xu, Z., et. al. (2019). DeepAtlas. MICCAI

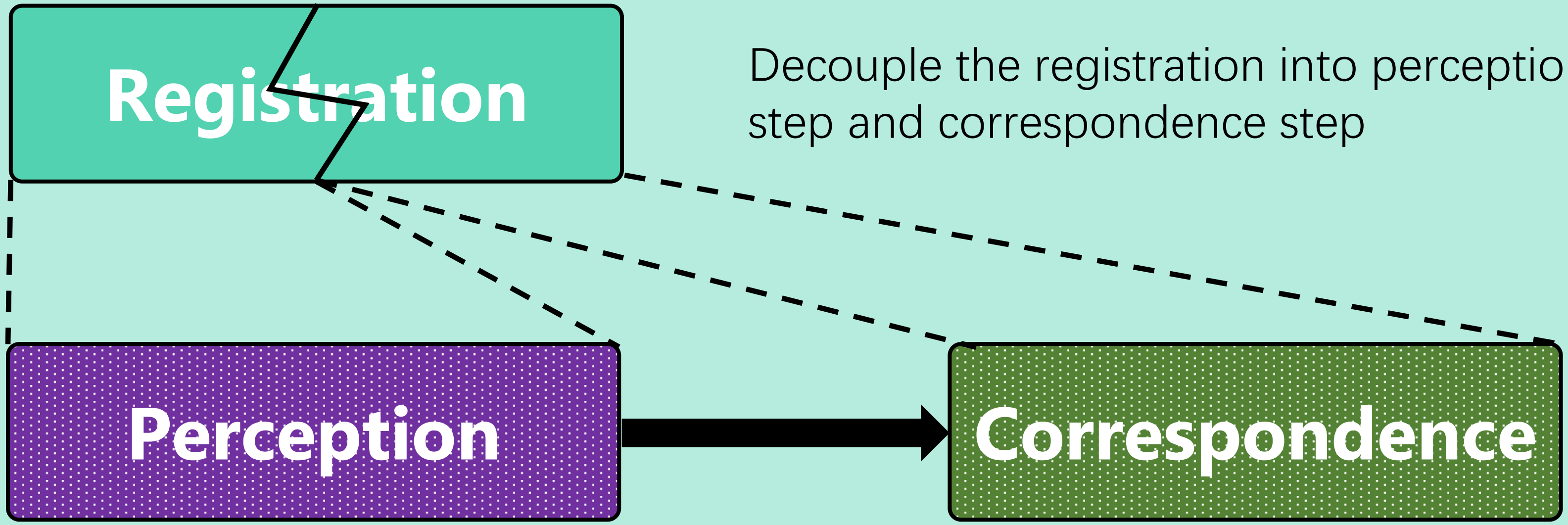
Still need too many labels
Still limited by significant background



Y. He, et al., "Few-shot Learning for Deformable Medical Image Registration with Perception-Correspondence Decoupling and Reverse Teaching," in IEEE J-BHI 2021, doi: 10.1109/JBHI.2021.3095409.

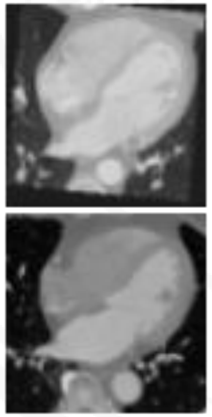
I: Learning segmentation to improve registration (Perception-Correspondence Decoupling)

Reduce interference of task-independent regions



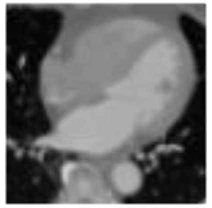
Decouple the registration into perception step and correspondence step

Forward inference: *less interference of background*



Focus on task-dependent regions

Align corresponding regions



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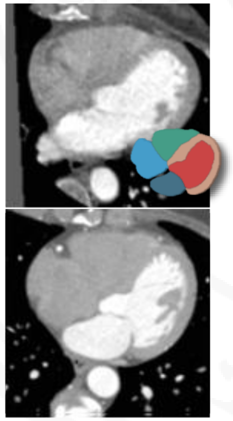
I: Learning segmentation to improve registration (Reverse Teaching)

Reduce label requirement

Reverse teaching: *reduce the label requirement*

Perception → **Correspondence**

Forward inference: *less interference of background*

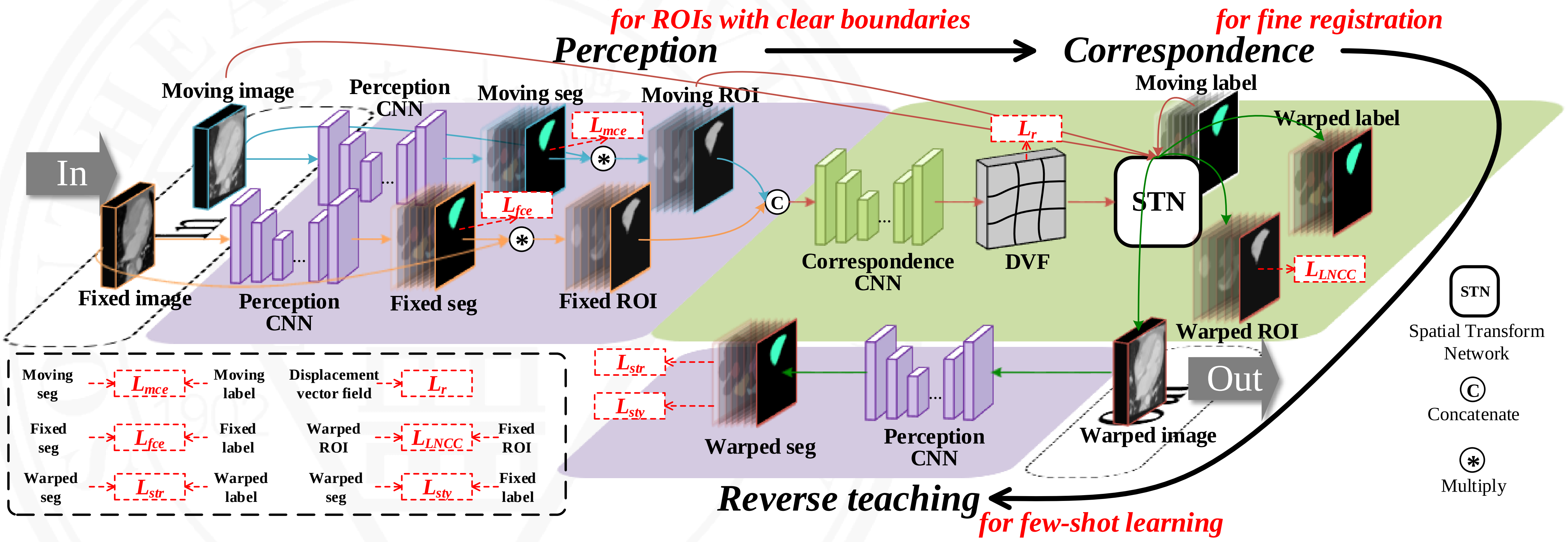


Training perception model in reverse

Align label to unlabeled images for weakly supervised image-label pairs

Y. He, et al., "Few-shot Learning for Deformable Medical Image Registration with Perception-Correspondence Decoupling and Reverse Teaching," in IEEE J-BHI 2021, doi: 10.1109/JBHI.2021.3095409.

I: Learning segmentation to improve registration (PC-Reg-RT)

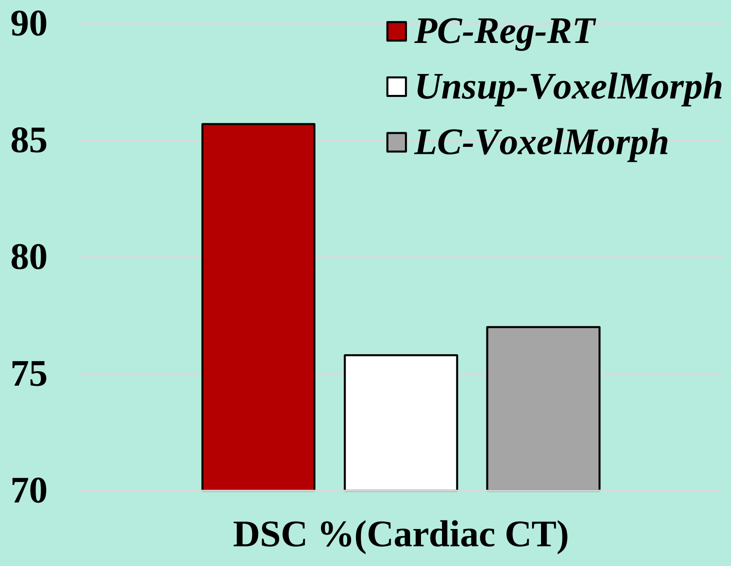


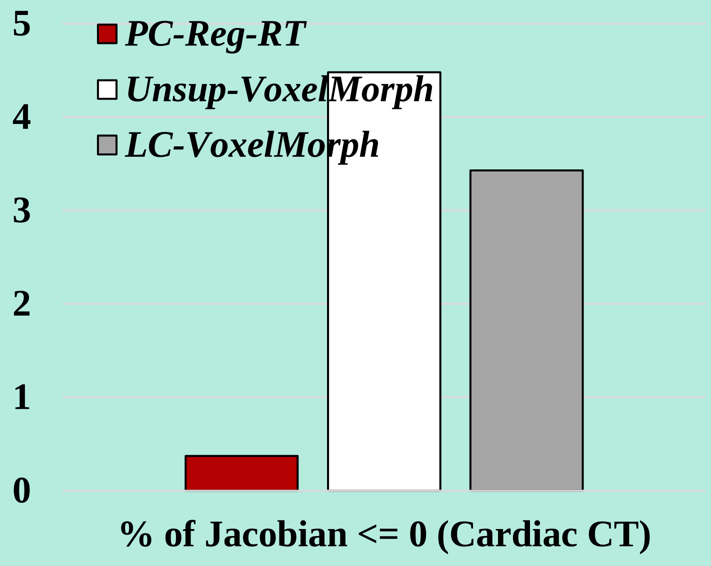
https://github.com/YutingHe-list/PC-Reg-RT

Y. He, et al., "Few-shot Learning for Deformable Medical Image Registration with Perception-Correspondence Decoupling and Reverse Teaching," in IEEE J-BHI 2021, doi: 10.1109/JBHI.2021.3095409.

I: Learning segmentation to improve registration (Results)

Only *5* labeled cases! *10%* DSC improvement! *4.11%* Jacobian matrix<= 0 reduction!





More accurate

More smooth

Y. He, et al., "Few-shot Learning for Deformable Medical Image Registration with Perception-Correspondence Decoupling and Reverse Teaching," in IEEE J-BHI 2021, doi: 10.1109/JBHI.2021.3095409.

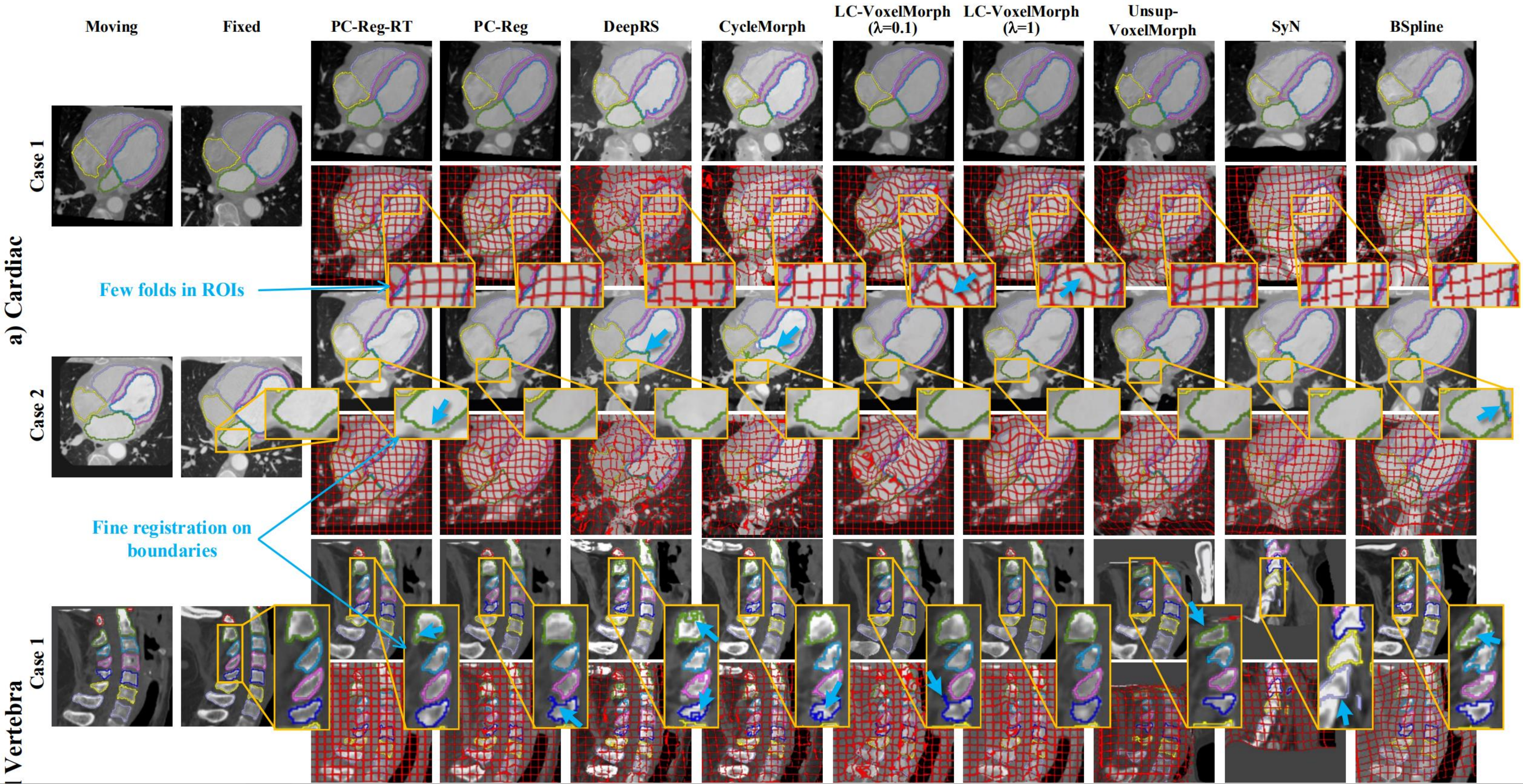
I: Learning segmentation to improve registration (Results)

Method	Reg-DSC (%)	ASD	$\lvert J_\phi \rvert \leq 0$ (%)	CPU time (s)	GPU time (s)	Seg-DSC (%)
a) Cardiac CT cross-object registration						
Affine only	64.0±12.5	3.37±0.86	-	5.98±0.55	-	-
BSpline [11]	80.8±10.4	1.69±0.63	**0.34±0.51**	40.19±1.59	-	-
SyN [12]	75.5±12.7	2.31±0.90	0.50±0.16	23.70±4.33	-	-
Unsup-VoxelMorph [1]	75.8±11.8	2.18±0.74	4.48±1.61	-	0.22±0.16	-
LC-VoxelMorph($\lambda = 1$) [4]	73.2±11.6	2.43±0.68	0.38±0.23	-	0.23±0.41	-
LC-VoxelMorph($\lambda = 0.1$) [4]	77.0±11.6	2.04±0.58	3.43±0.79	-	0.23±0.31	-
CycleMorph [19]	76.5±9.4	2.12±1.01	0.64±0.18	-	0.22±0.25	-
DeepRS [8]	81.5±7.2	1.71±0.77	7.03±1.18	-	0.65±0.10	87.4±6.4
(Our) PC-Reg	79.0±9.9	1.93±0.56	0.40±0.18	-	0.54±0.51	83.1±12.9
(Our) PC-Reg-RT	**85.7±7.3**	**1.32±0.38**	0.37±0.28	-	0.54±0.19	**89.4±6.1**
b) Cervical vertebra CT cross-object registration						
Affine only	64.8±10.2	1.37±0.34	-	6.35±0.70	-	-
BSpline [11]	74.2±18.5	1.15±1.58	0.45±0.98	38.62±1.72	-	-
SyN [12]	39.4±34.7	-	-	21.30±9.70	-	-
Unsup-VoxelMorph [1]	50.1±22.1	3.09±0.58	10.96±0.41	-	0.29±0.17	-
LC-VoxelMorph($\lambda = 1$) [4]	80.4±8.4	0.72±0.25	0.25±0.09	-	0.29±0.16	-
LC-VoxelMorph($\lambda = 0.1$) [4]	82.3±7.6	0.65±0.22	1.85±0.42	-	0.29±0.17	-
CycleMorph [19]	82.5±6.8	0.62±0.35	0.13±0.06	-	0.34±0.38	-
DeepRS [8]	81.7±5.7	0.65±0.31	2.06±0.39	-	0.86±0.13	**86.3±8.6**
(Our) PC-Reg	81.4±8.1	0.66±0.23	0.16±0.08	-	0.74±0.60	63.8±20.4
(Our) PC-Reg-RT	**86.7±5.0**	**0.41±0.15**	**0.11±0.06**	-	0.71±0.23	84.4±12.6
c) Brain MR cross-object registration						
Affine only	75.5±3.7	1.25±0.21	-	7.14±0.51	-	-
BSpline [11]	77.0±3.9	1.15±0.22	**0**	40.32±0.62	-	-
SyN [12]	78.5±3.8	1.07±0.21	**0**	19.67±1.46	-	-
Unsup-VoxelMorph [1]	76.5±3.7	1.09±0.19	1.37±0.19	-	0.30±0.30	-
LC-VoxelMorph($\lambda = 1$) [4]	79.0±4.1	1.07±0.22	0.14±0.03	-	0.30±0.29	-
LC-VoxelMorph($\lambda = 0.1$) [4]	79.9±3.9	1.02±0.20	1.37±0.15	-	0.30±0.28	-
CycleMorph [19]	77.7±3.7	1.06±0.20	**0**	-	0.32±0.42	-
DeepRS [8]	77.6±3.6	1.05±0.19	1.34±0.24	-	1.04±0.12	81.7±3.4
(Our) PC-Reg	79.0±3.4	1.03±0.18	0.02±0.01	-	0.71±0.39	79.4±3.5
(Our) PC-Reg-RT	**80.0±3.4**	**0.97±0.18**	0.04±0.02	-	0.71±0.40	**82.3±3.3**

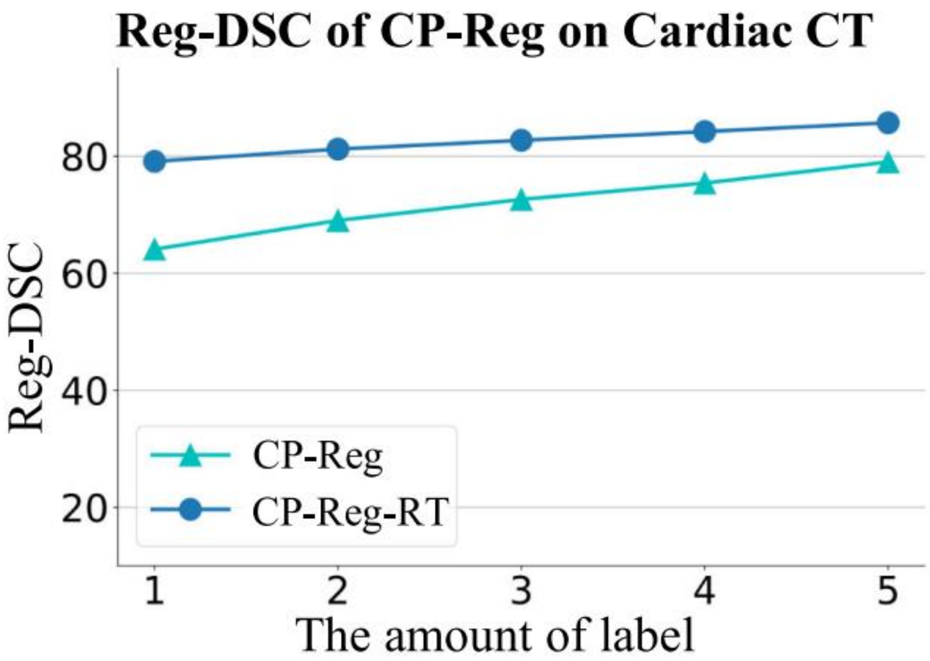
Compared with 8 methods:

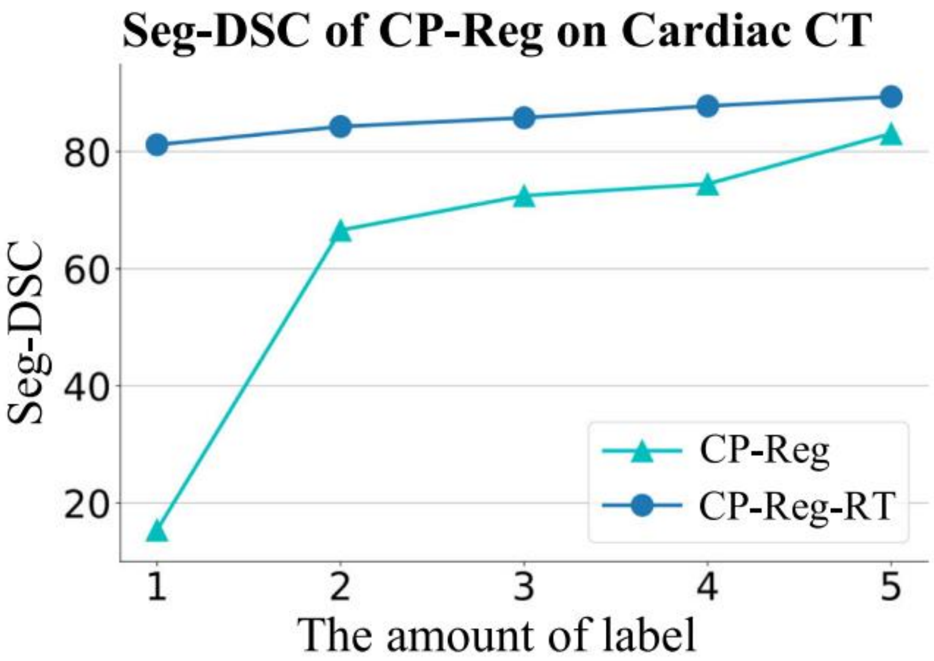
- **Great registration accuracy:** Only five labels, achieve the best registration accuracy in cardiac CT, cervical CT and brain MR registration tasks;
- **Effectively avoid distortion:** the irrelevant background is eliminated, the distortion of the misaligned edge area caused by the lack of real texture in the tag is avoided;
- **Excellent time efficiency:** the registration result can be obtained by one inference, the time efficiency of PC-Reg is more than 10 times faster than the traditional model.

I: Learning segmentation to improve registration (Results)



I: Learning segmentation to improve registration (Results)

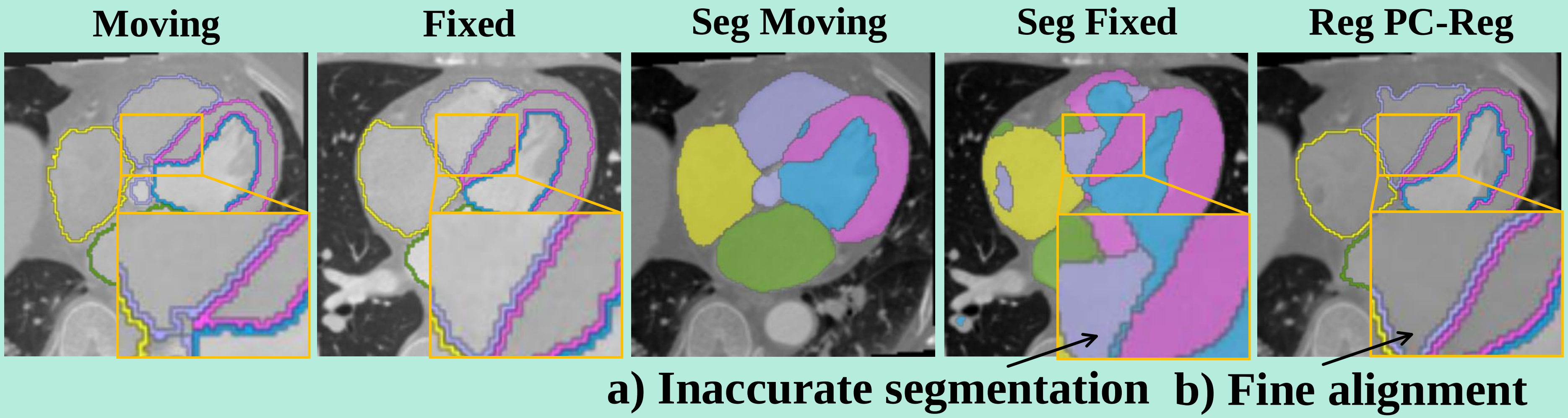




✓ With very few labels, the reverse teaching method can bring significant performance improvement, even if there is only one labeled image, it still has excellent registration performance;

✓ With the increase of the number of tags, the performance of PC-Reg-RT will be further improved.

I: Learning segmentation to improve registration (Phenomenon)



Poor segmentation still bring fine alignment.
(Due to the extrusion between the structures)

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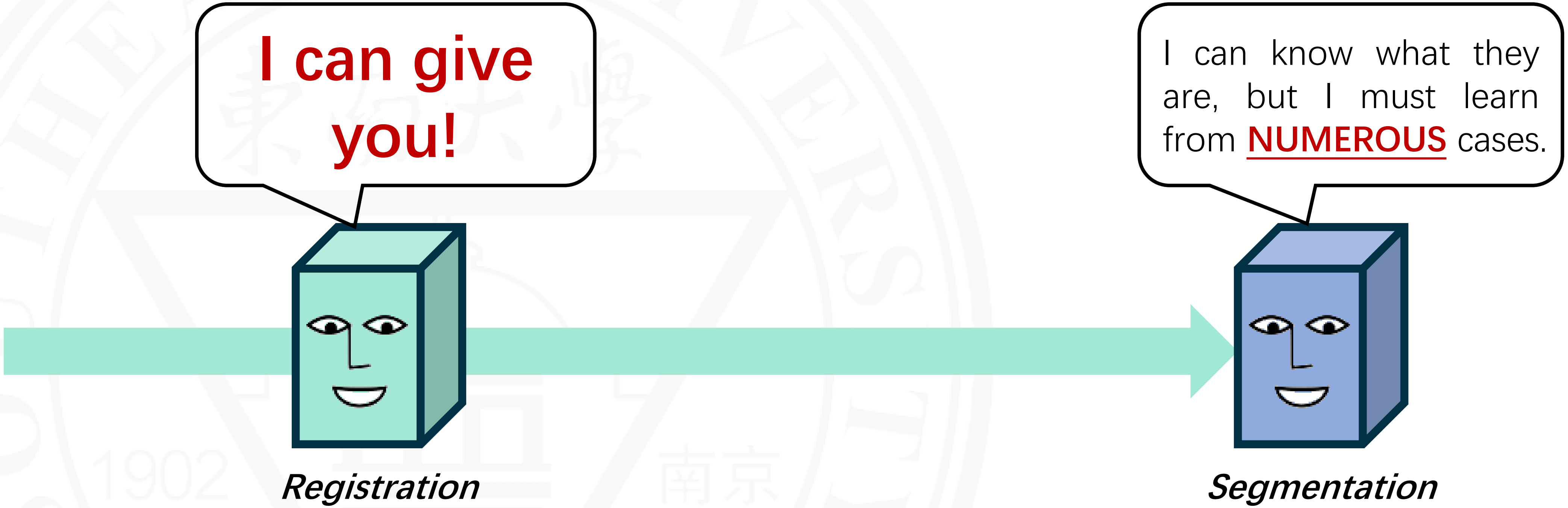
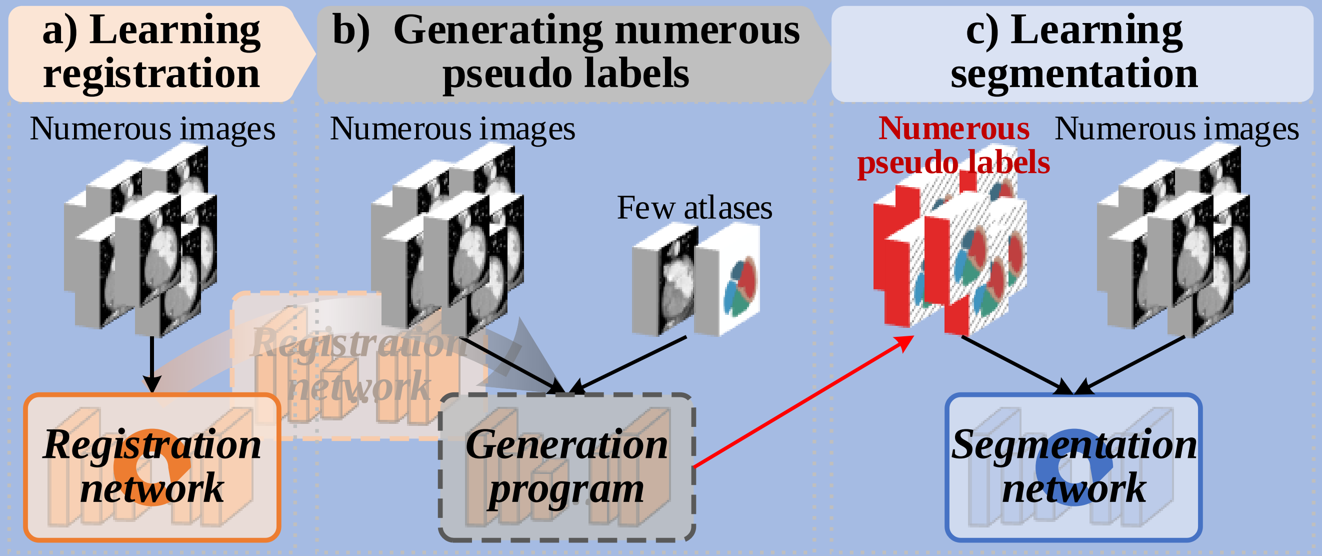
II: Learning registration to learn segmentation



Y. He, et al., "Learning Better Registration to Learn Better Few-Shot Medical Image Segmentation: Authenticity, Diversity, and Robustness," in IEEE TNNLS

II: Learning registration to learn segmentation (Paradigm)

Zhao A. et. al., (2019) DataAug. CVPR



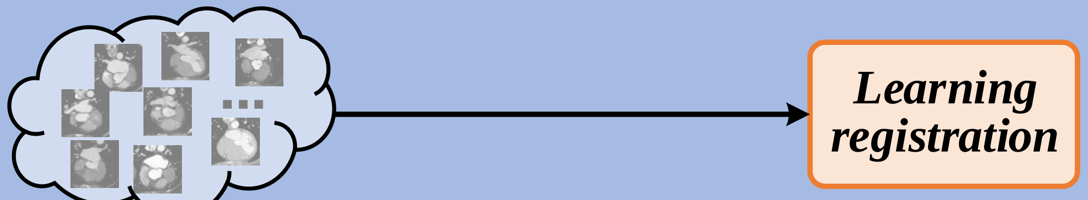
Registration aligns unlabeled images and labels for pseudo-labeled data, driving the learning of segmentation

Here, we talk three key limitations and their solutions.

Y. He, et al., "Learning Better Registration to Learn Better Few-Shot Medical Image Segmentation: Authenticity, Diversity, and Robustness," in IEEE TNNLS

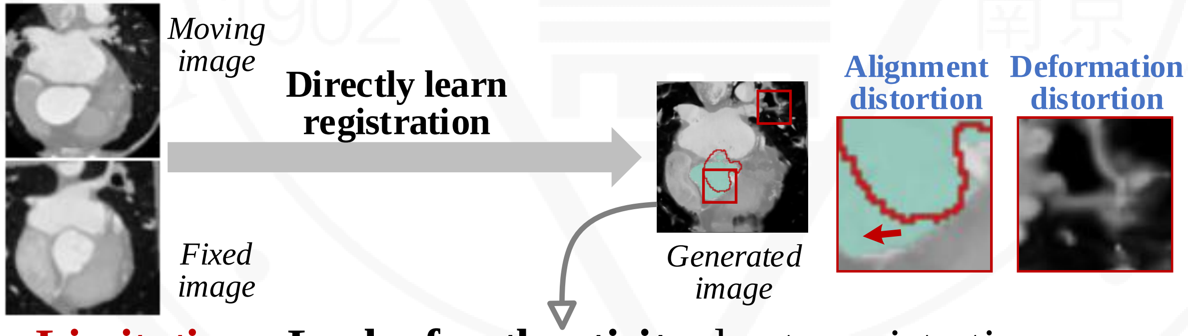
II: Learning registration to learn segmentation (Limitation 1) Zhao A. et. al., (2019) DataAug. CVPR

Step1. Unsupervised learning registration



Large unlabeled dataset

Existing method directly learns registration

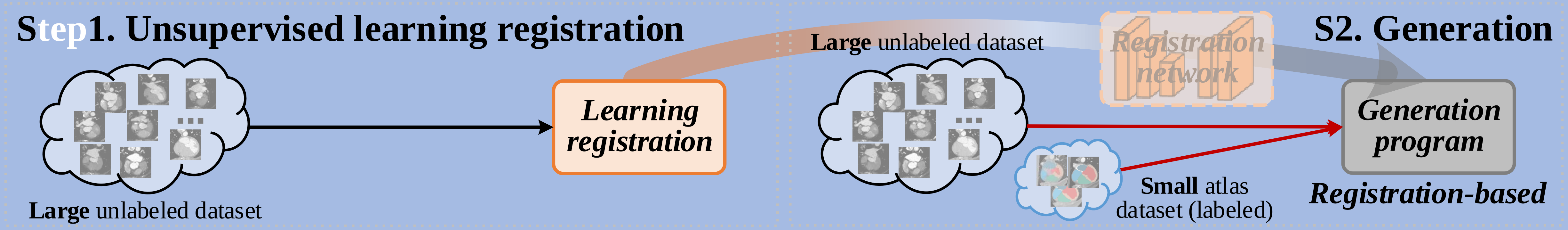


Limitation: **Lack of authenticity** due to registration error

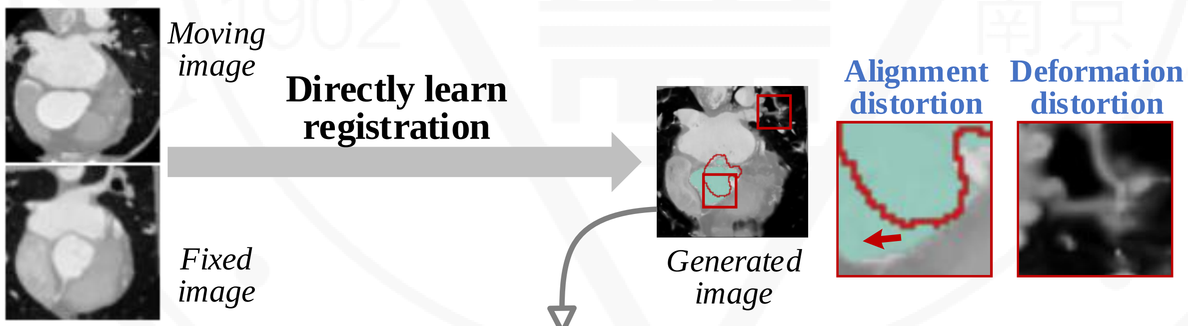
Y. He, et al., "Learning Better Registration to Learn Better Few-Shot Medical Image Segmentation: Authenticity, Diversity, and Robustness," in IEEE TNNLS

II: Learning registration to learn segmentation (Limitation 2)

Zhao A. et. al., (2019) DataAug. CVPR

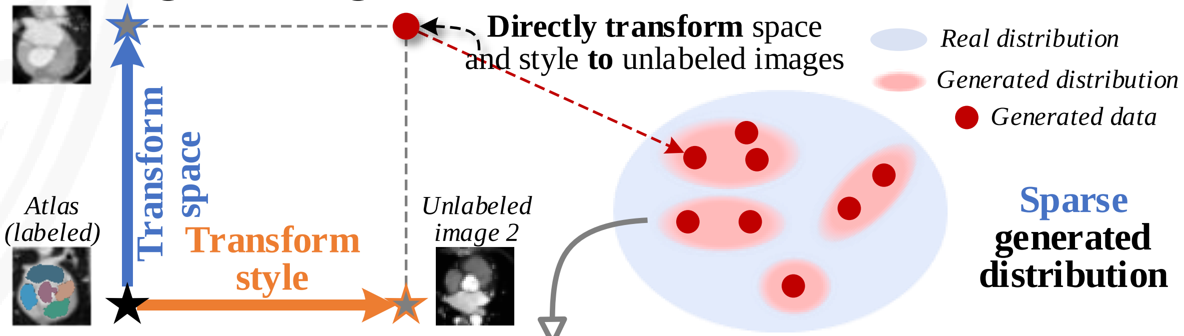


Existing method directly learns registration



Limitation: Lack of authenticity due to registration error

Existing method generates data in the end of transformation

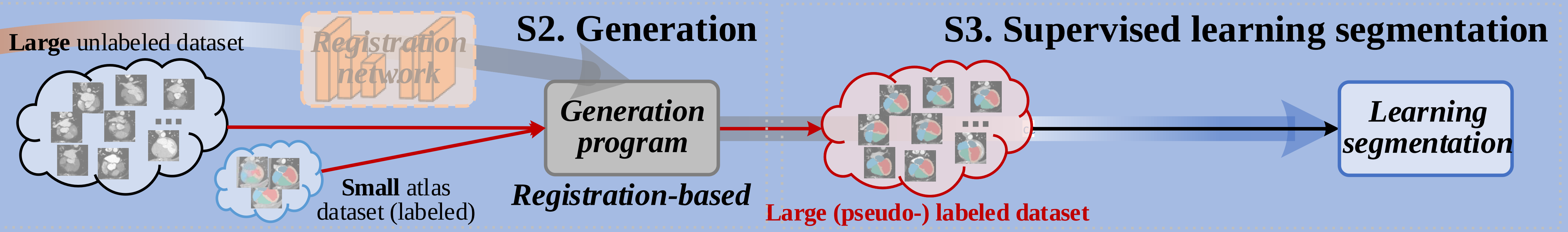


Limitation: Lack of diversity in generated sparse distribution

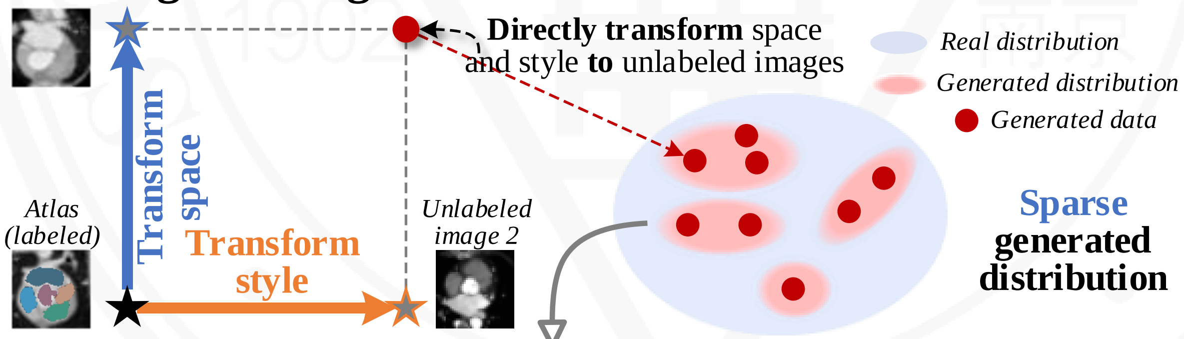
Y. He, et al., "Learning Better Registration to Learn Better Few-Shot Medical Image Segmentation: Authenticity, Diversity, and Robustness," in IEEE TNNLS

II: Learning registration to learn segmentation (Limitation 3)

Zhao A. et. al., (2019) DataAug. CVPR

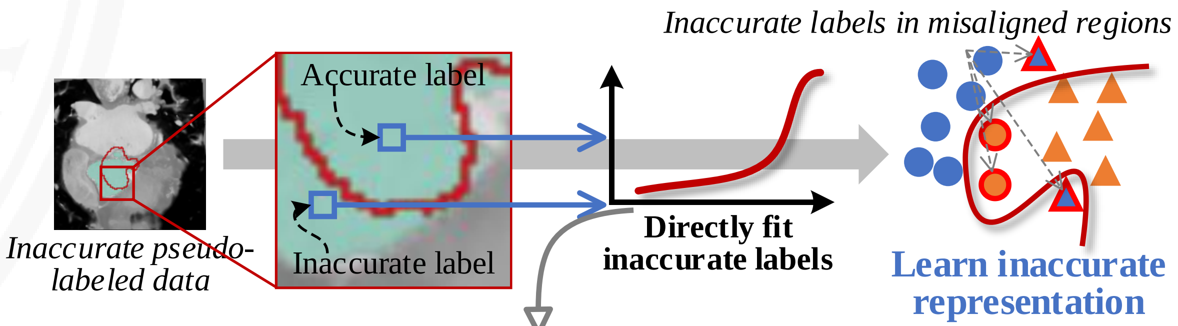


Existing method generates data in the end of transformation



Limitation: Lack of diversity in generated sparse distribution

Existing method fits inaccurate labels

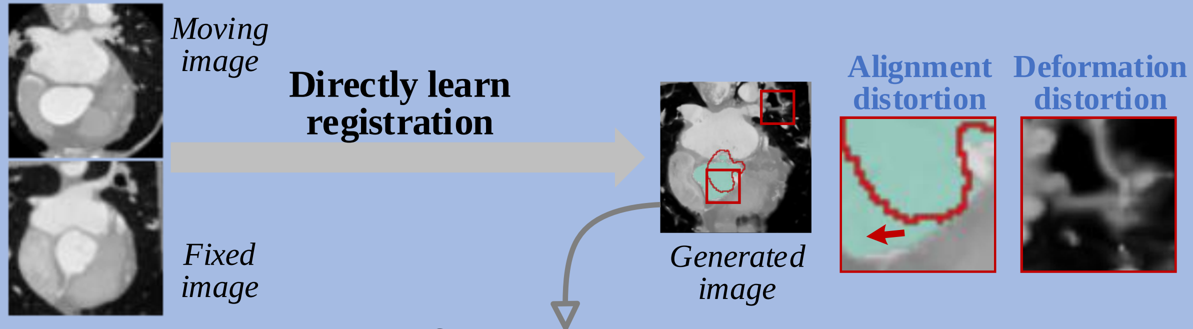


Limitation: Lack of robustness to learn with inaccurate data

Y. He, et al., "Learning Better Registration to Learn Better Few-Shot Medical Image Segmentation: Authenticity, Diversity, and Robustness," in IEEE TNNLS

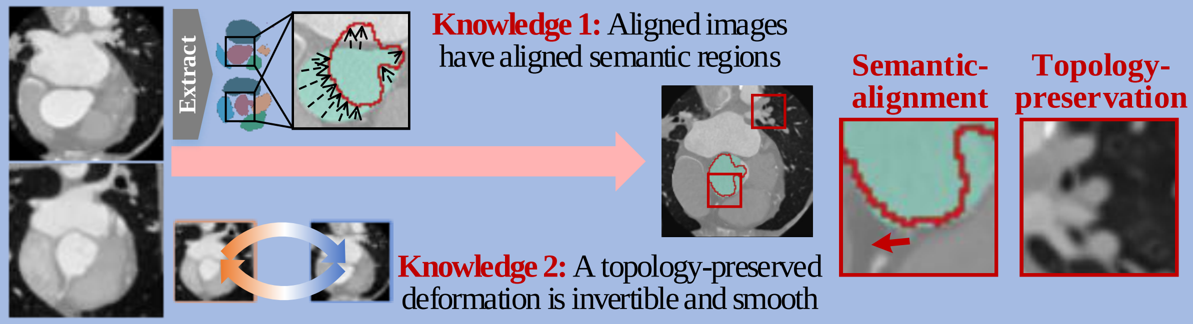
II: Learning registration to learn segmentation (Knowledge consistency constraint)

Existing method directly learns registration

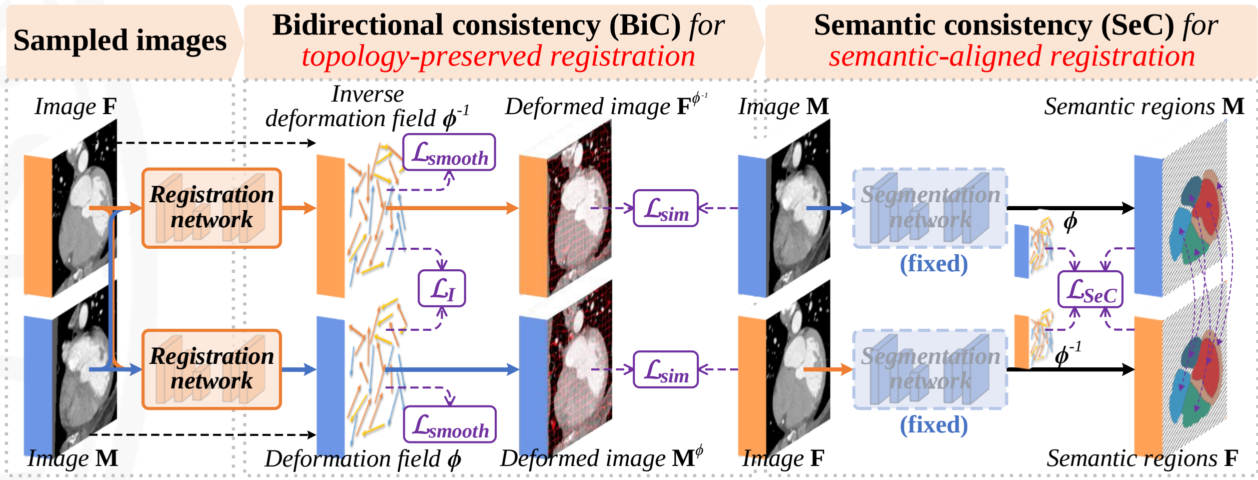


Limitation: Lack of authenticity due to registration error

Our KCC constrains registration learning



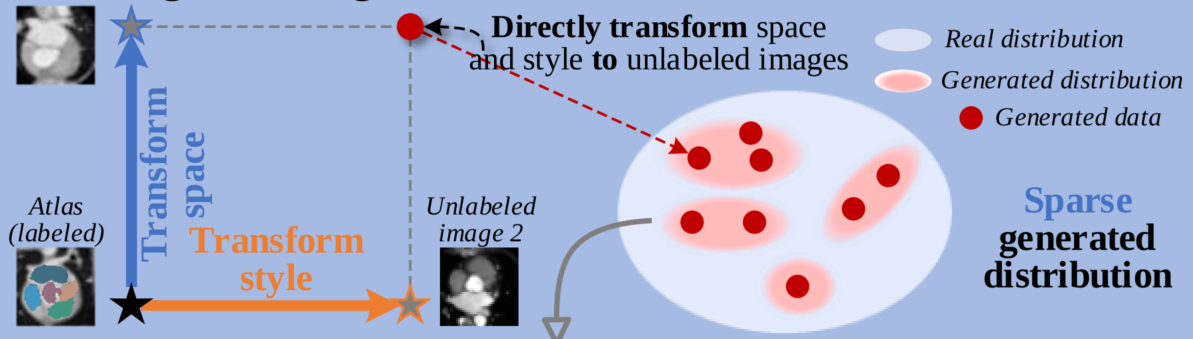
Advantage: Better authenticity with less registration error



Y. He, et al., "Learning Better Registration to Learn Better Few-Shot Medical Image Segmentation: Authenticity, Diversity, and Robustness," in IEEE TNNLS

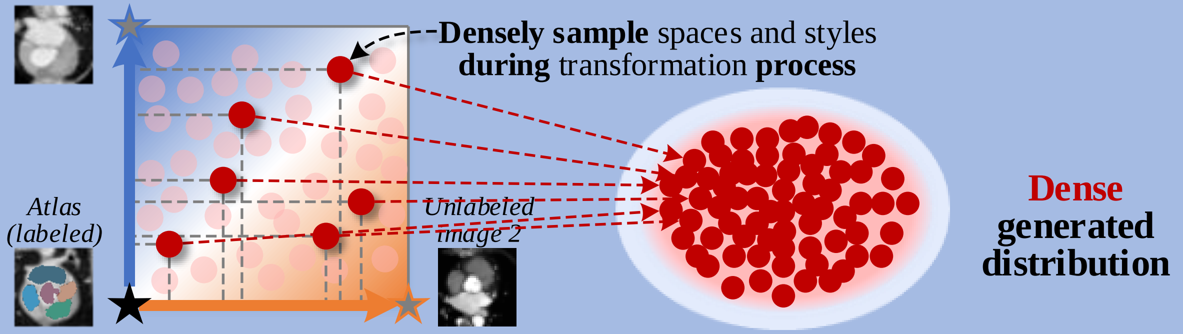
II: Learning registration to learn segmentation (Space-style sampling program)

Existing method generates data in the end of transformation

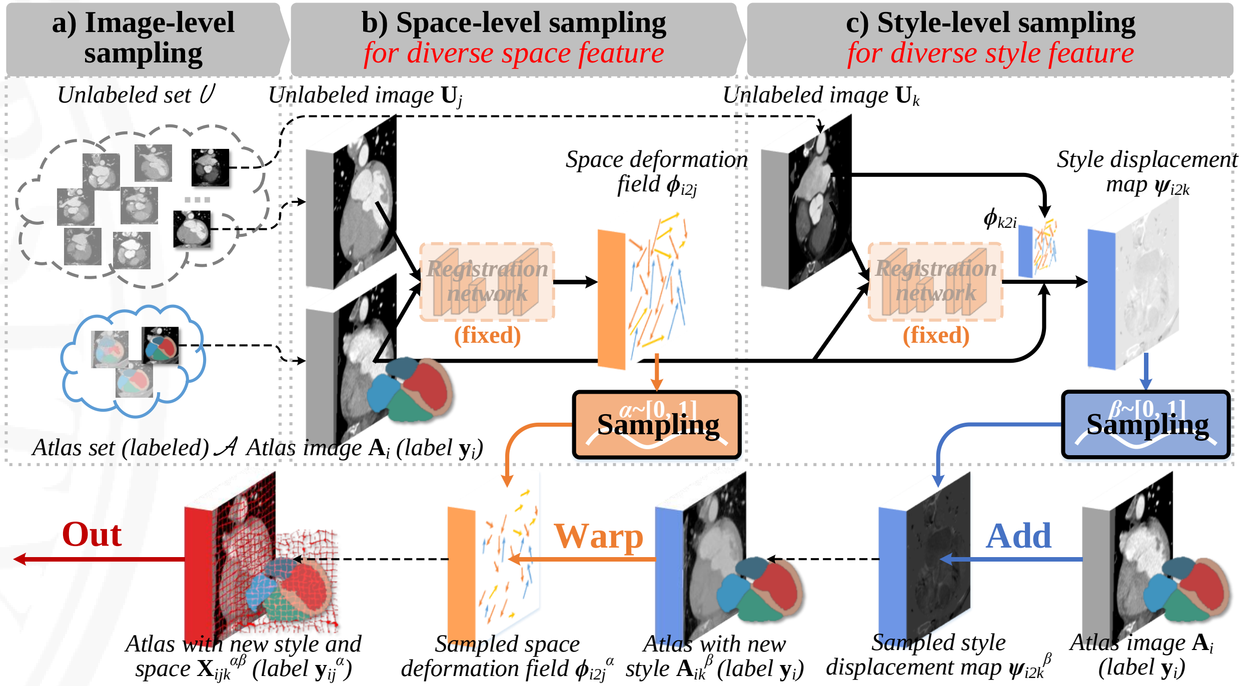


Limitation: Lack of diversity in generated sparse distribution

Our S3P generates data in continuous transformation process



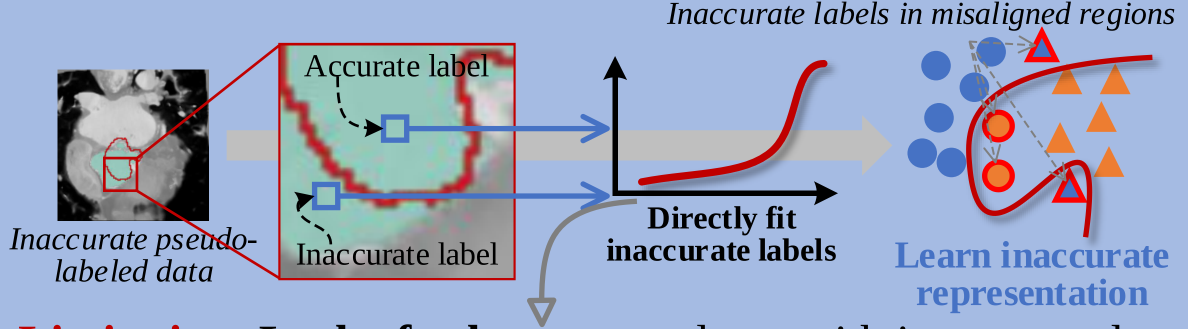
Advantage: Better diversity in generated dense distribution



Y. He, et al., "Learning Better Registration to Learn Better Few-Shot Medical Image Segmentation: Authenticity, Diversity, and Robustness," in IEEE TNNLS

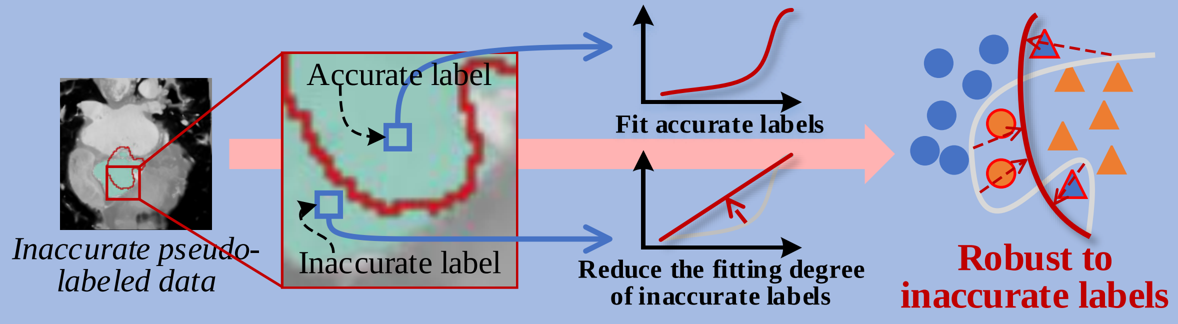
II: Learning registration to learn segmentation (Mix misalignment regularization)

Existing method fits inaccurate labels



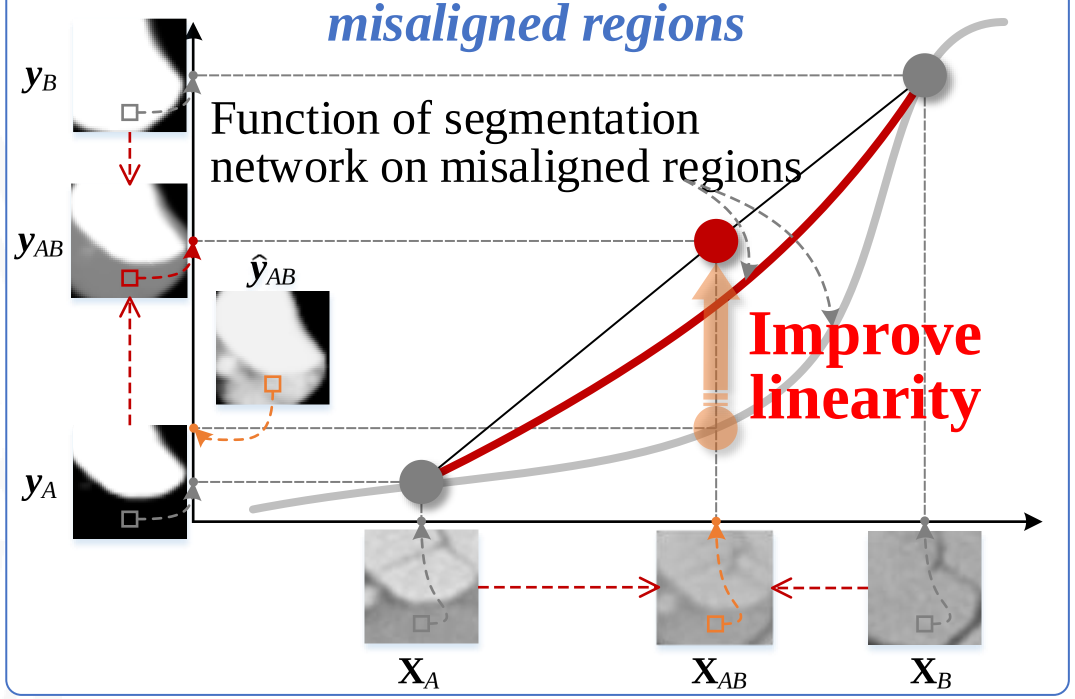
Limitation: Lack of robustness to learn with inaccurate data

Our MMR reduces fitting degree of inaccurate labels



Advantage: More robust to learn with inaccurate data

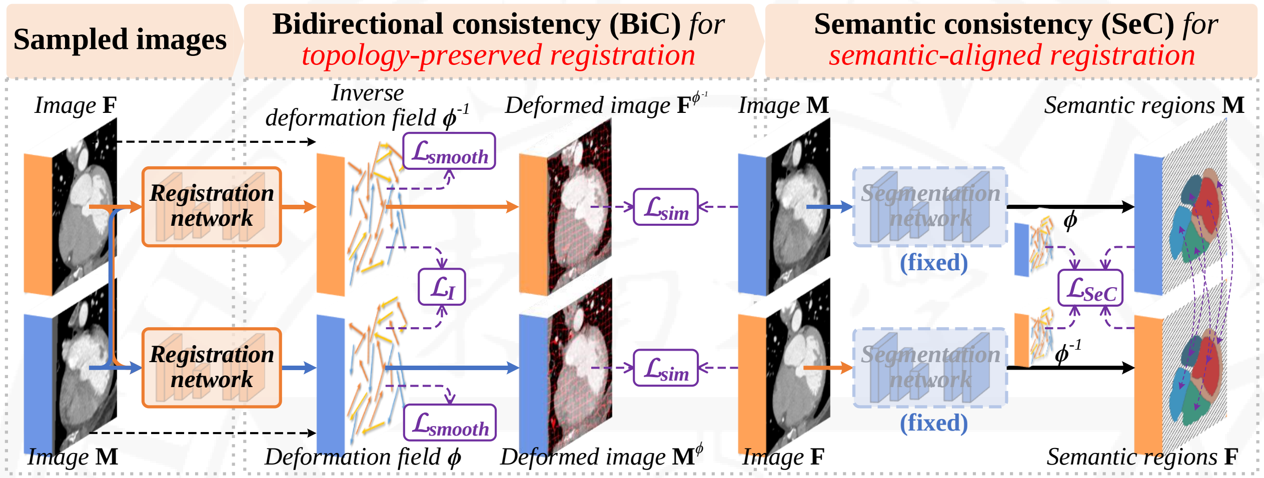
Improve linearity to reduce the fitting of misaligned regions

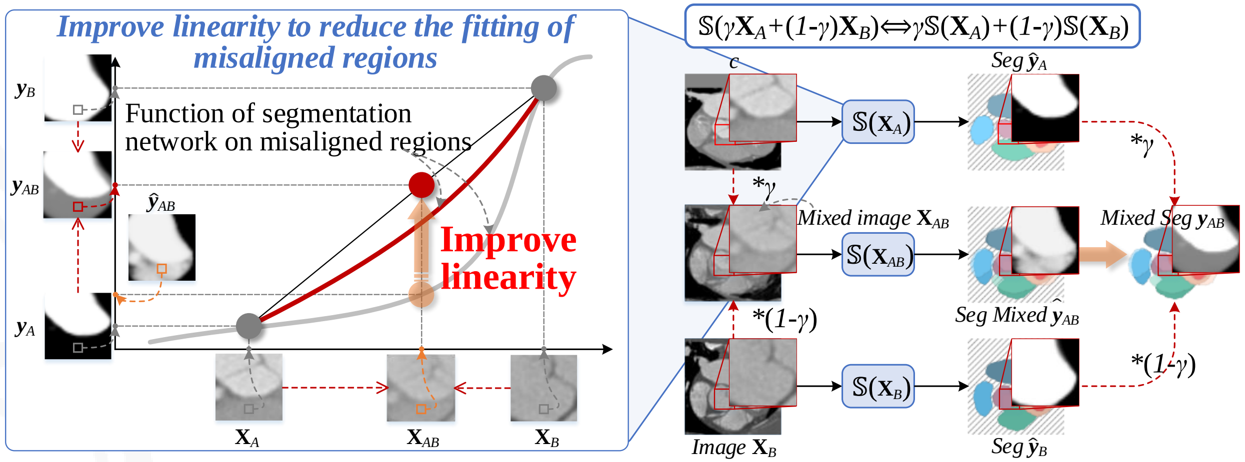


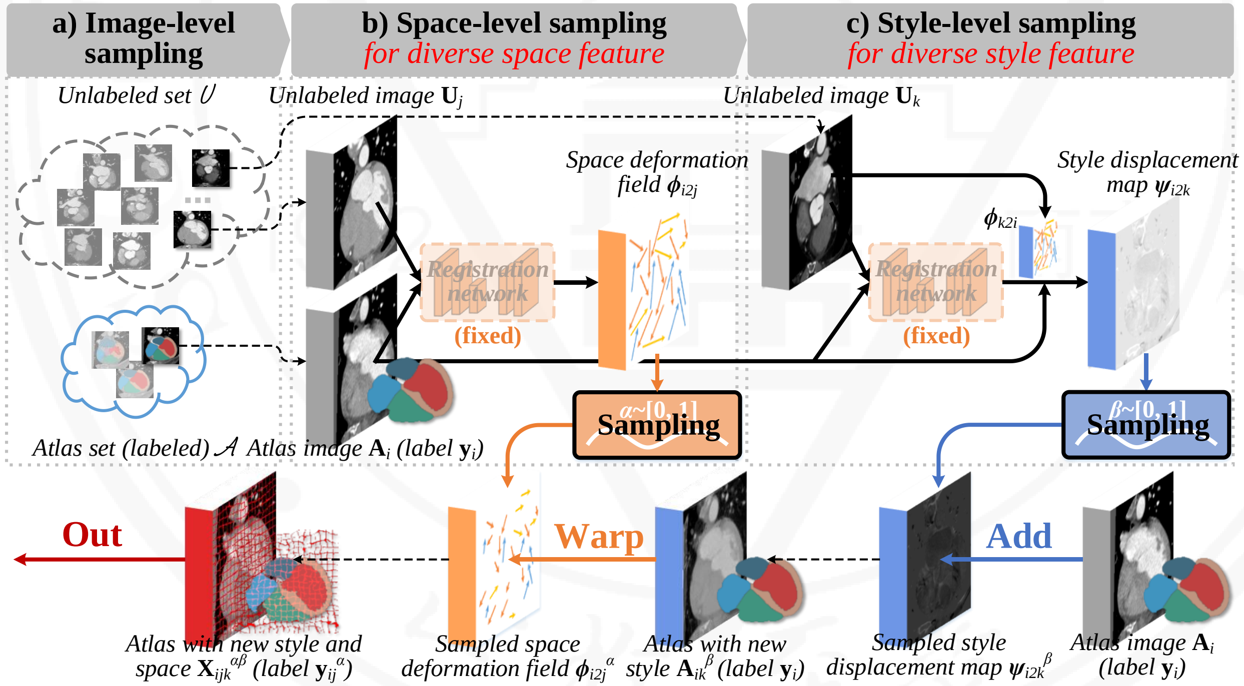
$$\mathbb{S}(\gamma \mathbf{X}_A+(1-\gamma)\mathbf{X}_B) \Leftrightarrow \gamma \mathbb{S}(\mathbf{X}_A)+(1-\gamma)\mathbb{S}(\mathbf{X}_B)$$

Y. He, et al., "Learning Better Registration to Learn Better Few-Shot Medical Image Segmentation: Authenticity, Diversity, and Robustness," in IEEE TNNLS

II: Learning registration to learn segmentation (BRBS)







https://github.com/YutingHe-list/BRBS

Y. He, et al., "Learning Better Registration to Learn Better Few-Shot Medical Image Segmentation: Authenticity, Diversity, and Robustness," in IEEE TNNLS

II: Learning registration to learn segmentation (BRBS)

Method	Type	(a)				(b)			
		1-shot$_{\pm std}$		5-shot$_{\pm std}$		1-shot$_{\pm std}$		5-shot$_{\pm std}$	
		DSC% ↑	AVDmm ↓	DSC% ↑	AVDmm ↓	DSC% ↑	AVDmm ↓	DSC% ↑	AVDmm ↓
3D U-Net [13]	LS	63.8$_{\pm 16.3}$	6.13$_{\pm 3.46}$	84.3$_{\pm 9.6}$	2.43$_{\pm 2.14}$	54.4$_{\pm 10.8}$	2.94$_{\pm 1.23}$	69.5$_{\pm 8.8}$	1.59$_{\pm 0.84}$
SegNet [14]	LS	57.5$_{\pm 17.4}$	7.01$_{\pm 4.53}$	78.8$_{\pm 10.5}$	2.68$_{\pm 1.72}$	52.3$_{\pm 4.9}$	3.18$_{\pm 0.37}$	62.7$_{\pm 7.0}$	1.98$_{\pm 0.72}$
U-Net++ [15]	LS	42.9$_{\pm 20.5}$	9.18$_{\pm 3.78}$	84.0$_{\pm 8.6}$	2.51$_{\pm 2.26}$	51.2$_{\pm 10.6}$	2.33$_{\pm 1.06}$	66.4$_{\pm 12.7}$	2.02$_{\pm 1.62}$
DBN [16]	LS	48.8$_{\pm 16.5}$	10.70$_{\pm 4.10}$	78.9$_{\pm 12.0}$	3.90$_{\pm 3.12}$	23.5$_{\pm 15.9}$	13.83$_{\pm 7.26}$	80.2$_{\pm 5.6}$	0.92$_{\pm 0.30}$
UA-MT [46]	SLS	54.8$_{\pm 17.0}$	9.44$_{\pm 4.77}$	66.4$_{\pm 16.2}$	4.69$_{\pm 2.27}$	36.7$_{\pm 8.4}$	8.69$_{\pm 2.29}$	75.5$_{\pm 3.4}$	1.31$_{\pm 0.95}$
CPS [48]	SLS	70.7$_{\pm 9.4}$	4.01$_{\pm 1.73}$	87.4$_{\pm 5.4}$	1.40$_{\pm 0.76}$	25.3$_{\pm 1.2}$	unable	37.1$_{\pm 1.8}$	unable
MASSL [47]	SLS	57.2$_{\pm 12.5}$	13.86$_{\pm 3.16}$	77.4$_{\pm 8.7}$	9.07$_{\pm 3.11}$	74.0$_{\pm 3.1}$	1.32$_{\pm 0.35}$	80.5$_{\pm 3.1}$	0.92$_{\pm 0.43}$
DPA-DBN [16]	SLS	49.0$_{\pm 14.4}$	10.47$_{\pm 3.81}$	68.0$_{\pm 14.5}$	5.75$_{\pm 3.89}$	28.1$_{\pm 7.6}$	7.75$_{\pm 1.78}$	68.7$_{\pm 8.2}$	3.90$_{\pm 2.39}$
VM [11]	ABS	77.6$_{\pm 6.0}$	2.49$_{\pm 0.73}$	81.0$_{\pm 6.1}$	2.13$_{\pm 0.78}$	78.7$_{\pm 1.8}$	0.73$_{\pm 0.07}$	83.1$_{\pm 1.8}$	0.56$_{\pm 0.08}$
LC-VM [26]	ABS	-	-	81.7$_{\pm 6.0}$	2.04$_{\pm 0.77}$	-	-	83.0$_{\pm 1.8}$	0.56$_{\pm 0.07}$
LT-Net [5]	ABS	67.2$_{\pm 6.5}$	3.55$_{\pm 0.90}$	77.8$_{\pm 7.8}$	2.25$_{\pm 0.95}$	76.9$_{\pm 1.5}$	0.75$_{\pm 0.51}$	82.6$_{\pm 1.2}$	0.57$_{\pm 0.05}$
DeepAtlas [1]	LRLS	85.4$_{\pm 4.5}$	1.59$_{\pm 0.56}$	87.9$_{\pm 4.3}$	1.30$_{\pm 0.57}$	73.0$_{\pm 2.4}$	1.02$_{\pm 0.10}$	79.3$_{\pm 2.6}$	0.74$_{\pm 0.12}$
DataAug [2]	LRLS	81.4$_{\pm 5.2}$	2.23$_{\pm 0.67}$	82.2$_{\pm 5.2}$	2.04$_{\pm 0.73}$	81.3$_{\pm 1.4}$	0.69$_{\pm 0.06}$	83.9$_{\pm 1.2}$	0.55$_{\pm 0.06}$
DeepRS [3]	LRLS	73.4$_{\pm 12.3}$	3.40$_{\pm 1.92}$	87.0$_{\pm 5.0}$	1.60$_{\pm 0.90}$	55.9$_{\pm 12.0}$	1.81$_{\pm 0.91}$	73.0$_{\pm 5.9}$	0.93$_{\pm 0.25}$
PC-Reg-RT [4]	LRLS	85.5$_{\pm 4.7}$	1.55$_{\pm 0.63}$	88.5$_{\pm 4.9}$	1.23$_{\pm 0.72}$	66.9$_{\pm 3.6}$	1.38$_{\pm 0.19}$	73.1$_{\pm 3.1}$	1.09$_{\pm 0.17}$
VAEAug [6]	LRLS	75.5$_{\pm 11.0}$	4.29$_{\pm 2.12}$	-	-	74.8$_{\pm 12.2}$	1.71$_{\pm 2.71}$	-	-
Our BRBS	LRLS	**89.2**$_{\pm 3.4}$	**1.24**$_{\pm 0.50}$	**91.1**$_{\pm 3.9}$	**0.93**$_{\pm 0.57}$	**85.7**$_{\pm 1.0}$	**0.49**$_{\pm 0.04}$	**87.2**$_{\pm 1.0}$	**0.43**$_{\pm 0.05}$

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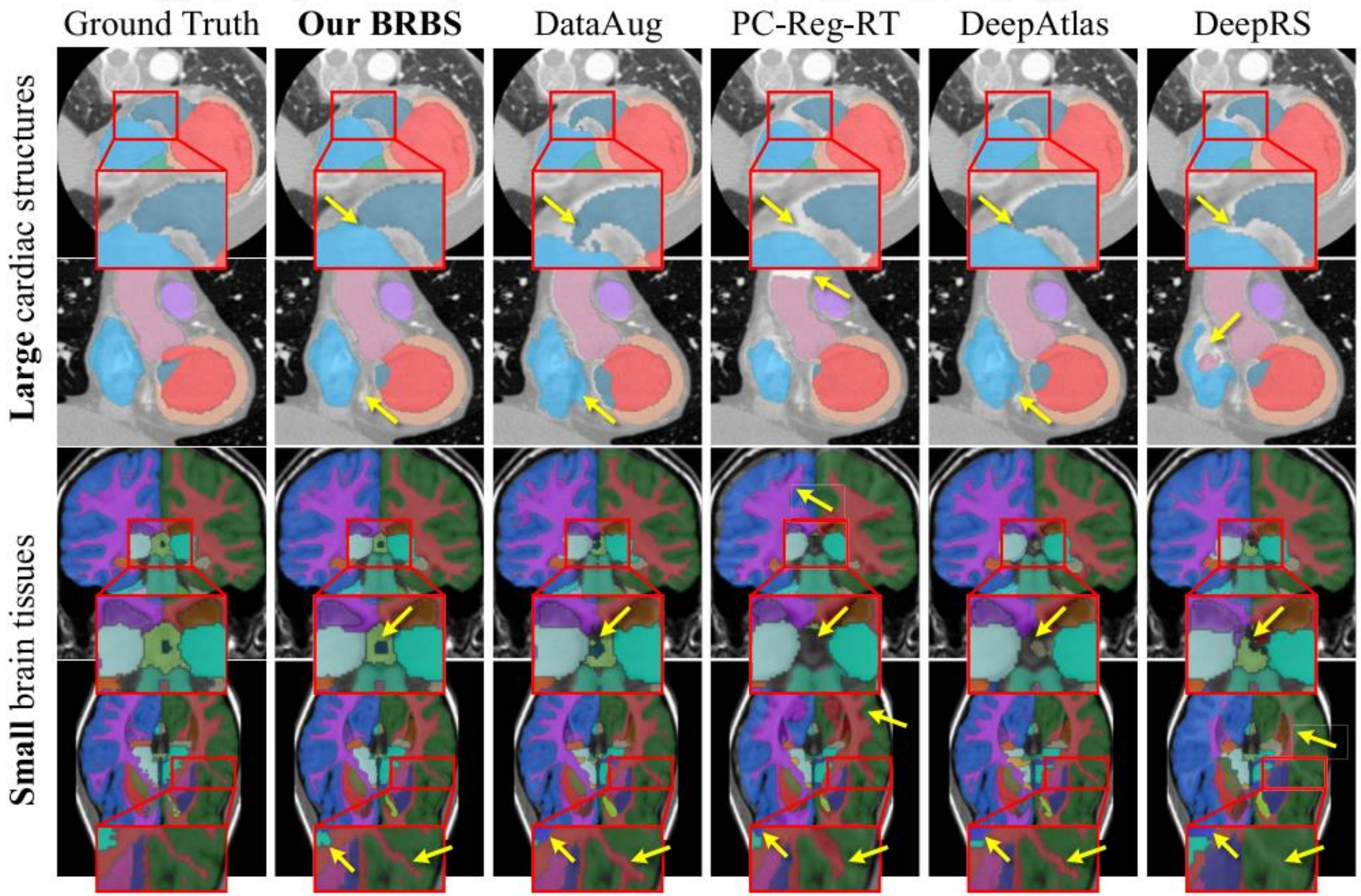

Compared with LRLS method:

- **For large heart structures**, BRBS performs better in the accuracy of boundary segmentation.
- **For small brain tissues,** BRBS shows better segmentation performance of fine structures.

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KCC		S3P			MMR	Segmentation		Registration		
SeC	BiC	Image	Space	Style		DSC% ↑	AVDmm ↓	DSC% ↑	AVDmm ↓	$\lvert J_\phi \rvert \leq 0\%$ ↓
						$84.3_{\pm 9.6}$	$2.43_{\pm 2.14}$	-	-	-
		✓				$80.7_{\pm 9.6}$	$2.52_{\pm 1.52}$	$72.6_{\pm 13.8}$	$2.89_{\pm 1.18}$	$3.3_{\pm 0.7}$
		✓	✓			$83.7_{\pm 8.0}$	$2.33_{\pm 2.03}$	$73.2_{\pm 13.8}$	$2.84_{\pm 1.17}$	$3.2_{\pm 0.7}$
		✓	✓	✓		$88.1_{\pm 4.7}$	$1.25_{\pm 0.63}$	$73.0_{\pm 13.9}$	$2.87_{\pm 1.20}$	$3.5_{\pm 0.8}$
		✓	✓		✓	$84.4_{\pm 6.5}$	$1.85_{\pm 0.89}$	$73.5_{\pm 13.8}$	$2.84_{\pm 1.18}$	$3.7_{\pm 0.8}$
✓		✓	✓	✓		$90.0_{\pm 3.8}$	$1.04_{\pm 0.49}$	$85.9_{\pm 13.5}$	$1.33_{\pm 0.67}$	$6.2_{\pm 1.2}$
✓	✓	✓	✓	✓		$90.4_{\pm 3.4}$	$1.00_{\pm 0.44}$	$86.0_{\pm 13.5}$	$1.31_{\pm 0.64}$	$2.5_{\pm 1.1}$
✓	✓	✓	✓	✓	✓	$\mathbf{91.1}_{\pm 3.9}$	$\mathbf{0.93}_{\pm 0.57}$	$\mathbf{86.7}_{\pm 13.6}$	$\mathbf{1.22}_{\pm 0.62}$	$\mathbf{1.7}_{\pm 0.8}$

Each module plays a certain role in improving performance. When all modules are added to the model, the performance of BRBS reaches the best.

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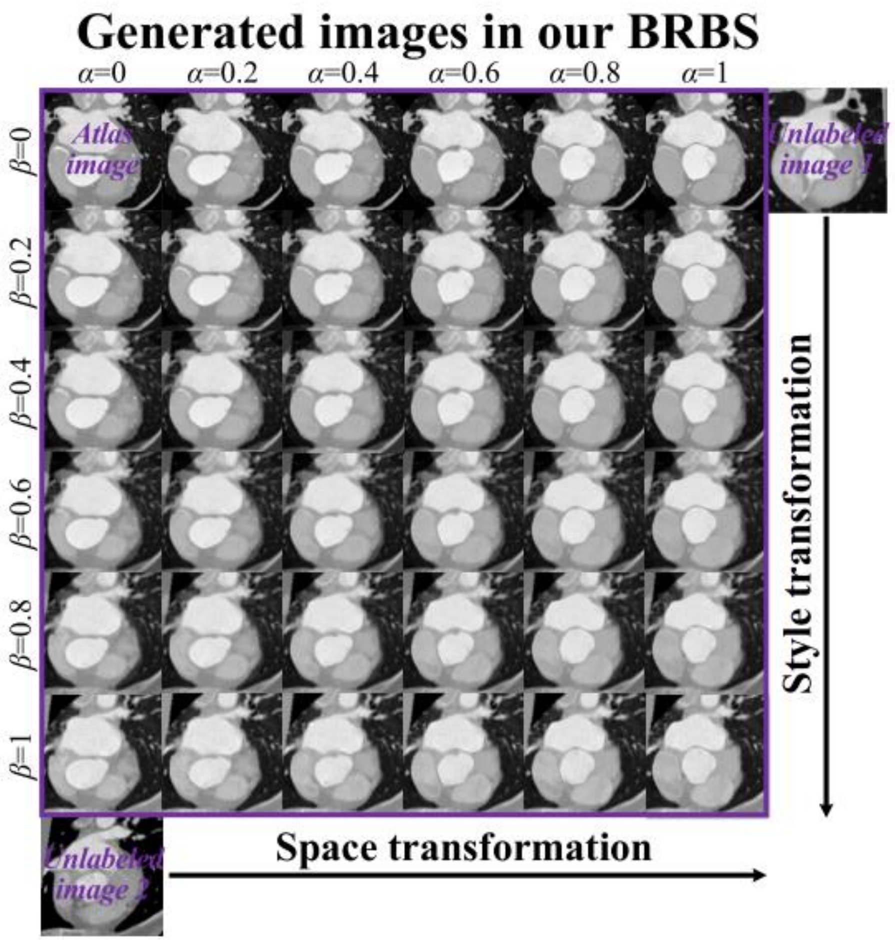

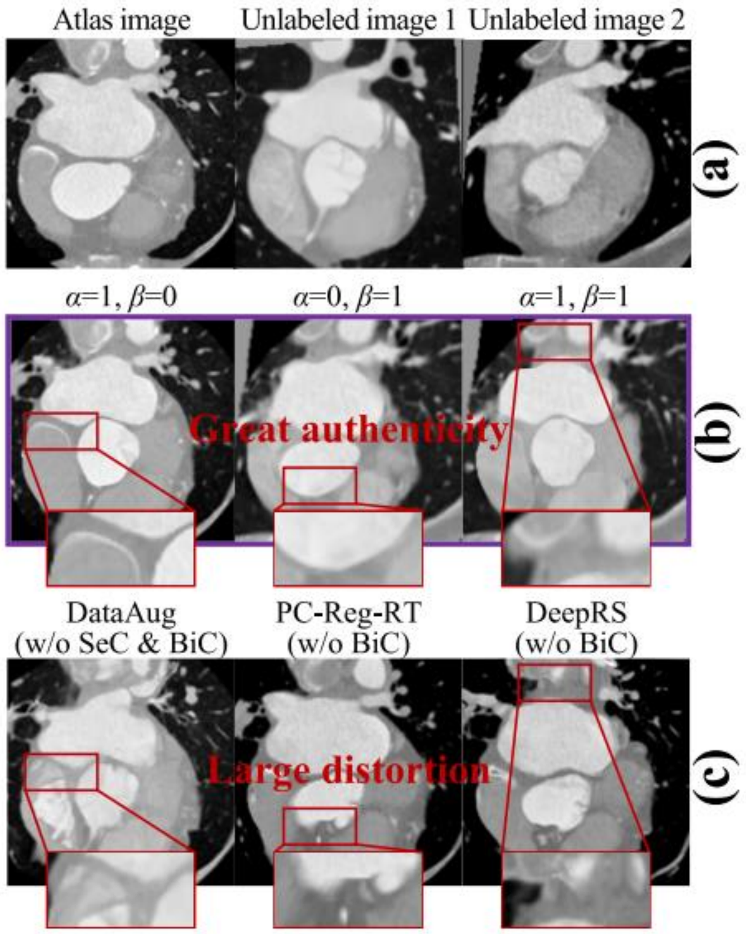

1. **Compared with other methods based on LRLS**, BiC and SeC effectively improve the authenticity of images generated by BRBS model.
2. **Compared with the real images**, the images generated by BRBS also have high similarity, so the trained segmentation network will learn the representation ability that matches the real data and obtain good generalization ability.

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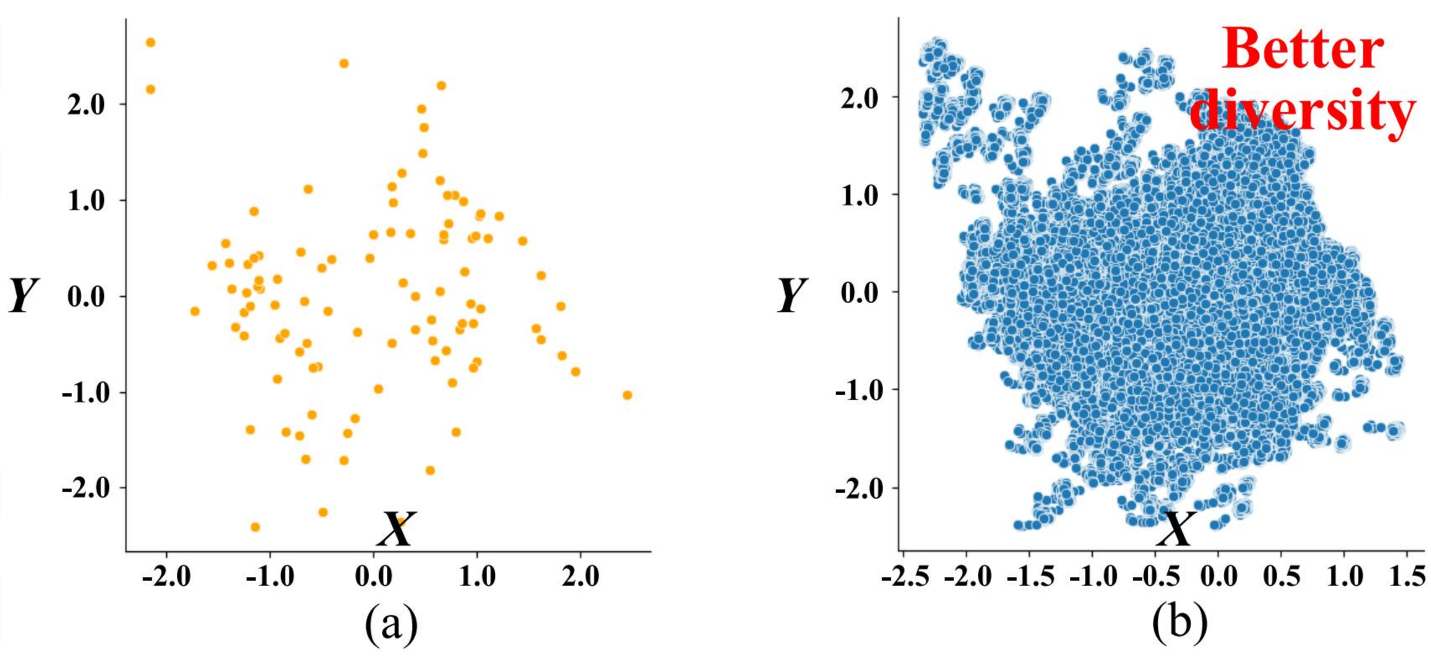

a) **Without S3P**, the generated image only has sparse feature distribution and poor diversity.

b) **S3P** constructs a distribution with continuous space and style, and samples densely on this distribution, so a large number of images with different space and style characteristics are generated.

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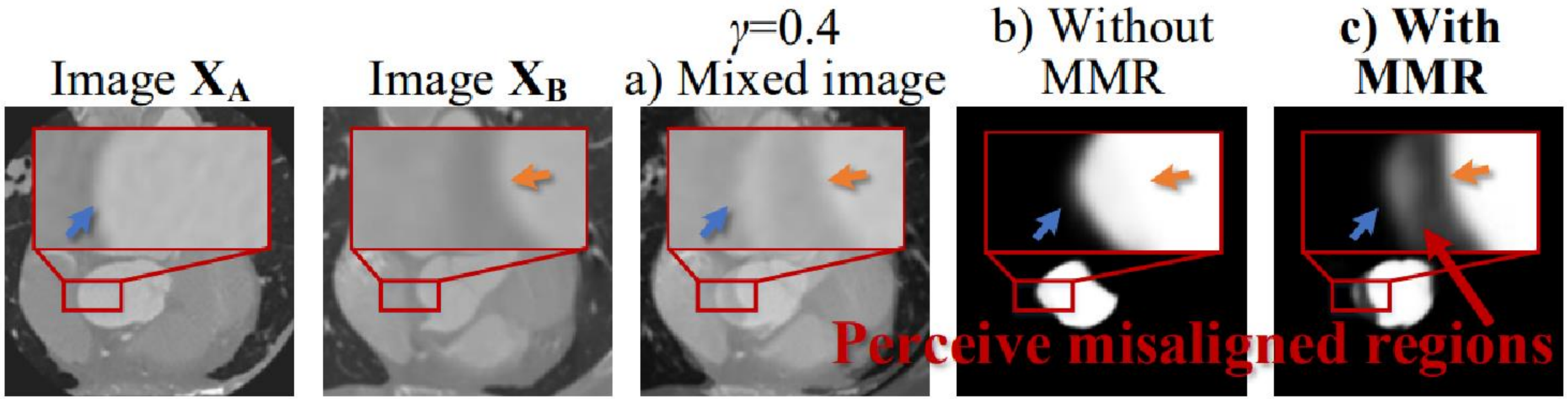

1. 3D U-Net (MMR-free) can't perceive these misaligned regions (b), and it is easy to over-fit to inaccurate information, and it shows too high confidence in the segmentation results for mismatched regions.

2. The MMR training model fits a linear function to the misaligned regions, thus producing a lower response (C) to these misaligned regions, and improving the robustness of the segmentation model to alignment distortion.

Questions?

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