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TU/e Technische Universiteit Eindhoven University of Technology

Guest lecture

Summary of guest lecture

1. Applications
    1. Application: adapative radiotherapy
    2. Radiotherapy workflow
    3. Image registration for contour propagation in adaptive radiotherapy

2. Challenges in image registration
    1. Large deformations
    2. Small datasets, no ground truth

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Background – Applications

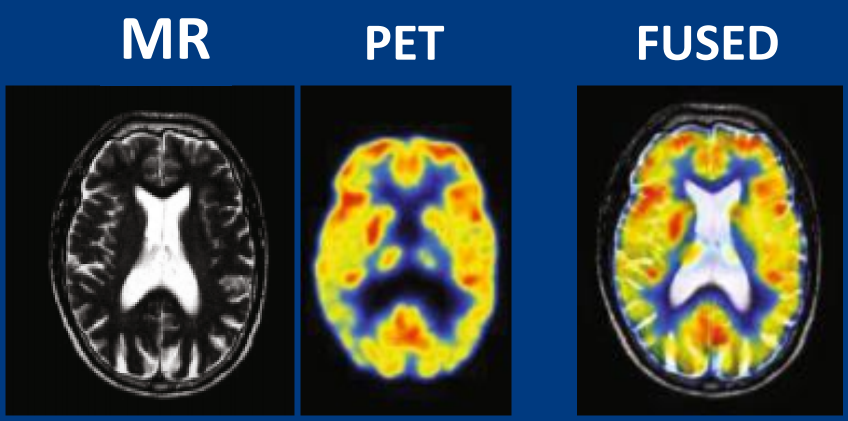
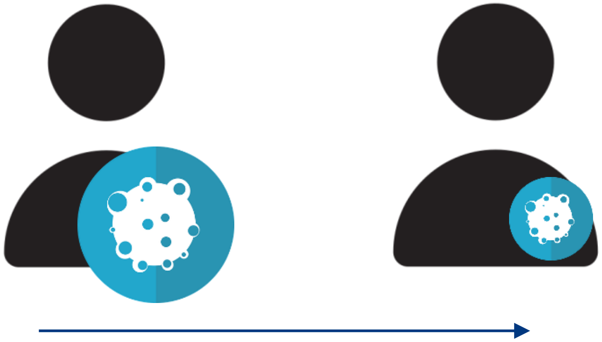
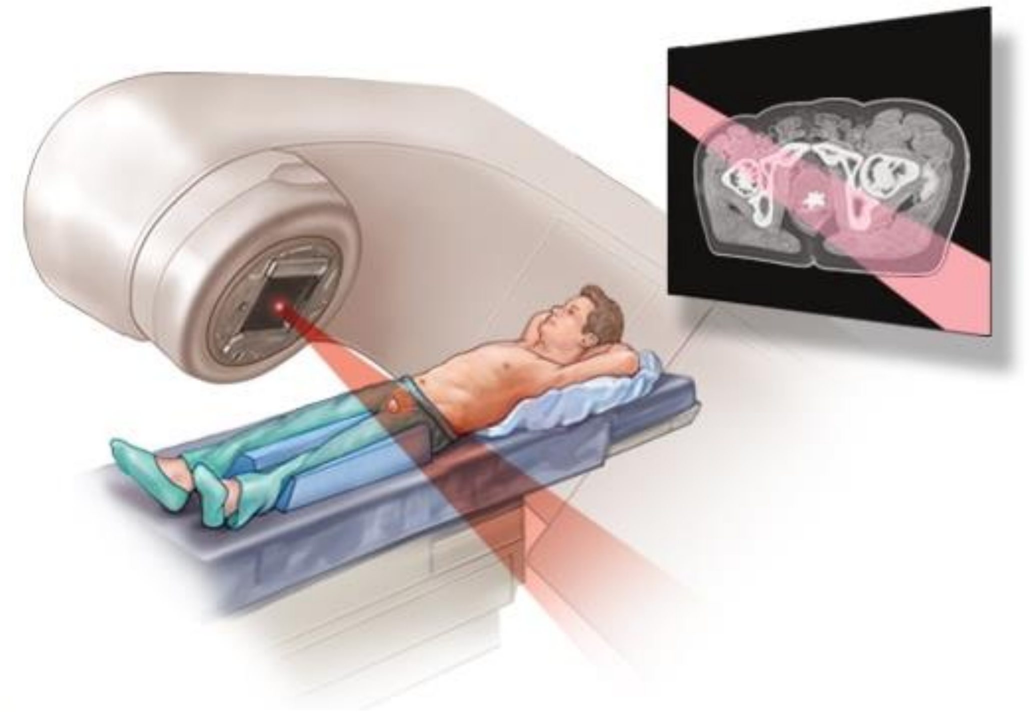


IMAGE FUSION



MONITOR CHANGES

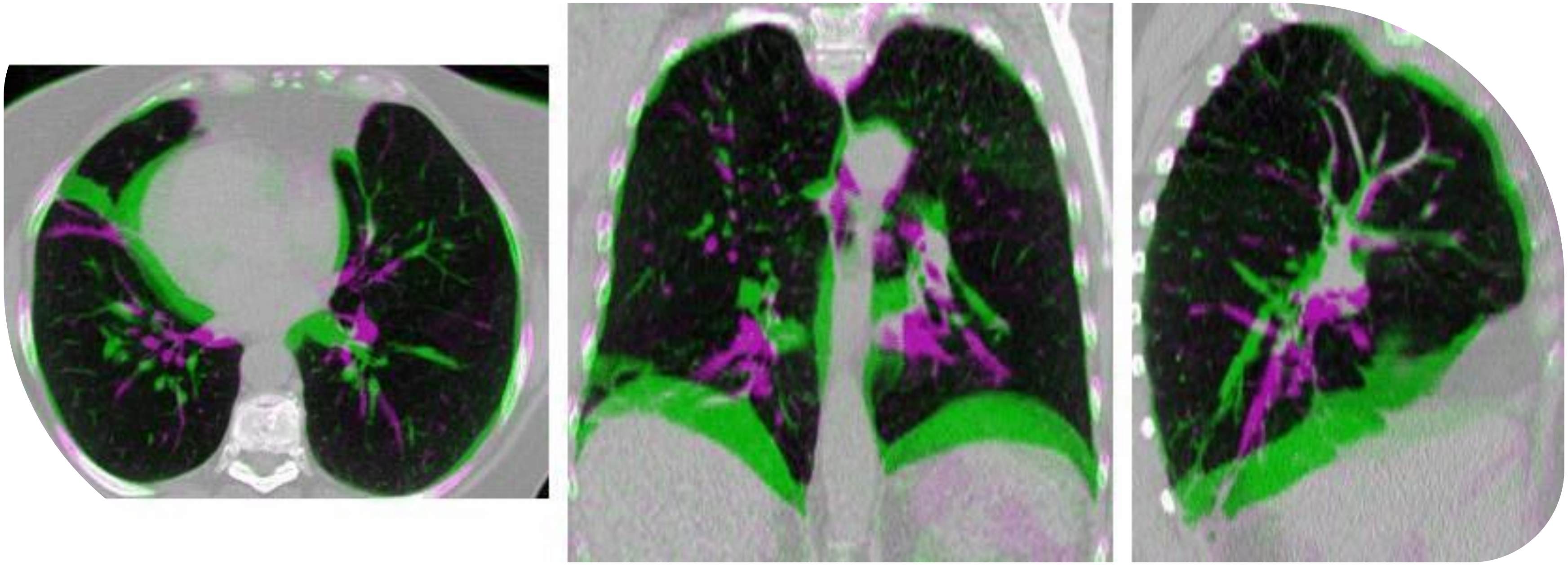
Background – Applications



GOALS

1. Patient positioning
2. Contour propagation
3. Dose accumulation

REAL-TIME ADAPTIVE RADIOTHERAPY

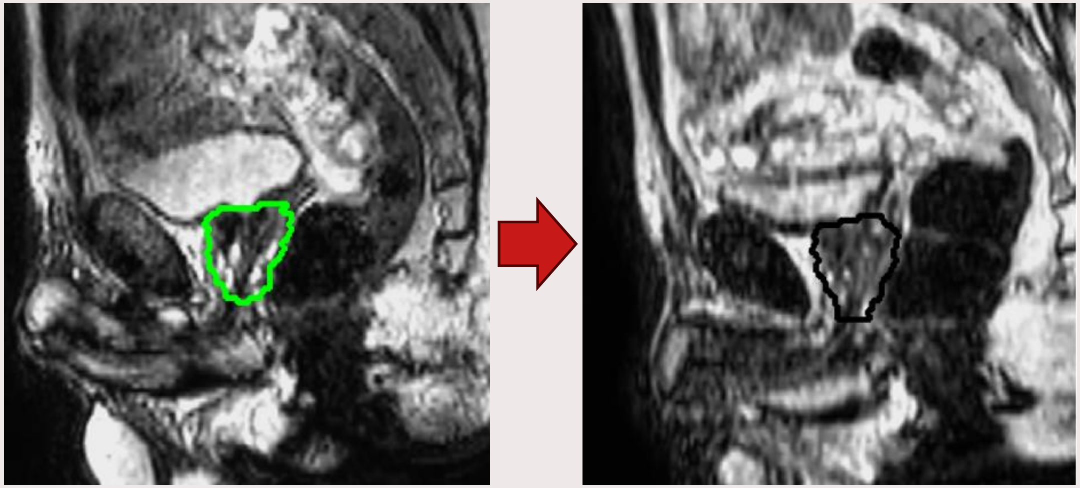


Total latency < 500ms

- acquisition, e.g. undersampled MRI
- deformable image registration

Deep learning-based joint rigid and deformable contour propagation for magnetic resonance imaging-guided prostate radiotherapy

Iris Kolenbrander, Matteo Maspero, Allard Hendriksen, Ryan Pollitt, Jochem van der Voort van Zyp, Nico van den Berg, Josien Pluim and Maureen van Eijnatten



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Background

Prostate cancer

- Second most commonly diagnosed cancer
- Fifth leading cause of death in men worldwide

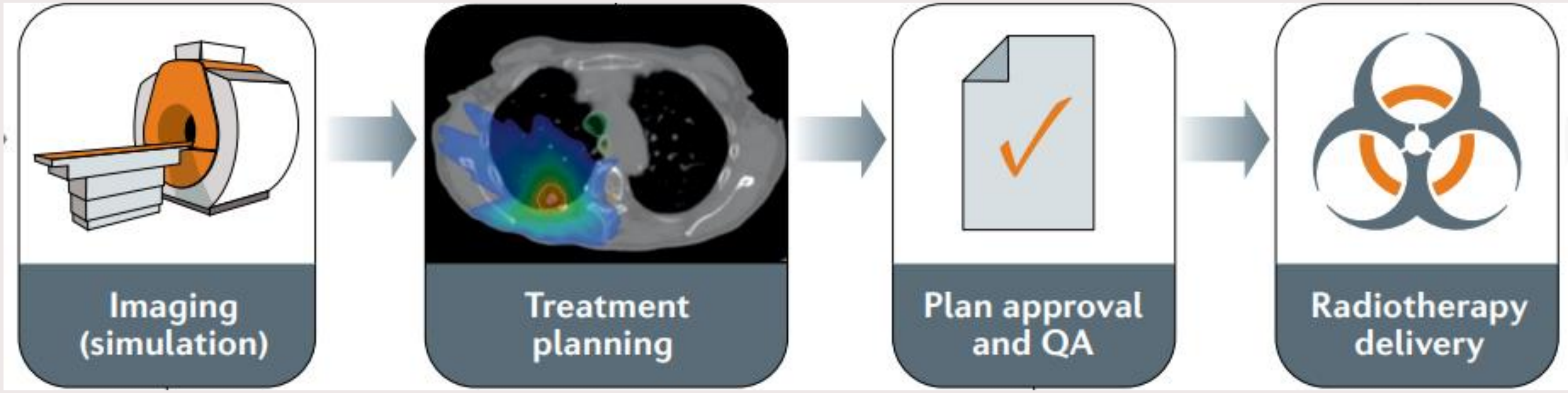
Standard treatment = External-beam radiotherapy (RT)

- delivers radiation over multiple sessions/fractions (~35)

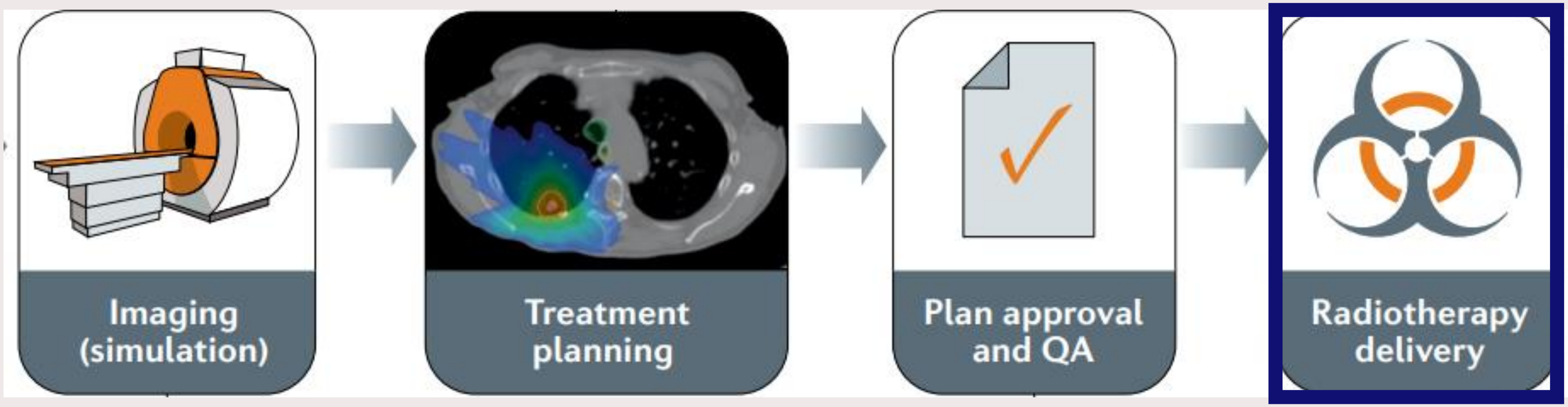
New trend = Hypofractionated RT

- Few irradiations (5-20)
- Higher irradiation dose
- Requires accurate target (prostate) localization

Radiotherapy workflow



Radiotherapy workflow



MR-Linac

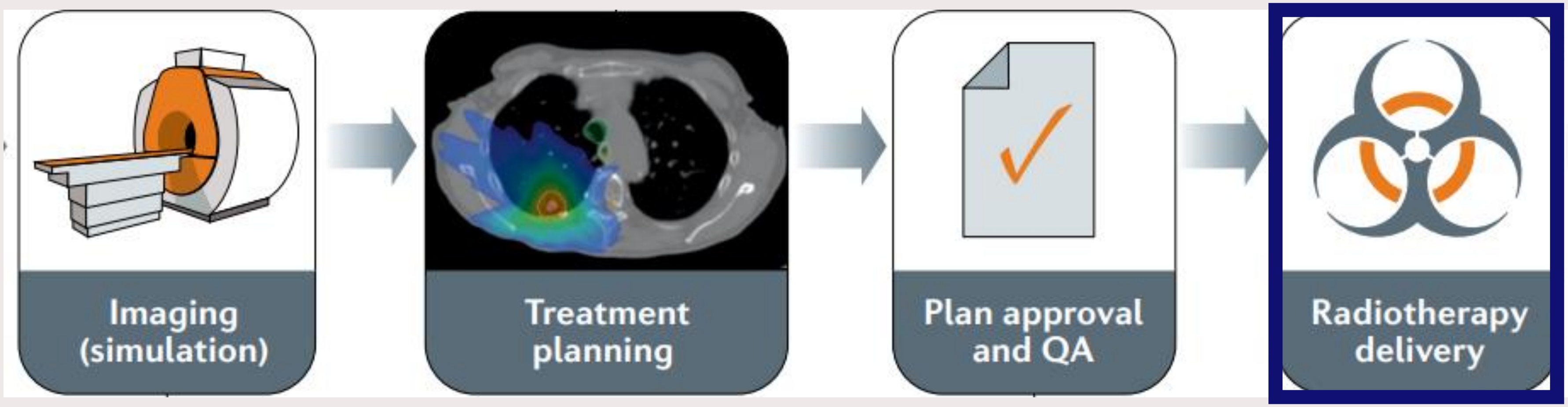
MRI
Initial daily

Re-contour and adapt plan

MRI
Verify position

IN EACH RADIOTHERAPY FRACTION (SESSION)

Radiotherapy workflow



MR-Linac

MRI
Initial daily

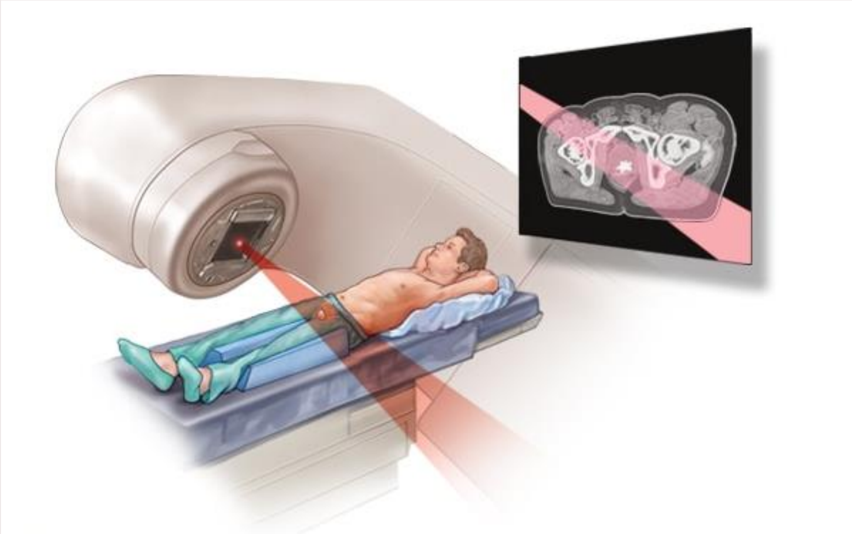
Re-contour and adapt plan

MRI
Verify position

WHILE PATIENT IS LYING ON TREATMENT TABLE

IN EACH RADIOTHERAPY FRACTION (SESSION)

Obtain accurate target localization



Manual delineation of prostate

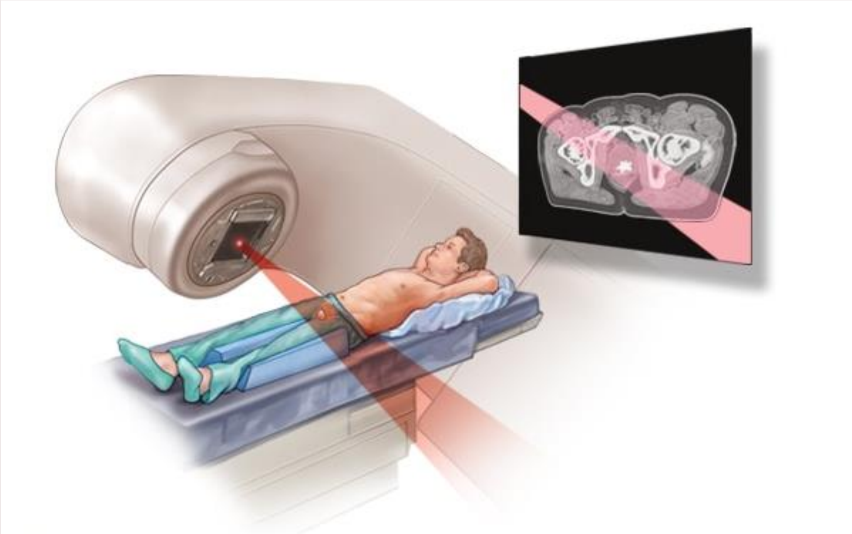
SLOW

Automatic delineation

Segmentation

Registration

Obtain accurate target localization



Manual delineation of prostate

SLOW

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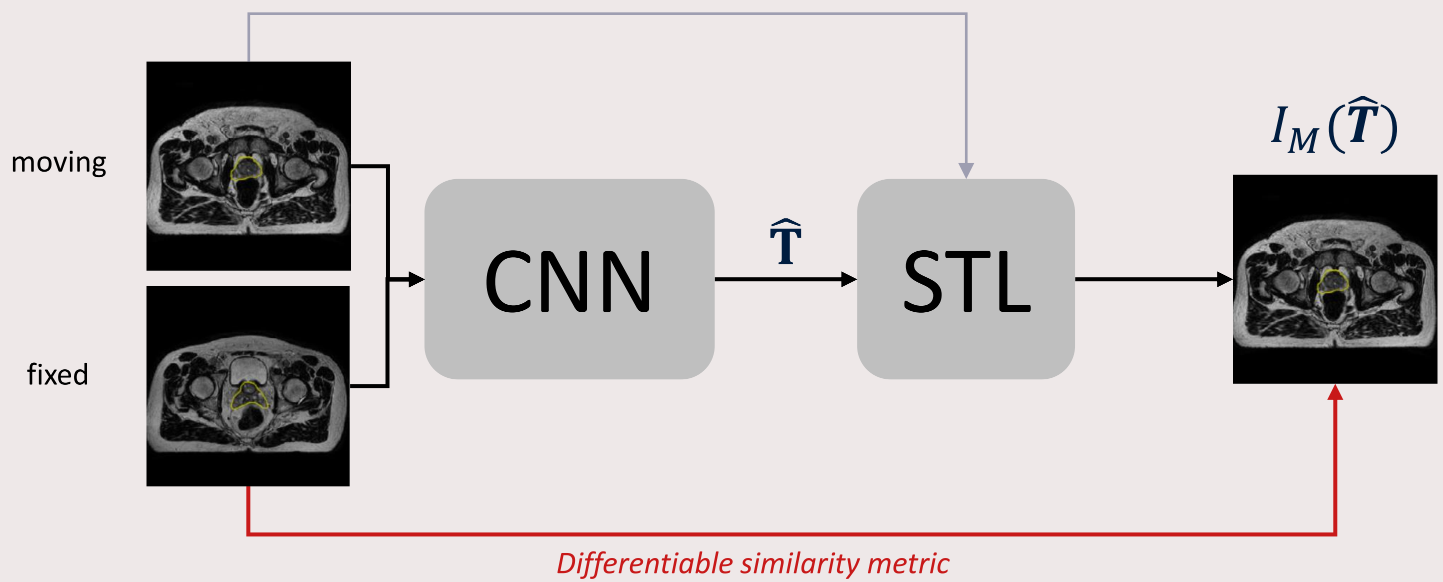
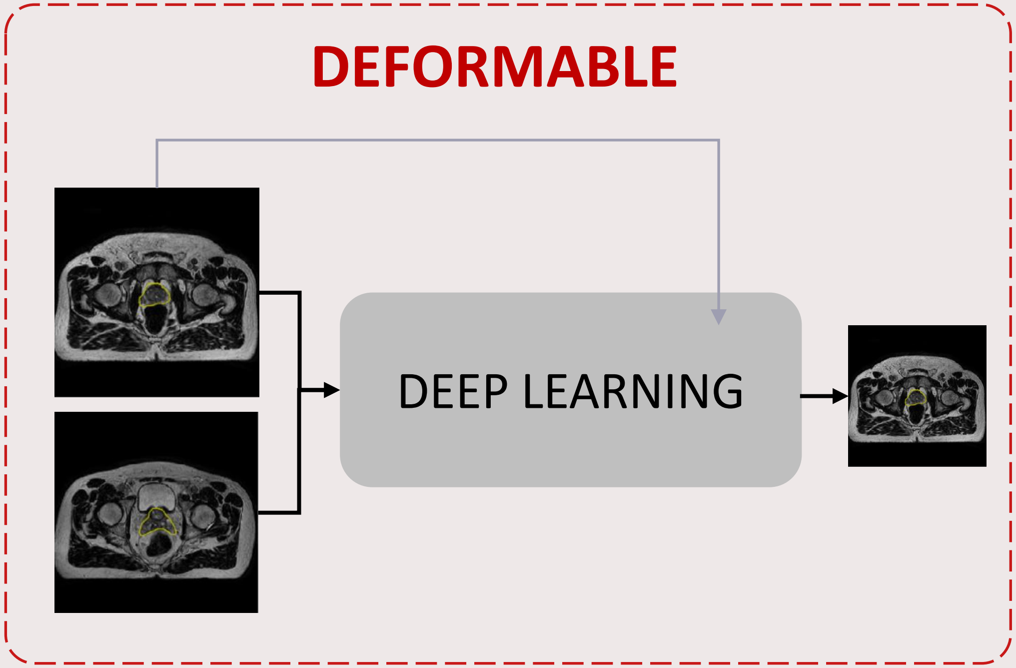
Deep learning-based registration (unsupervised)



Typical framework



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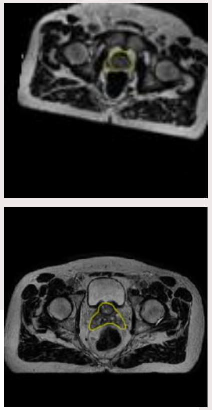

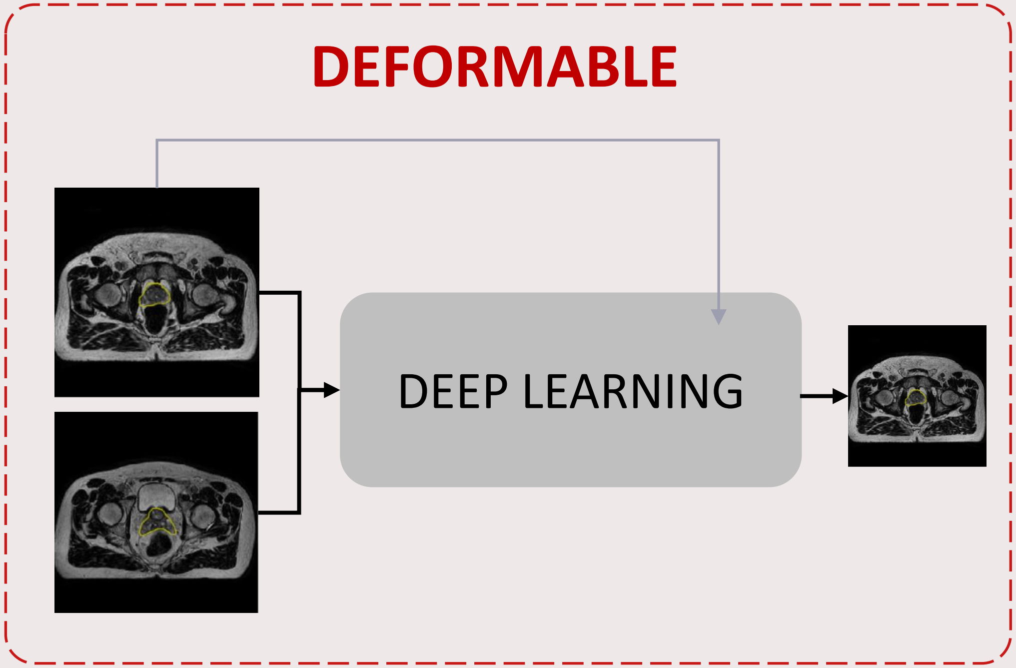

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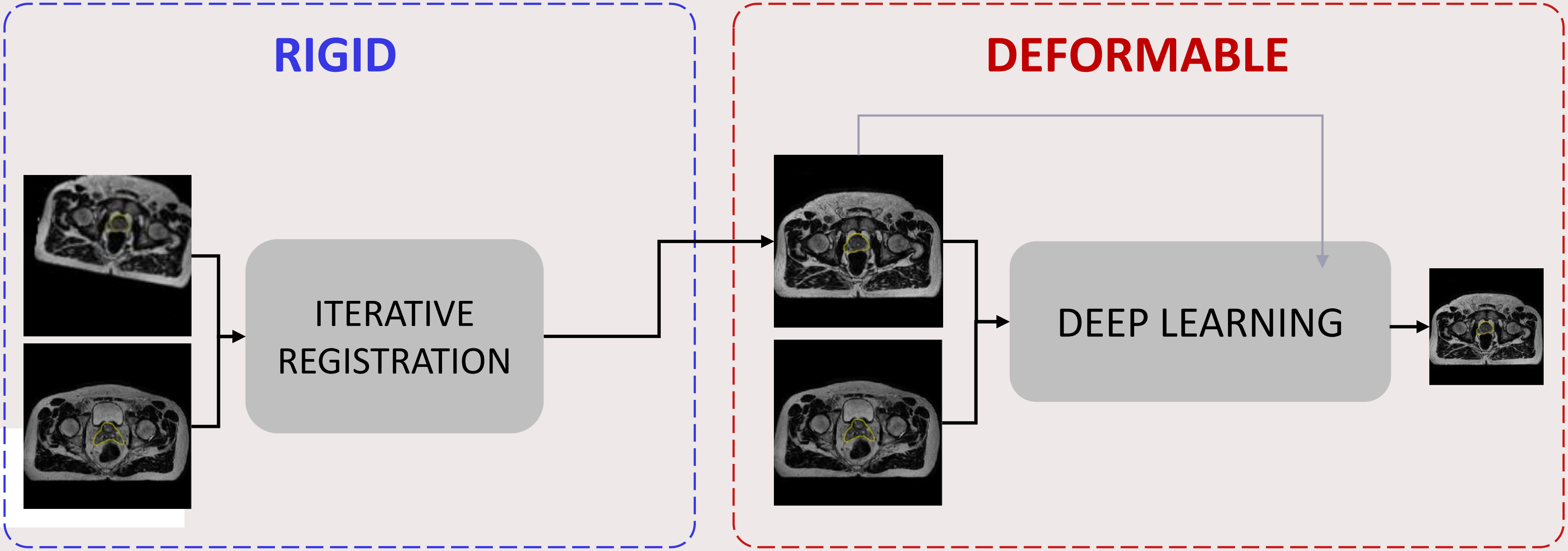

SLOW AND INEFFICIENT!!

Aim

We propose a framework using CNNs for unsupervised, **joint rigid and deformable image registration** to facilitate accurate contour propagation in prostate MRgRT

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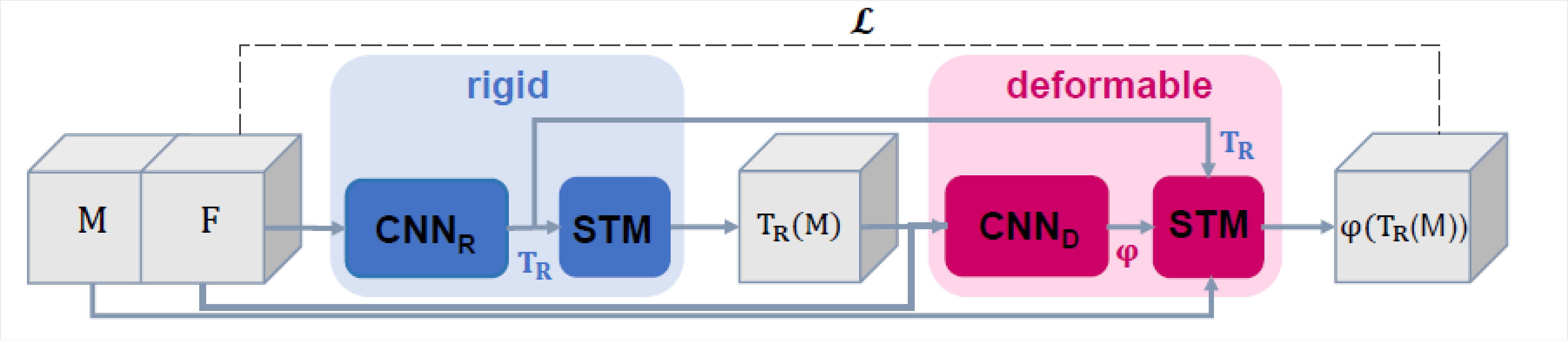

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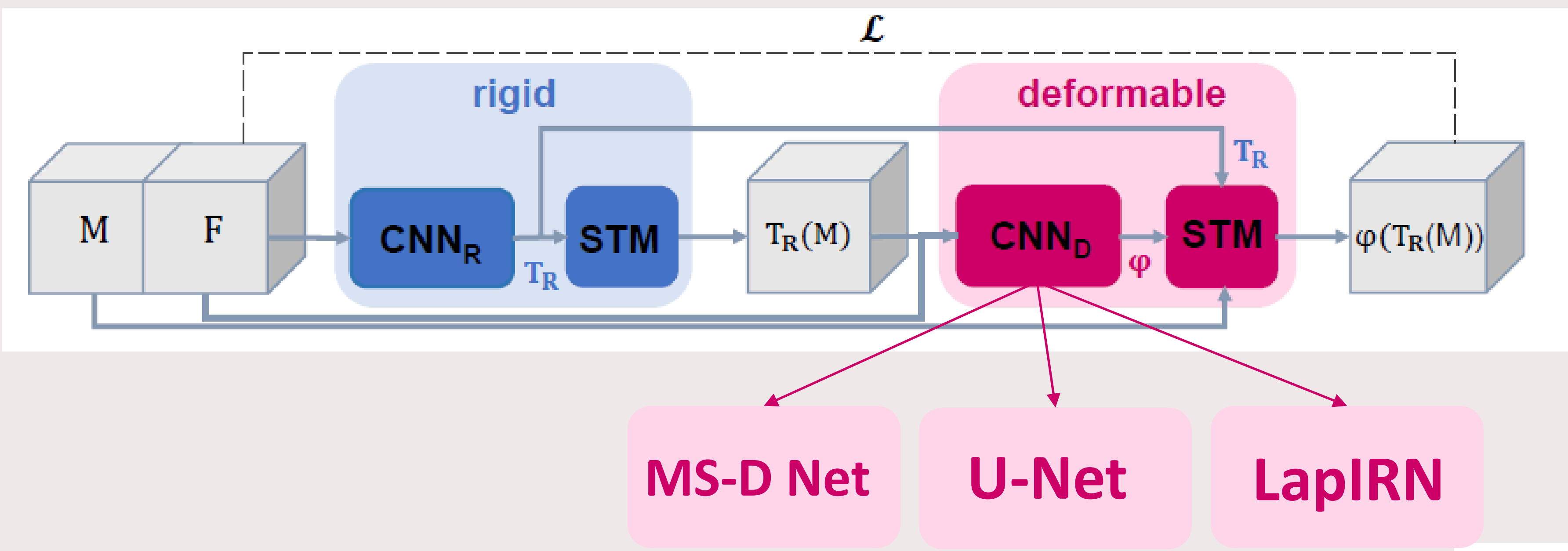
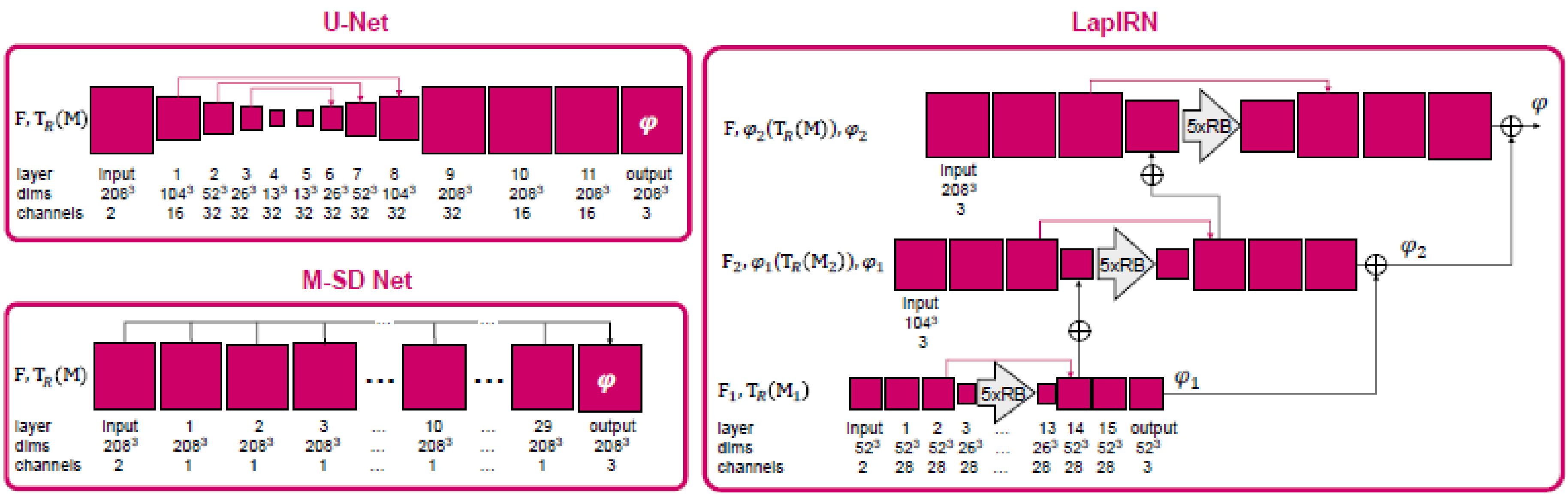
Aim

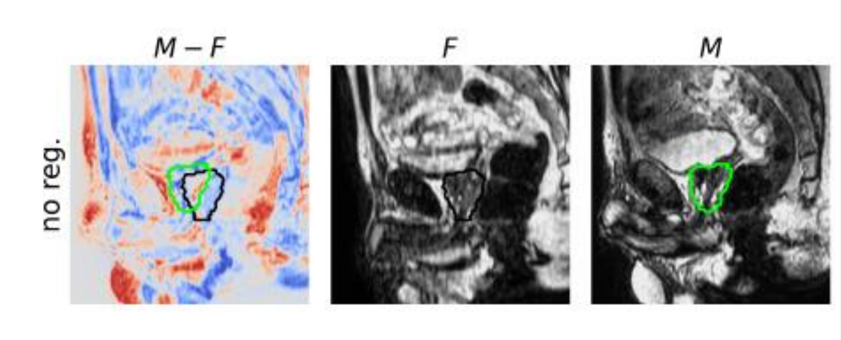
We propose a framework using CNNs for unsupervised, **joint rigid and deformable image registration** to facilitate accurate contour propagation in prostate MRgRT

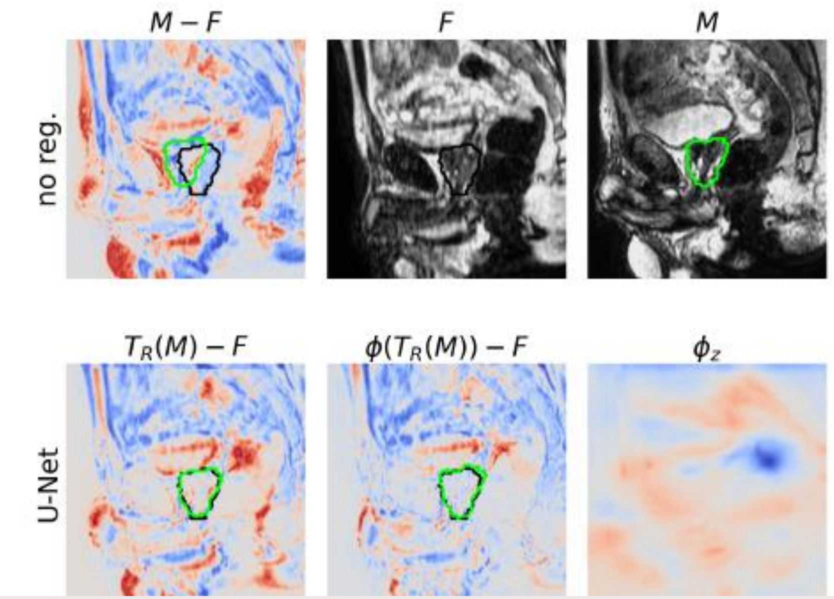
1. We compare three different CNN architectures
2. We evaluate their registration accuracy, speed, and robustness



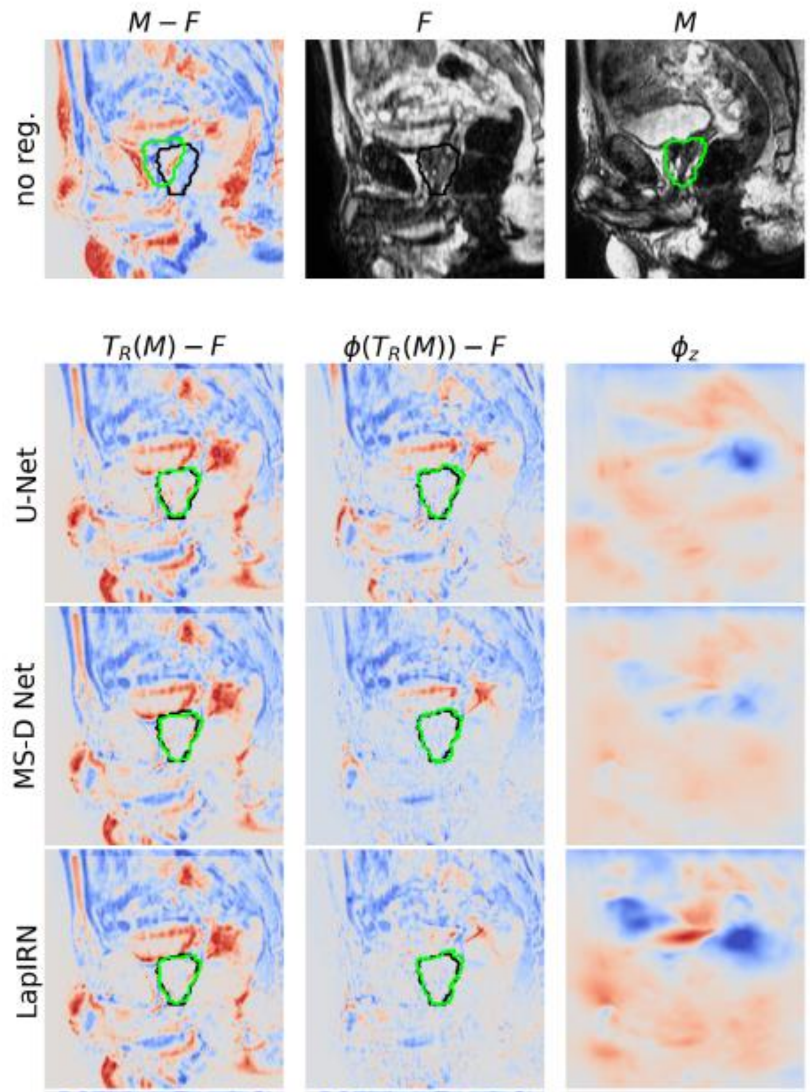
Detailed network architectures …



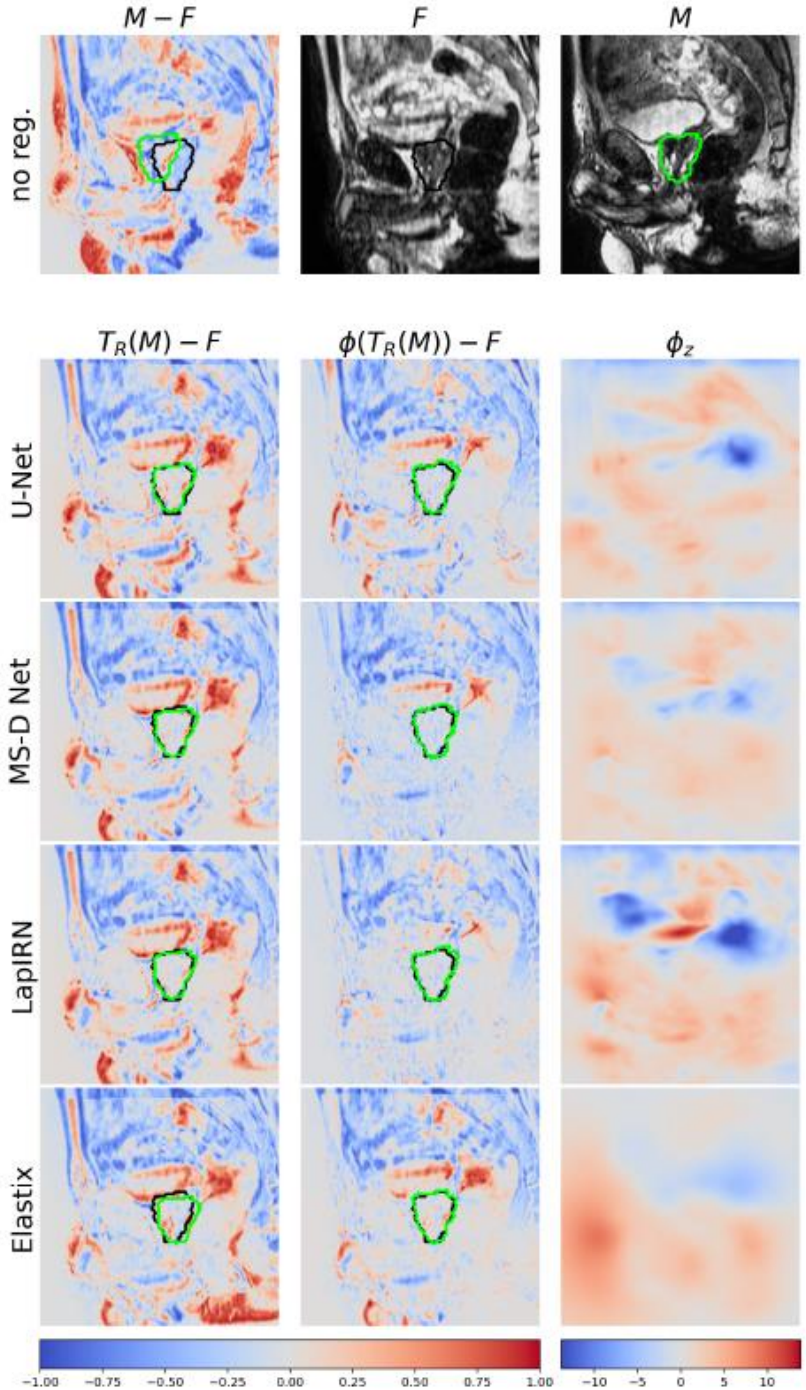

M − F
F
M
no reg.



$M - F$
F
M
no reg.
$T_R(M) - F$
$\phi(T_R(M)) - F$
ϕ_z
U-Net



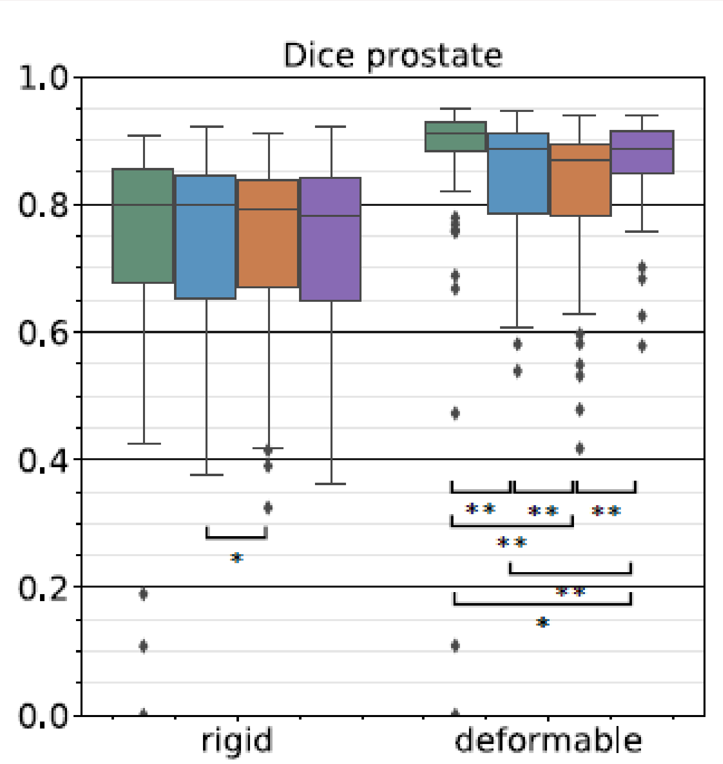
$M-F$
F
M
no reg.
$T_R(M)-F$
$\phi(T_R(M))-F$
ϕ_z
U-Net
MS-D Net
LapIRN

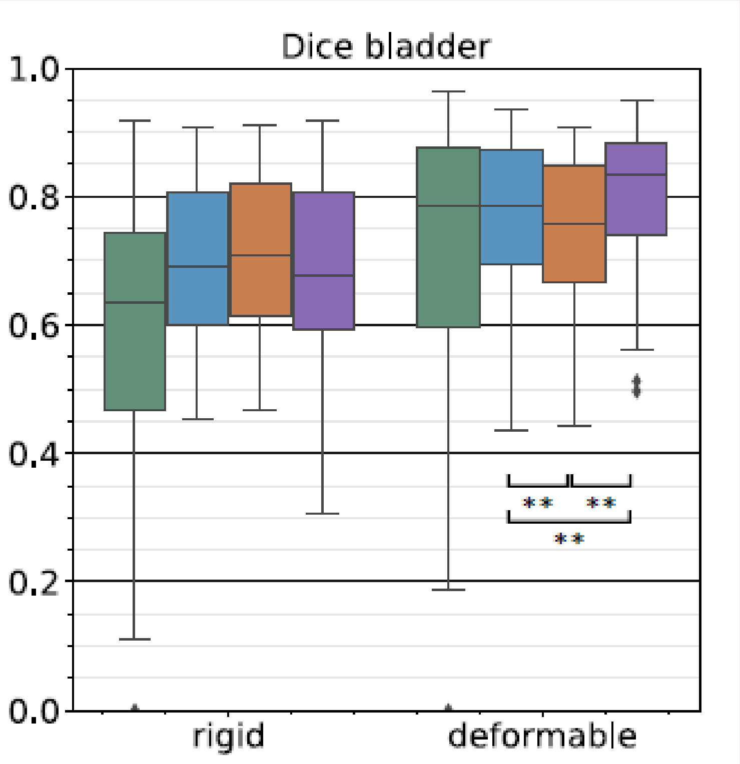


$M-F$
F
M
no reg.
$T_R(M)-F$
$\phi(T_R(M))-F$
ϕ_z
U-Net
MS-D Net
LapIRN
Elastix
−1.00 −0.75 −0.50 −0.25 0.00 0.25 0.50 0.75 1.00
−10 −5 0 5 10

Quantitative results

registration accuracy, speed, and robustness





LapIRN performs best among CNN architectures

Quantitative results

registration accuracy, <u>speed</u>, and robustness

			Latency (s)	Trainable parameters
DL-based	Rigid		0.002 (0.0005)	111,110
	Deformable	LapIRN	0.74 (0.43)	615,076
		U-Net	0.34 (0.21)	301,411
		MS-D Net	0.22 (0.03)	13,494
Elastix	Rigid		14.8 (0.5)*	n.a.
	Deformable		51.5 (0.9)*	n.a.

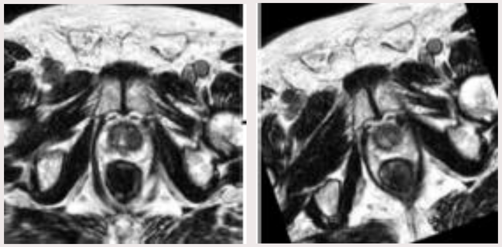
Quantitative results

registration accuracy, speed, and robustness

How do we investigate a model's robustness?

Using perturbations:

Original Perturbed



- Rigid rotations
- Nonlinear deformations
- Synthetic bias field

Quantitative results

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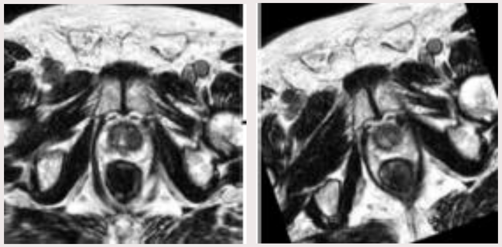
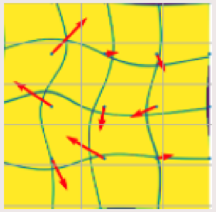
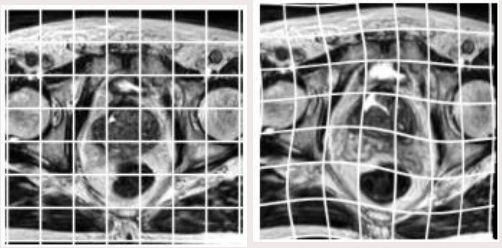


- Nonlinear deformations





- Synthetic bias field

Quantitative results

registration accuracy, speed, and <u>robustness</u>

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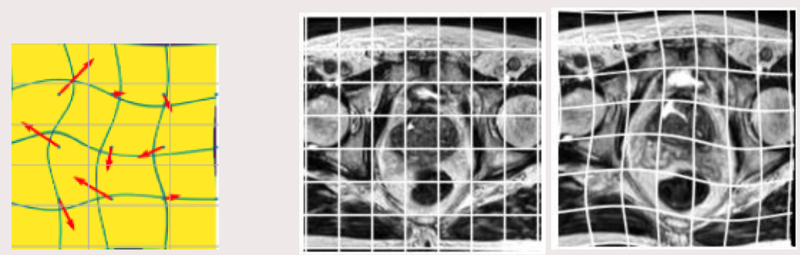

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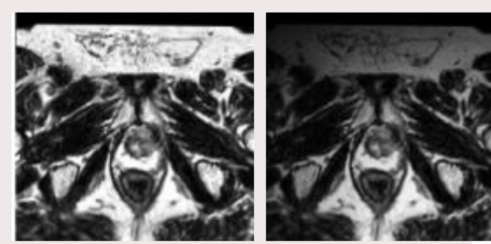

Quantitative results

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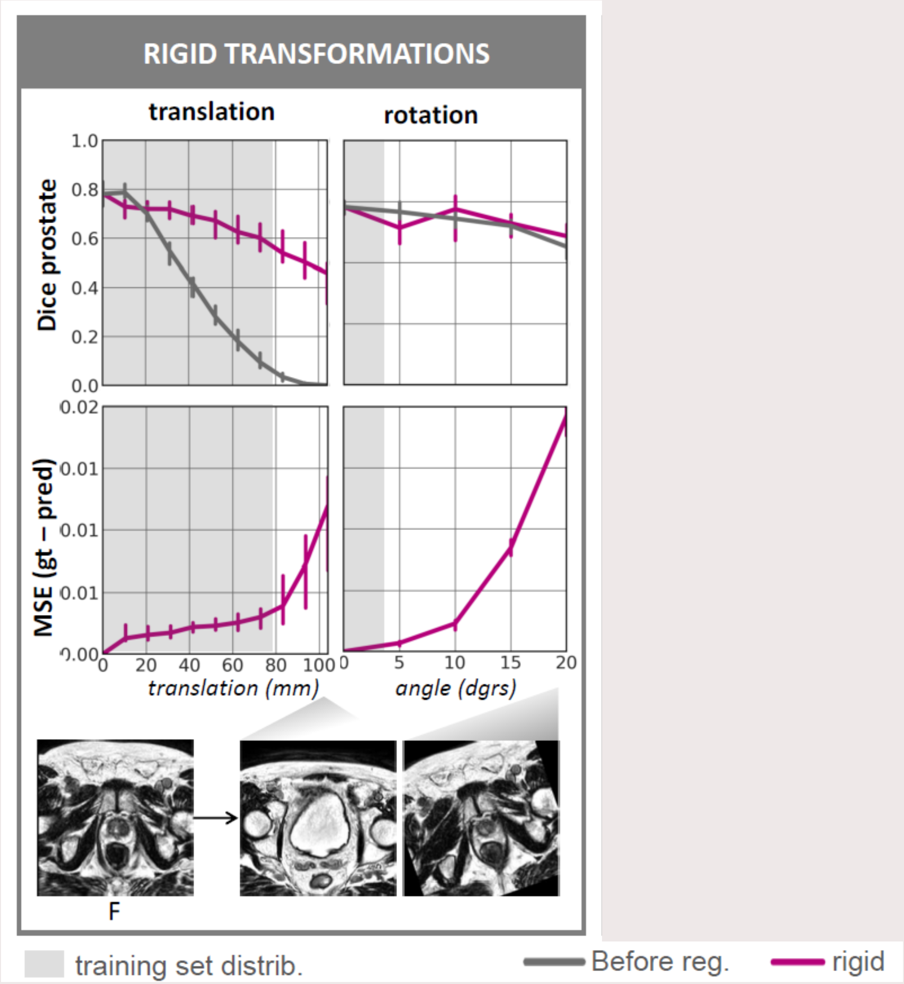

Quantitative results

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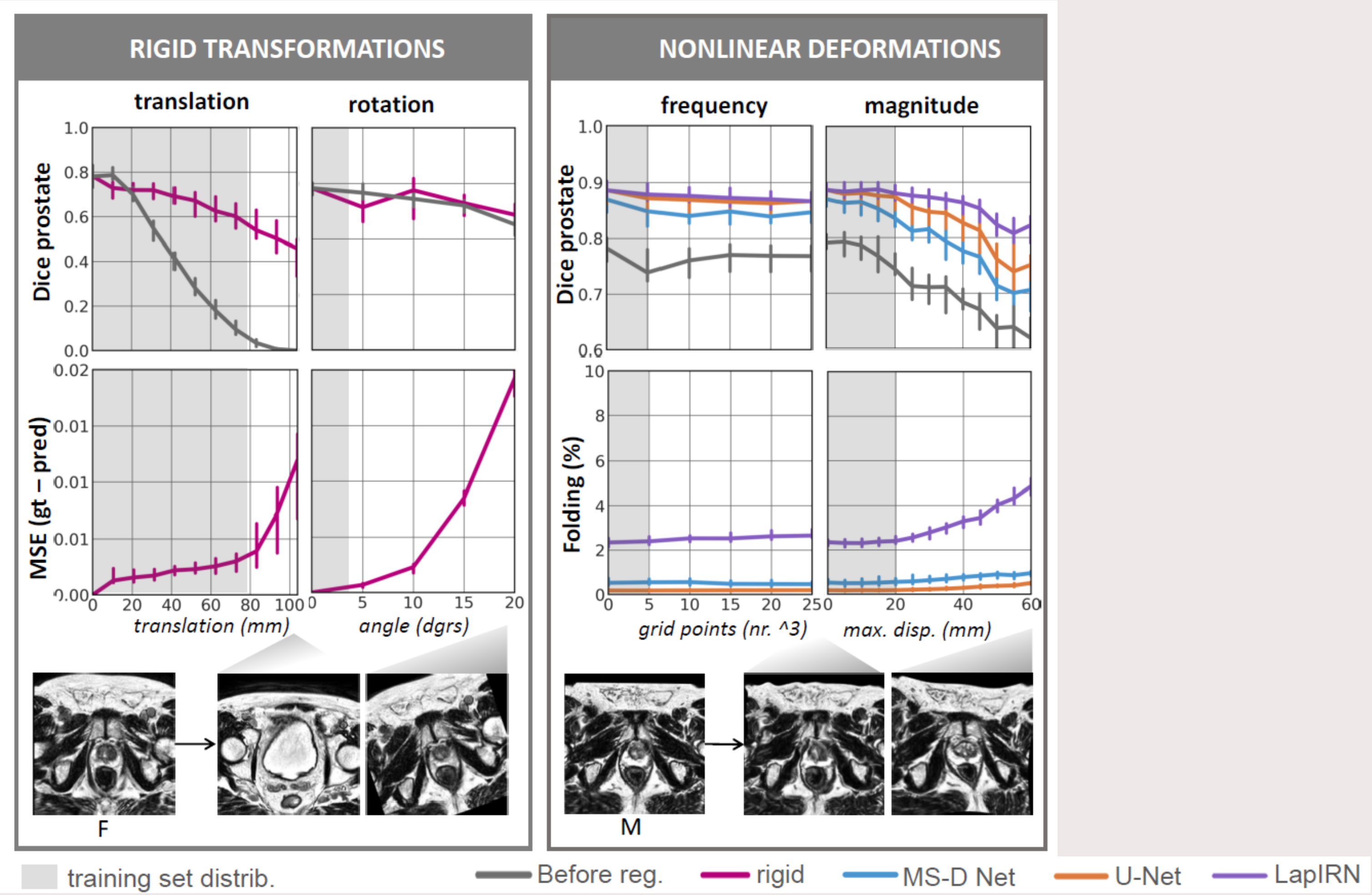
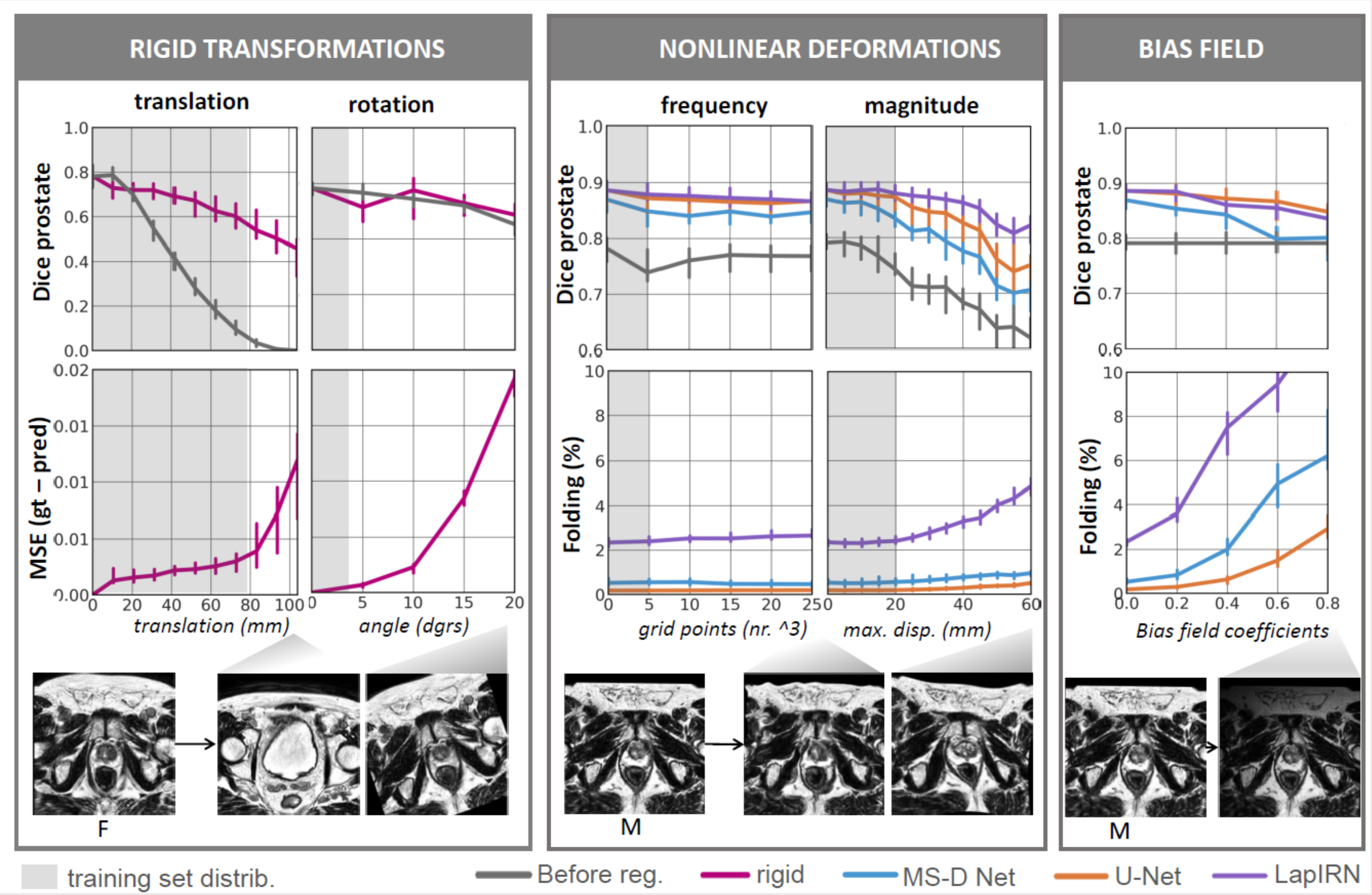


Quantitative results

registration accuracy, speed, and robustness



Discussion

We proposed an unsupervised, joint rigid and deformable image registration framework for contour propagation in prostate MRgRT

Accuracy:
- The LapIRN network performed best
- Benefits of coarse-to-fine, cascaded approach of LapIRN
- Accuracy was on par with iterative registration

Speed:
- The framework achieves sub-second contour propagation (compared to ~10 minutes in current MRgRT workflow)

Robustness (to simulated perturbations):
- The LapIRN network performed best

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<u>Deep learning facilitates fast contour propagation in online adaptive MRgRT</u> to reduce daily treatment times and improve conformity to the daily anatomy

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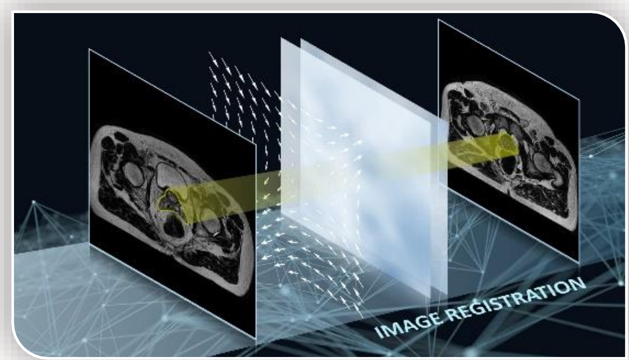
Applications

Contour propagation in adaptive radiotherapy

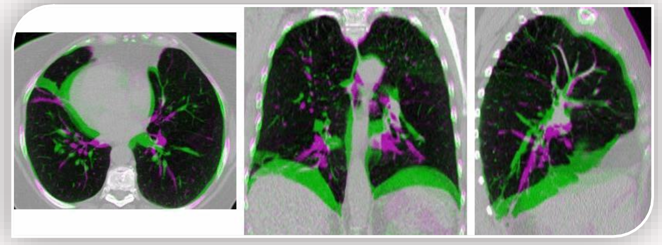
rigid & deformable,
fast, accurate and robust registration



Challenges

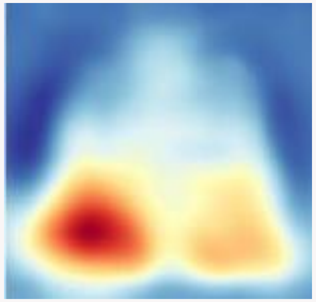
Large and complex deformations

- e.g. bladder, rectum filling
- e.g. respiratory motion



Small datasets

Deformation generation



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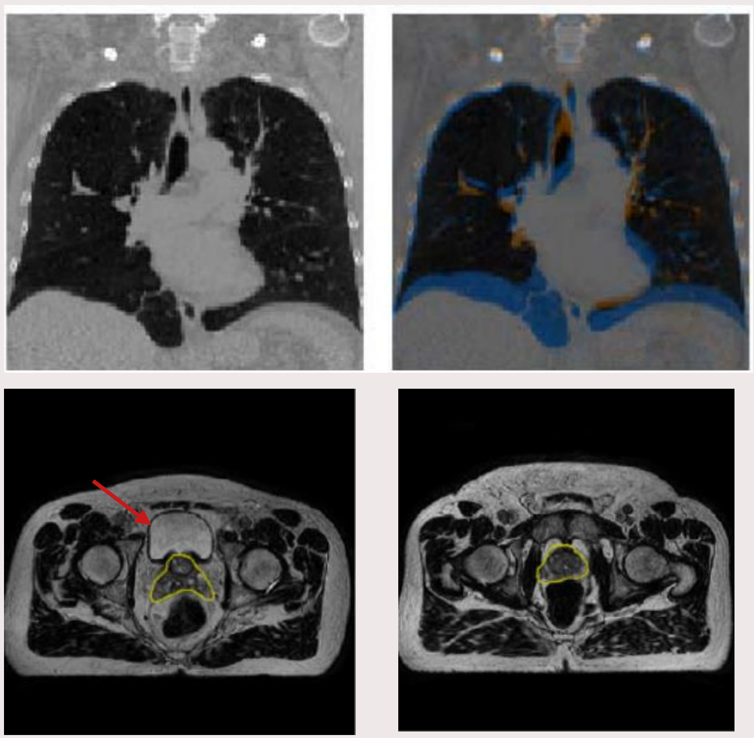
Challenges: large and complex deformations



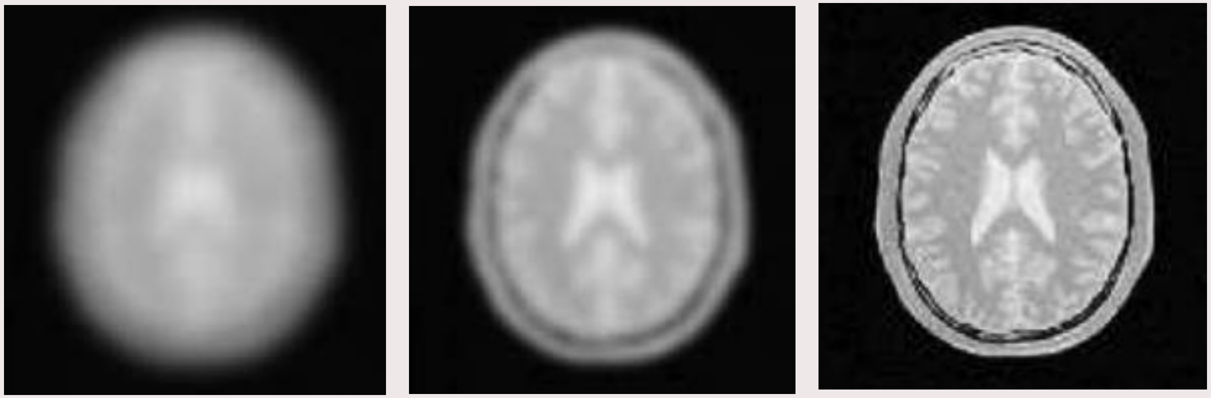
global → local

bladder, rectum filling and emptying

(left) *Learn2Reg Grand Challenge 2021*
(right) *Maspero, M., Raaymakers, B. W. & Veta, M. (2020)*

Existing solution

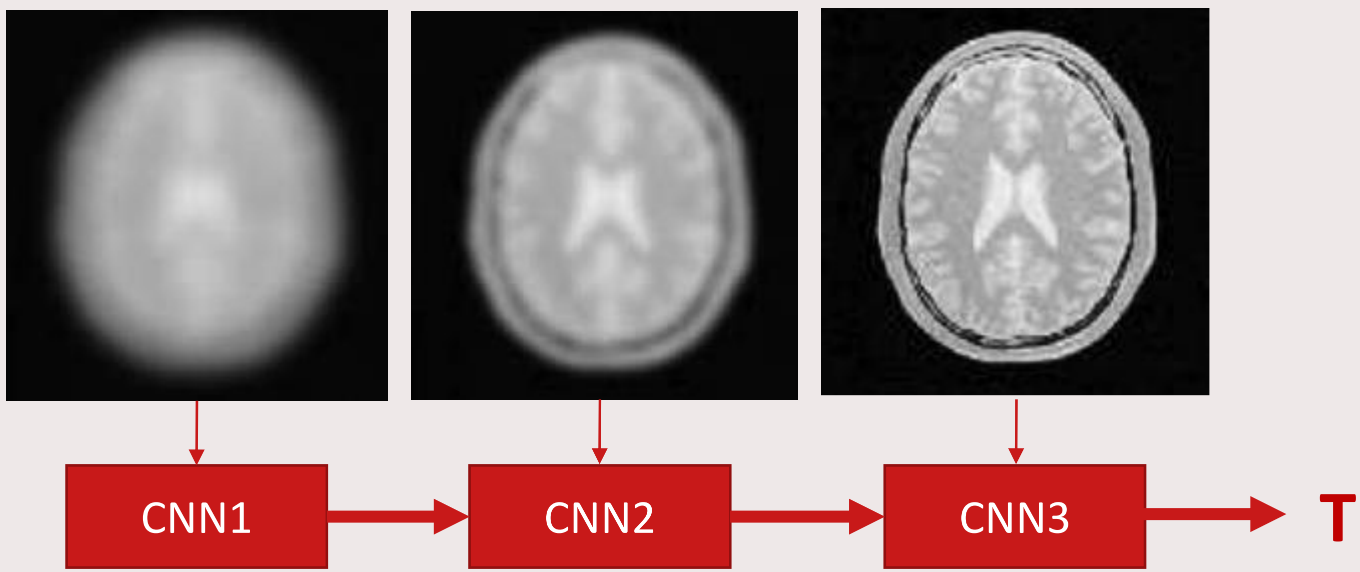
Multi-scale approaches



(brain image) Klein, S. et al. Elastix: A toolbox for intensity-based medical image registration. 2010

Jiang, Z. et al. (2020)

Existing solution
Multi-scale approaches



(brain image) Klein, S. et al. Elastix: A toolbox for intensity-based medical image registration. 2010

Jiang, Z. et al. (2020)

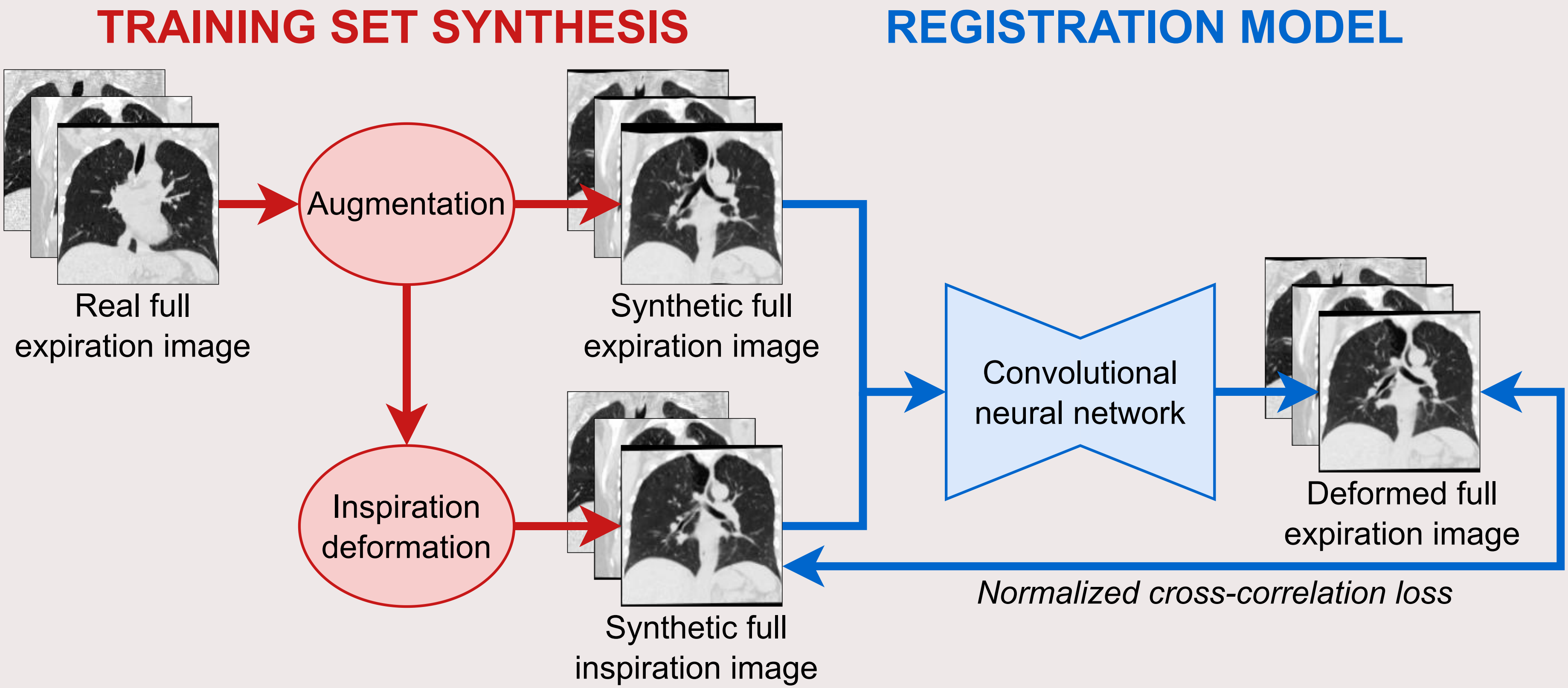
Challenge: small open-source datasets

BACKGROUND

- Deep learning requires large training datasets
- These are scarce
- Potential solution: synthetic data!

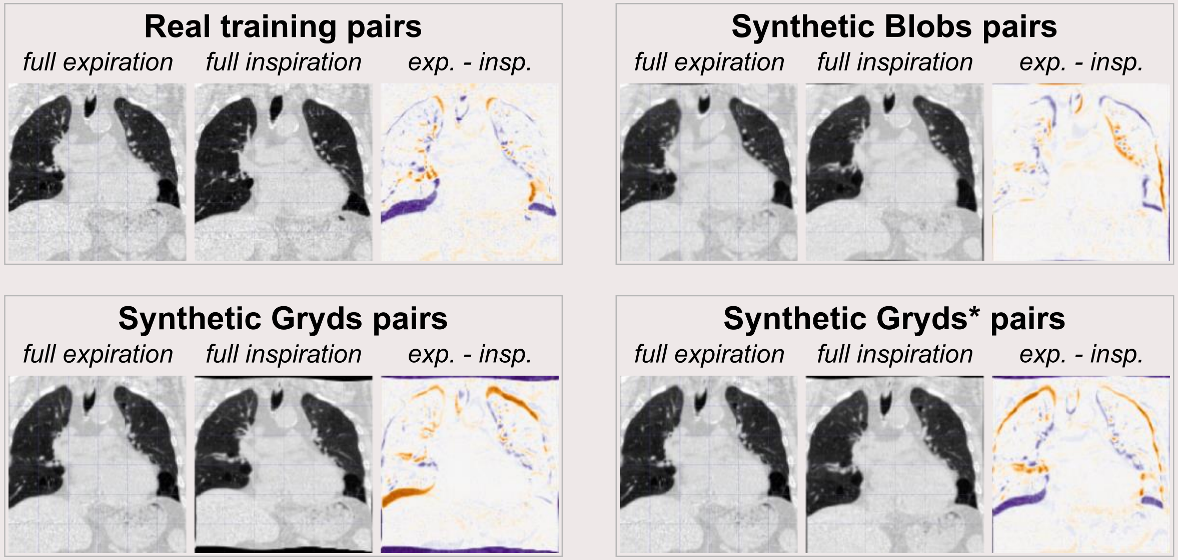
We propose a method that incorporates prior knowledge of the physiological motion to generate realistic deformations.

TRAINING PIPELINE



RESULTS

1. Blobs - displacements smoothed with Gaussian kernel
2. Gryds - fixed control point grid upsampled by B-spline interp.
3. Gryds* (proposed) - enforcing caudal motion in the lower half of the lungs while constraining the upper half motion → to obtain more realistic deformations



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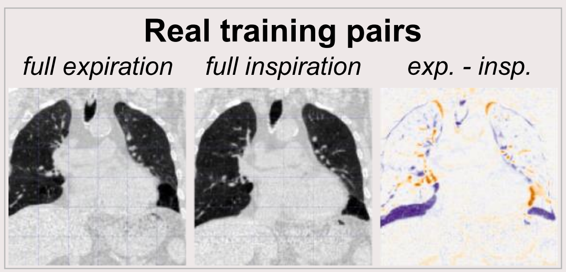

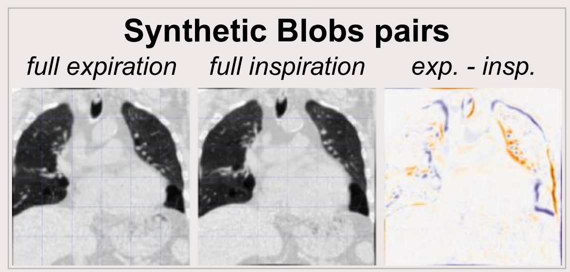

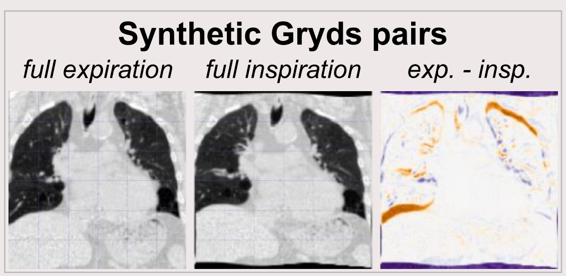

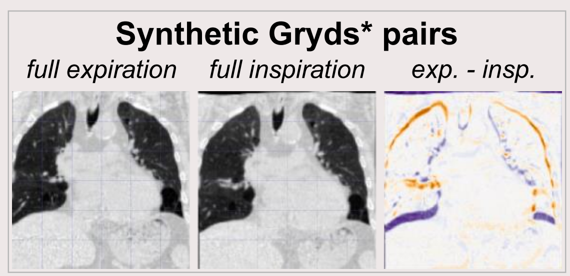

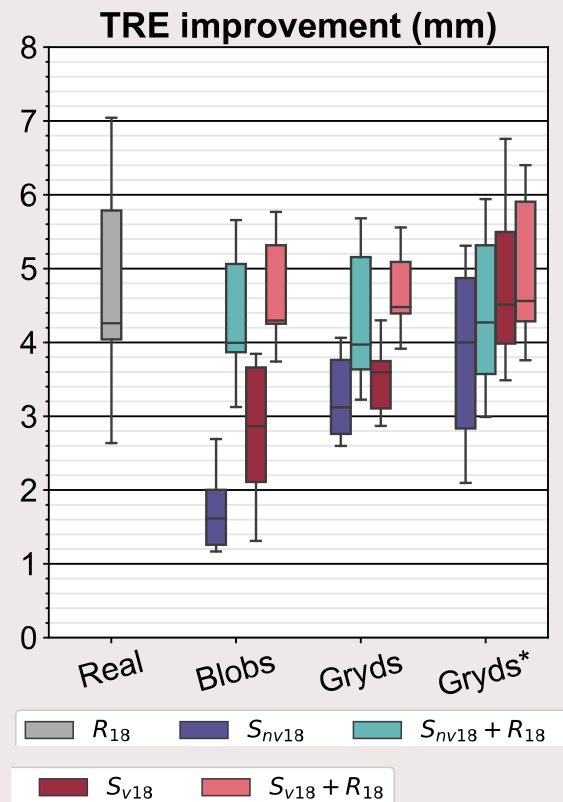

Conclusion: it is important to use realistic deformations during training

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Applications

Challenges

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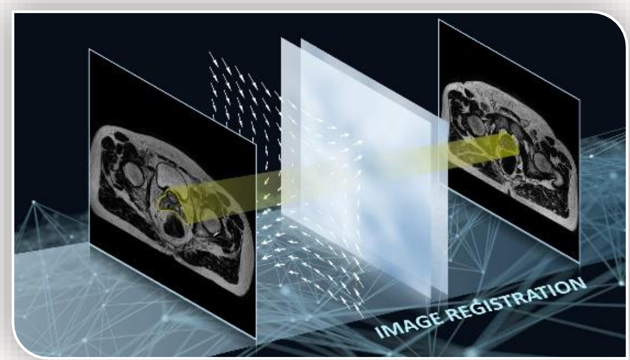

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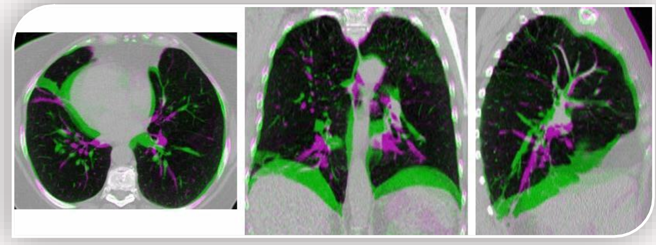
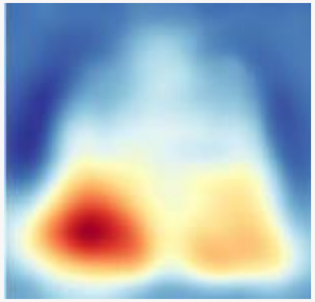
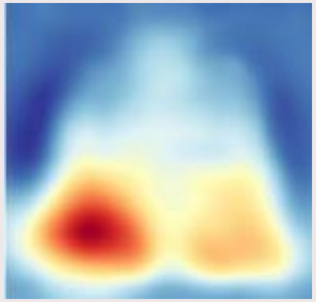
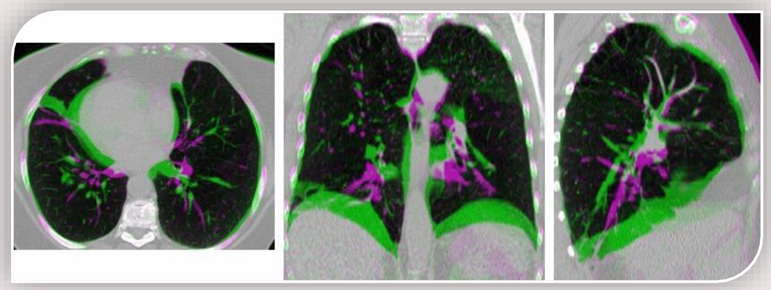


Small datasets

Deformation generation







Questions?