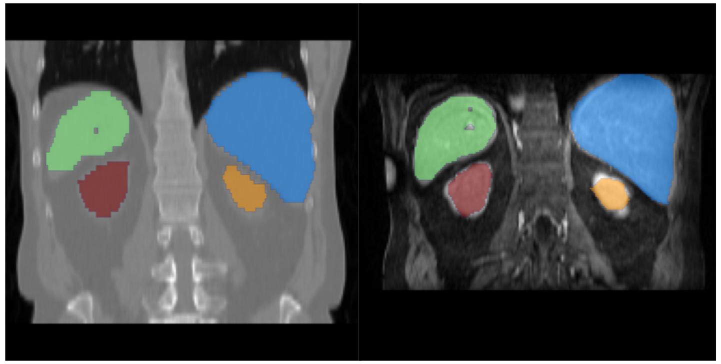
Conditional Deep Laplacian Pyramid Image Registration Networks

Tony C. W. Mok and Albert C. S. Chung

The Hong Kong University of Science and Technology

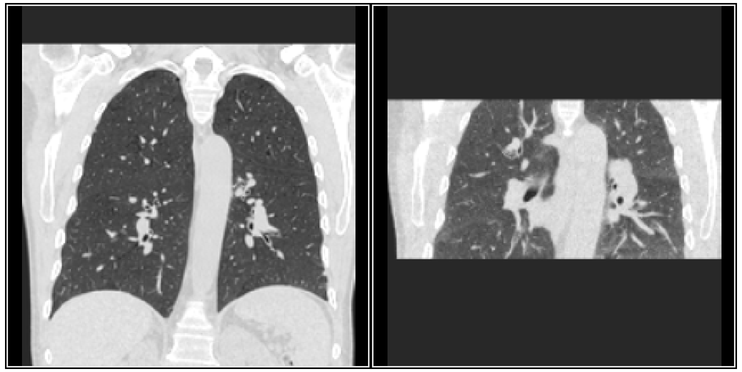
THE HONG KONG UNIVERSITY OF SCIENCE AND TECHNOLOGY

Learn2Reg 2021 Challenge



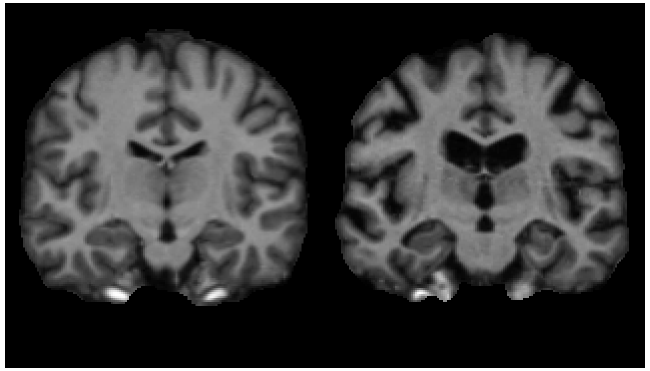
CT-MR thorax-abdomen intra-patient registration

- Multi-modal registration



CT lung inspiration-expiration registration

- Learning from small datasets



MR brain inter-patient registration

- Large inter-variance in anatomical structures

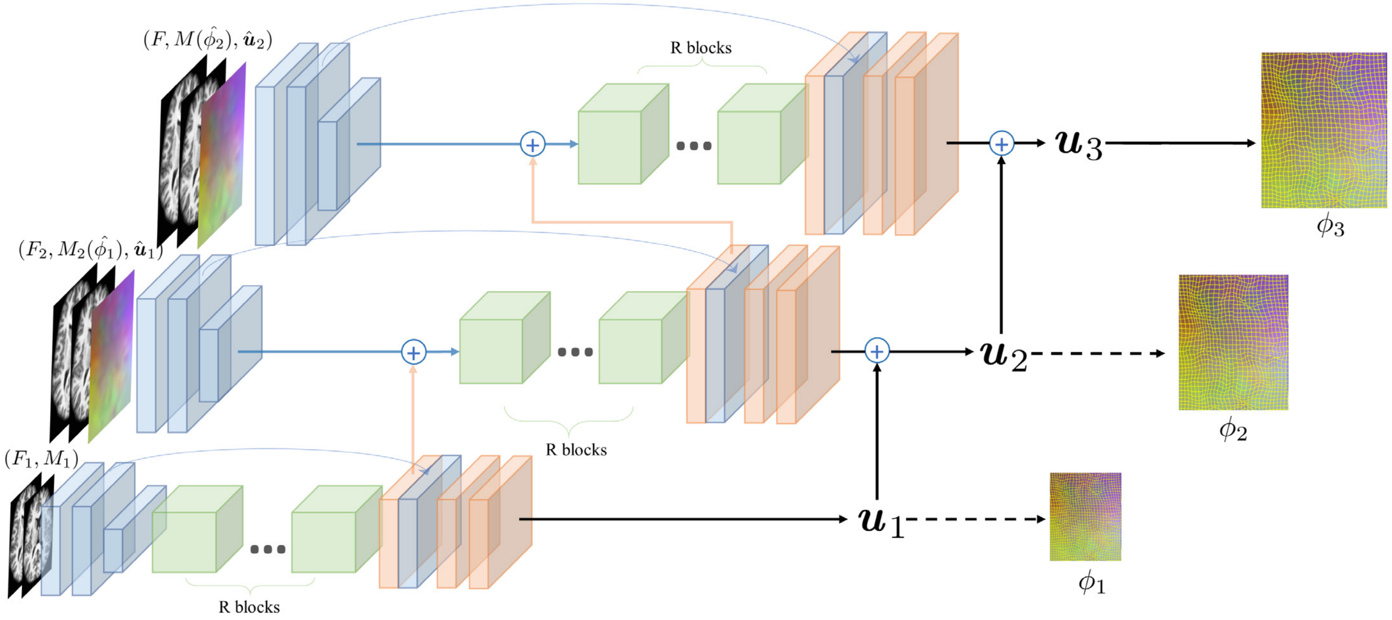
Conditional Deep Laplacian Pyramid Image Registration Networks (c-LapIRN)

Deep Laplacian Pyramid Image Registration Networks

Deep Laplacian Pyramid Image Registration Networks (LapIRN)

Tony C. W. Mok and Albert C. S. Chung (MICCAI2020)

- SOTA large deformation image registration method
- Rank 1st in the Learn2Reg 2020 challenge



Deformable Image Registration

Deformable image registration is a process of warping a moving image (***M***) to align with a fixed image (***F***) subject to the weighted smoothness regularization of the transformation field $\lambda \mathcal{L}_{reg}(\phi_\theta)$.

- Deep learning-based method (**Fixed λ during training**)

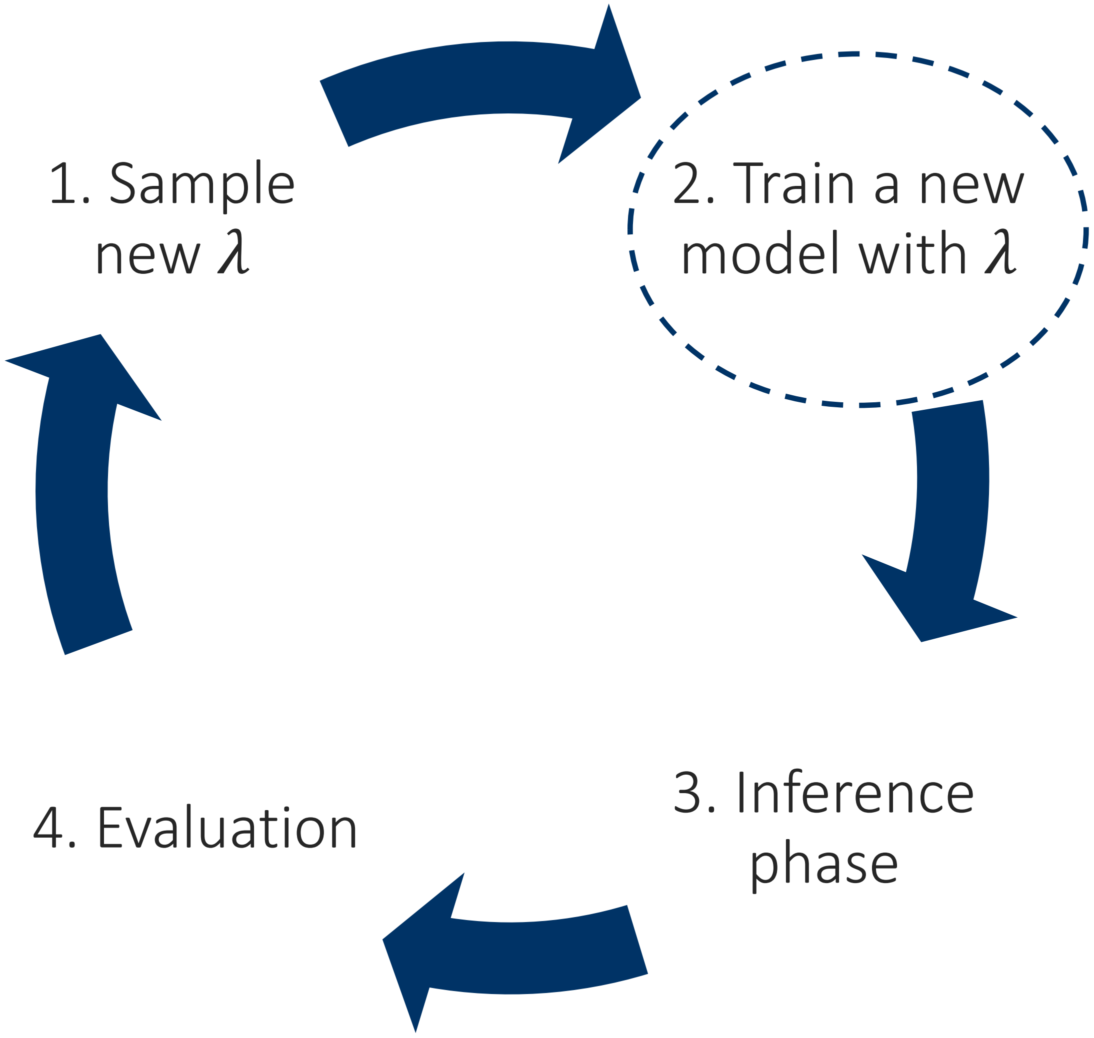
$$\phi_f = f_\theta(F, M) \quad \text{(CNN-based image registration network)}$$

$$\theta^* = \arg\min_\theta \mathcal{L}_{sim}(F, M(\phi_f)) + \lambda \mathcal{L}_{reg}(\phi_f)$$

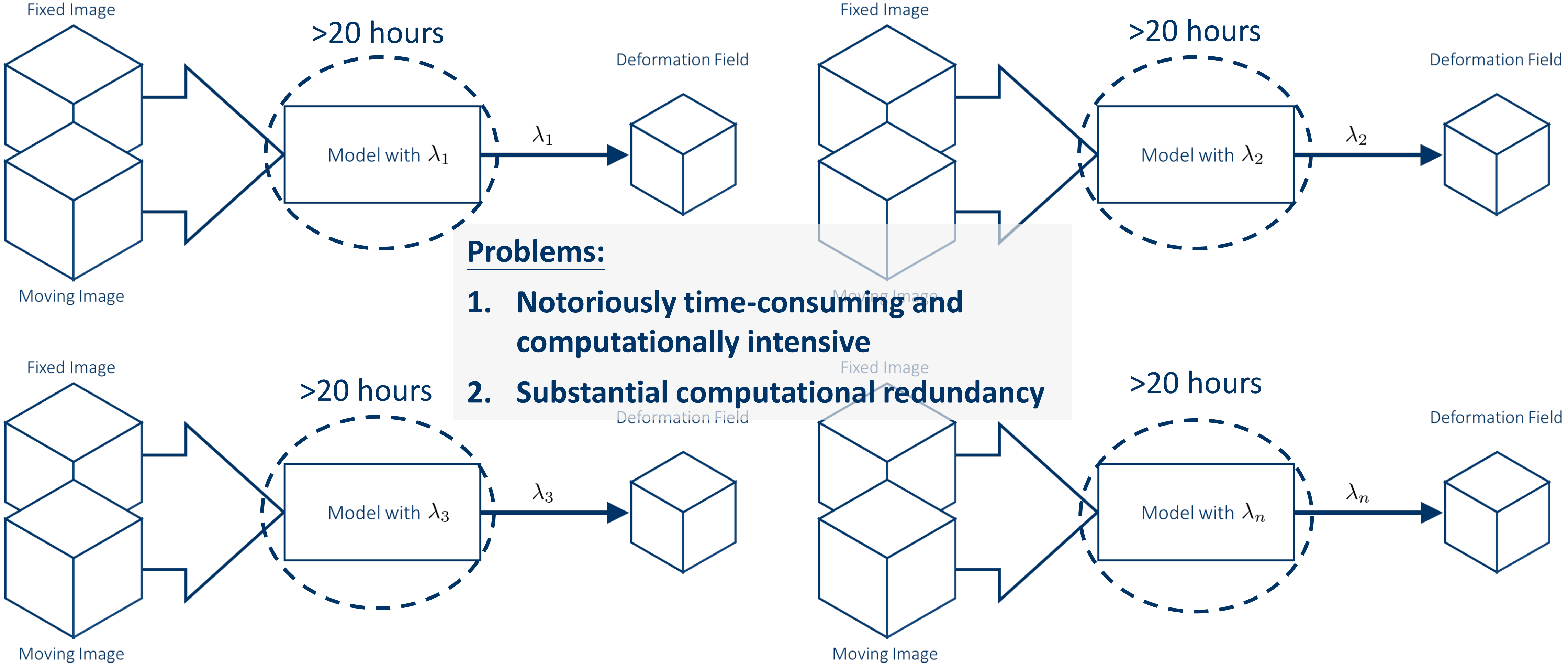
Hyperparameter Tuning

Deep learning-based

- **Grid search**



Hyperparameter Tuning

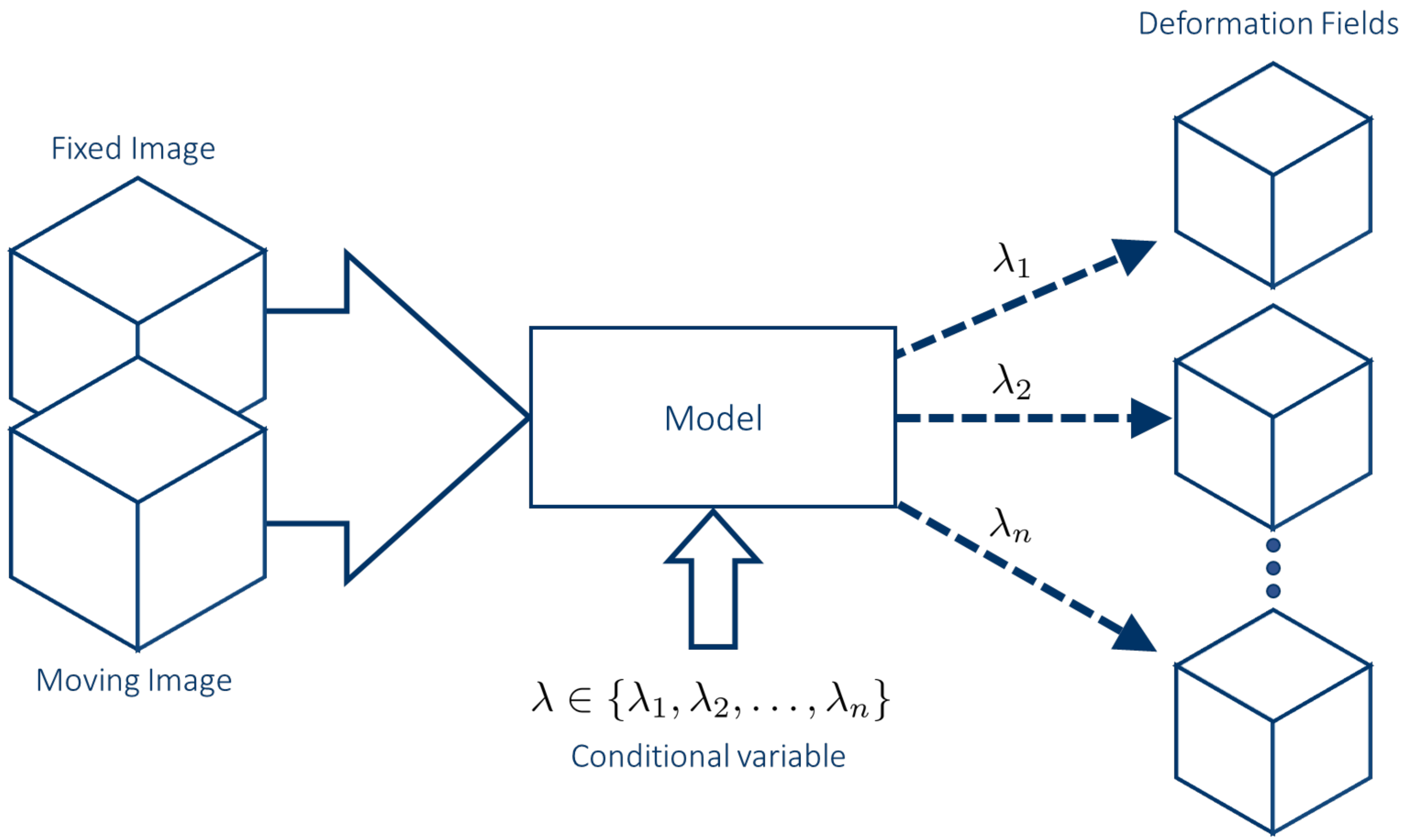


Problems:

1. **Notoriously time-consuming and computationally intensive**
2. **Substantial computational redundancy**

Typical deep learning-based method

Conditional Deformable Image Registration Framework

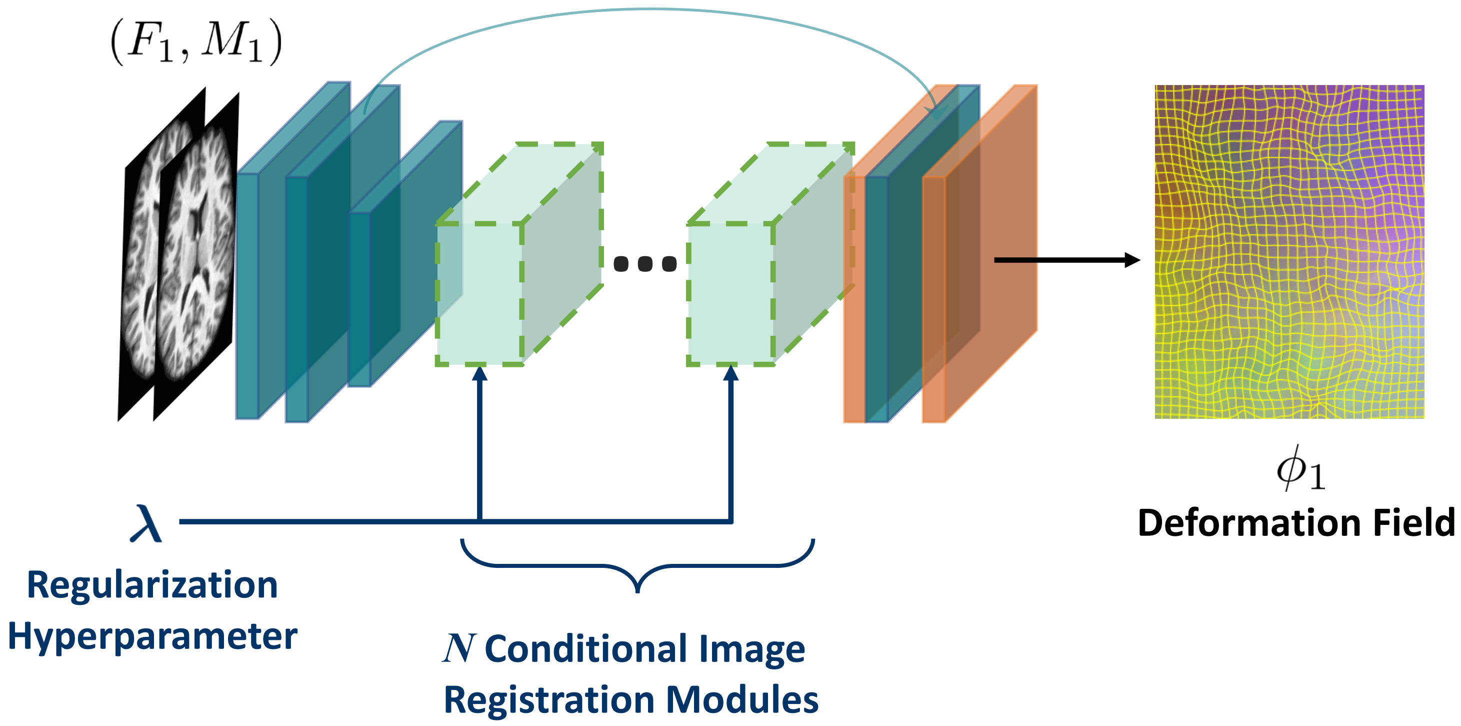


Conditional Deformable Image Registration with Convolutional Neural Network

Tony C. W. Mok and Albert C. S. Chung (MICCAI2021)

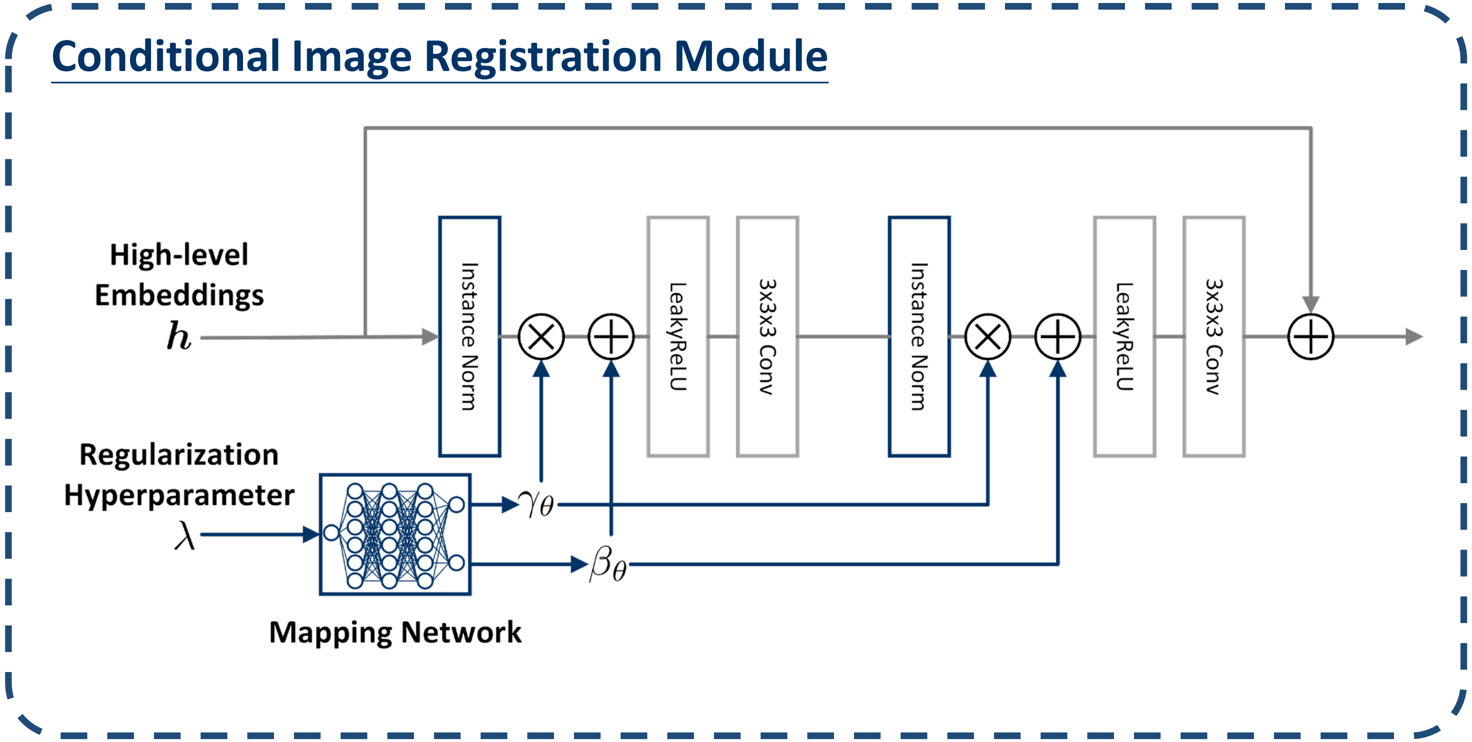
Conditional Deformable Image Registration with CNN

- Formulate the problem as a conditional image registration problem
- Learn the effect of the regularization hyperparameter with a **single model**



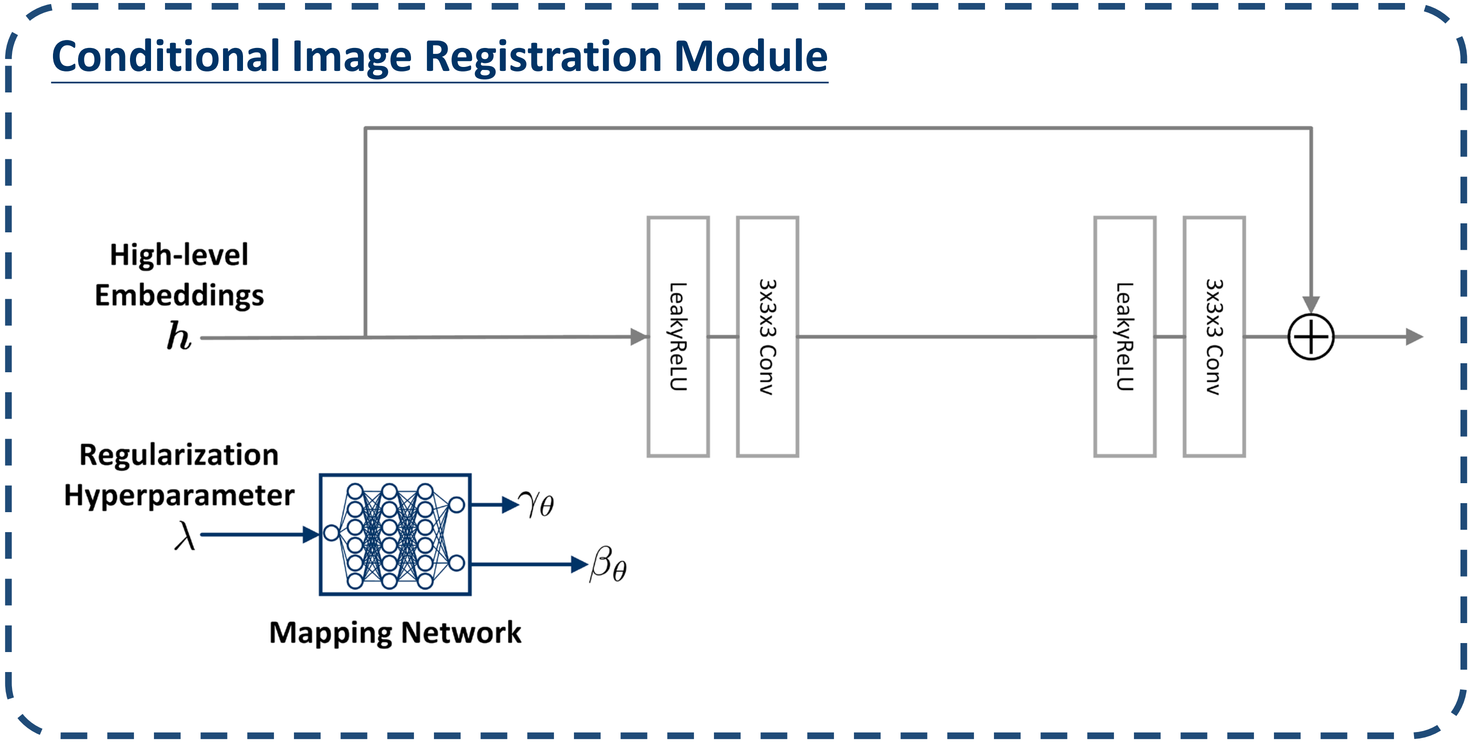
Conditional Image Registration Module

- **Purpose**: To condition on the high-level features with the regularization hyperparameter



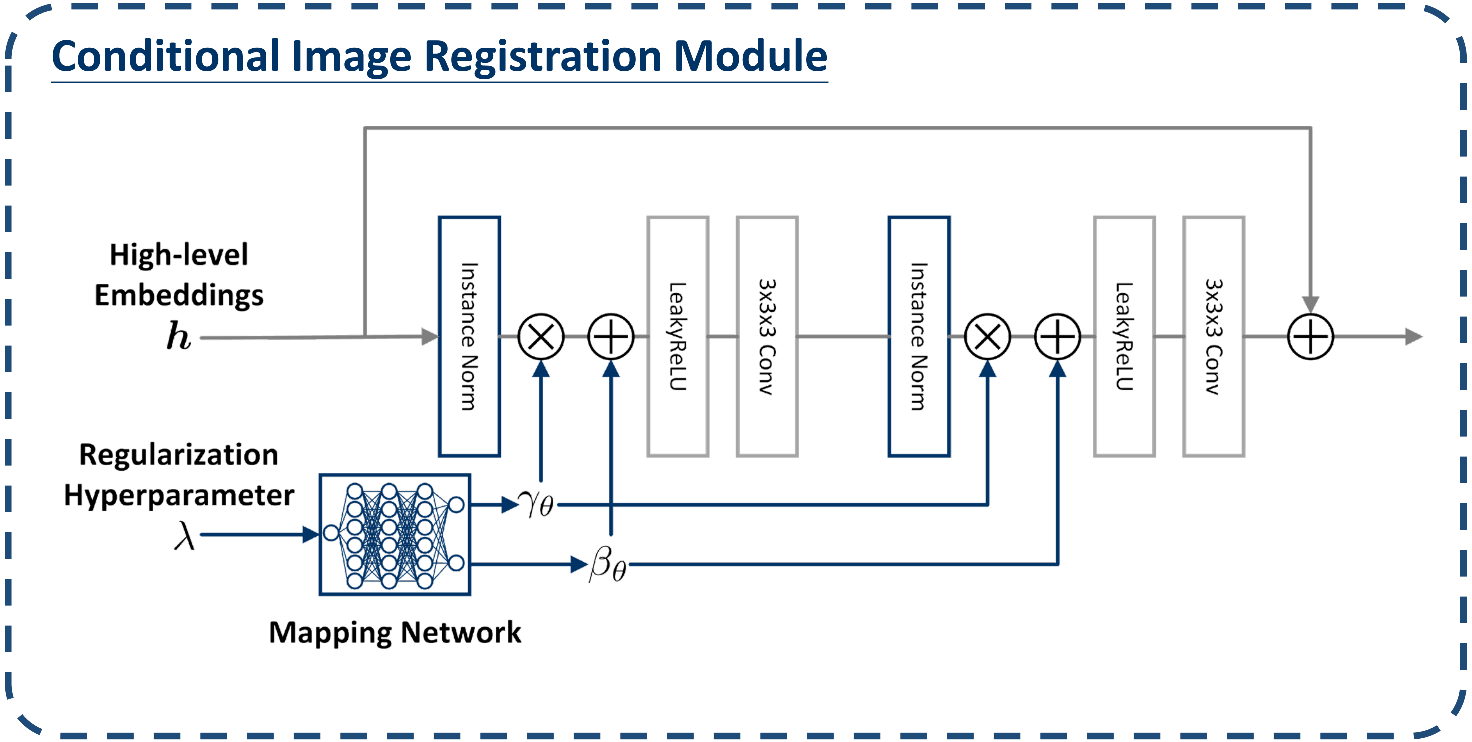
Conditional Image Registration Module

- Mapping network learns to map λ to a latent code, which specializes to the smoothness regularization
- γ_θ and β_θ: learning parameters learned from the latent code



Conditional Image Registration Module

- Manipulate the feature statistics of high-level layers with γ_θ and β_θ
- Condition on the high-level layers using conditional instance normalization



Self-supervised Learning

- **Objective function**
  - Learn to optimize the objective function over a predefined range of hyperparameter instead of a fixed hyperparameter value.
  - λ_p is uniformly sampled over a predefined range
  - Such that:

$$\phi^* = \arg\min_{\phi} \mathcal{L}_{sim}(F, M(\phi)) + \lambda_p \mathcal{L}_{reg}(\phi) \qquad \text{where } \lambda_p \in [0, 10]$$

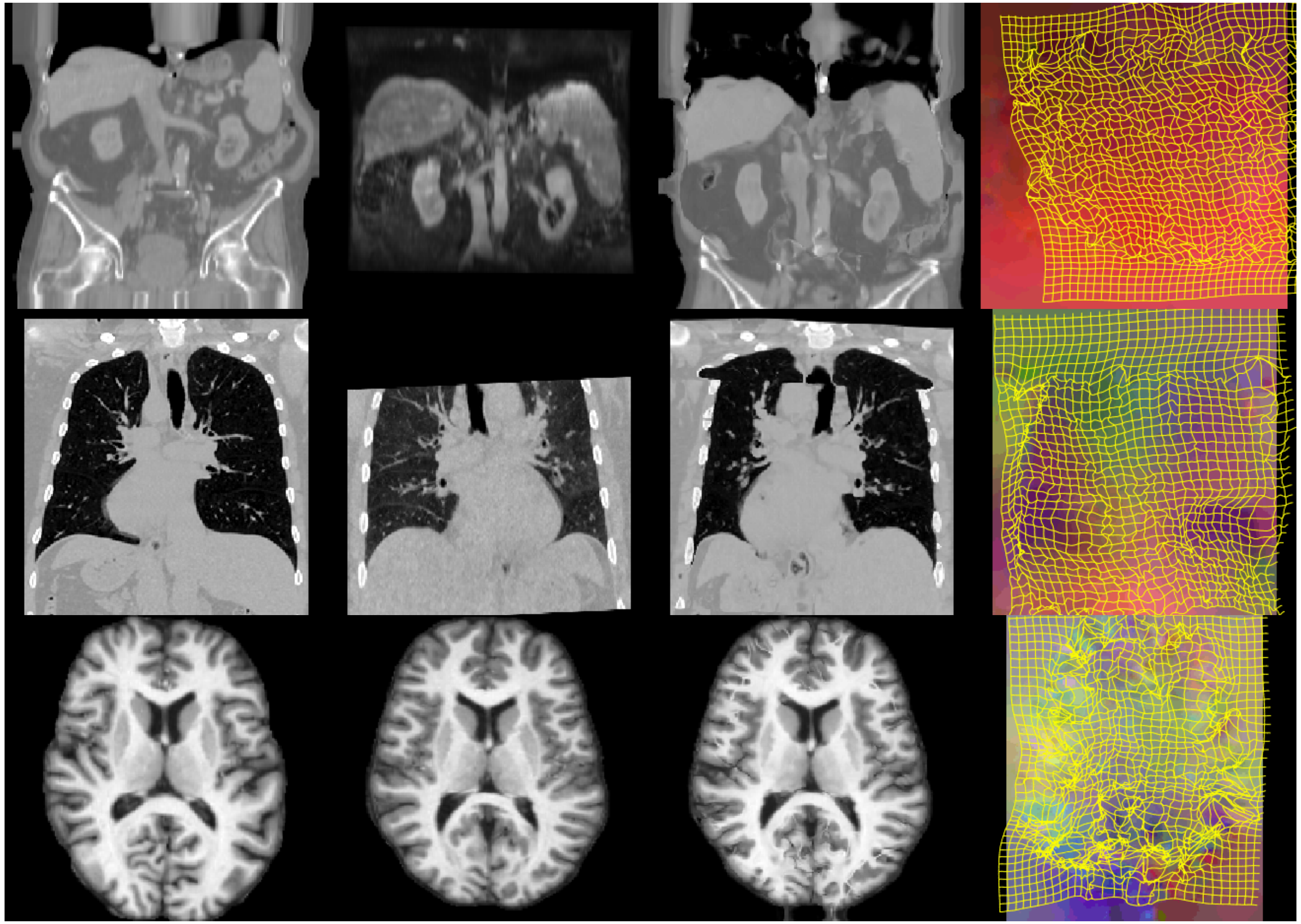
Normalized [1]

$$\phi^* = \arg\min_{\phi} (1 - \lambda_p) \mathcal{L}_{sim}(F, M(\phi)) + \lambda_p \mathcal{L}_{reg}(\phi) \qquad \text{where } \lambda_p \in [0, 1]$$

[1] A. Hoopes et al. HyperMorph: Amortized Hyperparameter Learning for Image Registration. IPMI2021

Manipulating the hyperparameter

Moving image | Fixed image | Warped image | Deformation field



$\lambda = 0.0/10$

$\lambda = 0.0/10$

$\lambda = 0.0/10$

Challenges

- ~~Searching for optimal hyperparameter~~
- Multi-modal registration (Task 1)
  - Non-linear intensity correspondence
- Learning from small datasets (Task 2)
  - Overfitting
- Large inter-variation in anatomical structures (Task 3)
  - Large deformation

CT-MR Thorax-abdomen Intra-patient Registration

Preprocessing

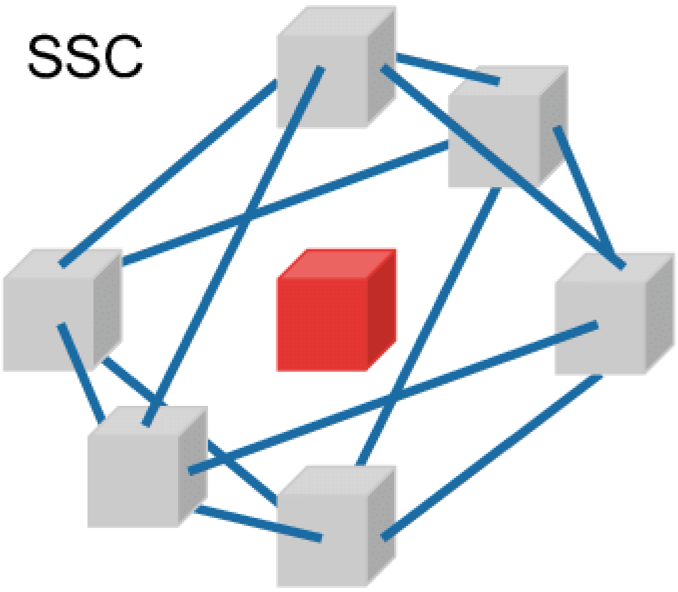
- Windowing - CT: [-400, 400], MR: [0, 0.63*max. intensity)
- Min-max normalization, i.e. [0, 1]

Method

- Baseline: 3-level c-LapIRN + MIND-SSC [1] (Feature extraction)
- Similarity function:
    - Mean squared error (MSE) of MIND-SSC features
    - Dice loss
- Smoothness regularization: Diffusion regularizer

Training Strategies

- Inter-patient registration (CT-MR, paired and unpaired)
- Finetune: Intra-patient registration (only on paired training data)
- Affine augmentation with p=0.20 (Translation, scaling and rotation)
- Half-resolution (96 x 80 x 96)



Semantic representation of the MIND-SSC [1]

[1] MP Heinrich et al. *Towards Realtime Multimodal Fusion for Image-Guided Interventions Using Self-similarities*. MICCAI2013

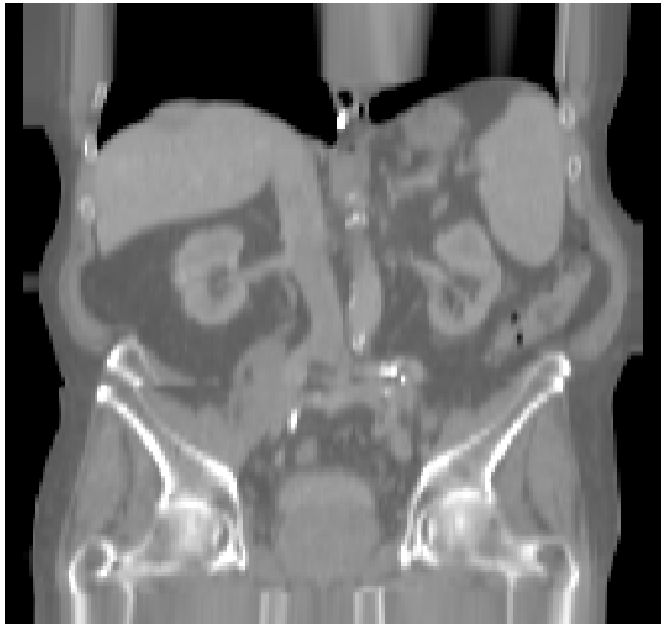
Results: CT-MR Thorax-abdomen Intra-patient Registration

Result on the validation set

- Dice: Dice similarity coefficient of segmentations (4 classes)
- HD95: 95% percentile of Hausdorff distance of segmentations
- SDlogJ: standard deviation of log Jacobian determinant of the deformation field
- NMI: Normalized mutual information

Method	Dice	HD95	SdlogJ
c-LapIRN + NMI + Dice	0.8295 (0.084)	4.1925 (1.425)	0.06802 (0.008)
c-LapIRN + MIND-SSC + Dice	0.8867 (0.015)	3.6087 (0.2251)	0.0831 (0.004)
c-LapIRN + MIND-SSC + Dice + Finetune	0.9006 (0.009)	2.7498 (0.1014)	0.0818 (0.011)

Qualitative Results

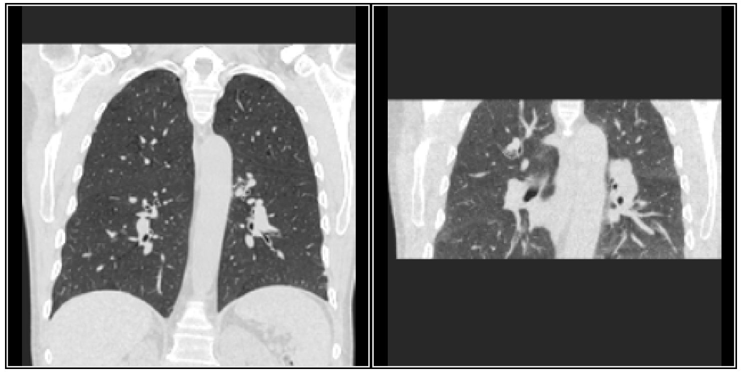


Moving image (CT)

Fixed image (MR)

Warped moving image

CT Lung Inspiration-expiration Registration



Preprocessing
- Windowing – [100, 1518]
- Min-max normalization, i.e. [0, 1]

Method
- Baseline: 3-level c-LapIRN
- Similarity function:
    - Local normalized cross-correlation (NCC) with similarity pyramid
- Smoothness regularization: Diffusion regularizer
- Postprocessing: Instance optimization with the Adam optimizer
    - lr = 5e-4, max. iteration = 60, NGF

Training Strategies
- Affine augmentation with p=0.95 (Translation, scaling and rotation)
- Half-resolution (96 x 96 x 104)

Results: CT Lung Inspiration-expiration Registration

Result on the validation set

- TRE (pseudo): Target registration error of pseudo landmarks (mm)
- TRE: Target registration error of manual landmarks (mm)
- SDlogJ: Standard deviation of log Jacobian determinant of the deformation field
- Aug: Augmentation, NGF: Normalized gradient fields, NCC: Local normalized cross-correlation, IO = Instance optimization

Method	TRE (pseudo)	TRE	SDlogJ
c-LapIRN + NGF	9.3072	-	0.0950
c-LapIRN + Aug + NGF	3.4856	2.6664	0.0781
c-LapIRN + Aug + NCC	3.0665	-	0.0956
c-LapIRN + Aug + NCC + IO	2.8667	2.1316	0.0668

Qualitative Results

Moving image (CT)

Fixed image (MR)

Warped moving image

MR Brain Inter-patient Registration

Preprocessing

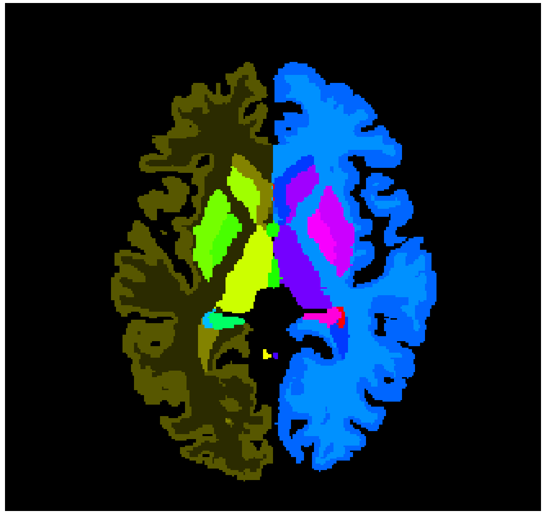
- Min-max normalization, i.e. [0, 1]

Method

- Baseline: 3-level c-LapIRN
- Similarity function:
  - Local normalized cross-correlation (NCC) with similarity pyramid
  - Dice loss (Merge left and right structures as 1 class)
- Smoothness regularization: Diffusion regularizer

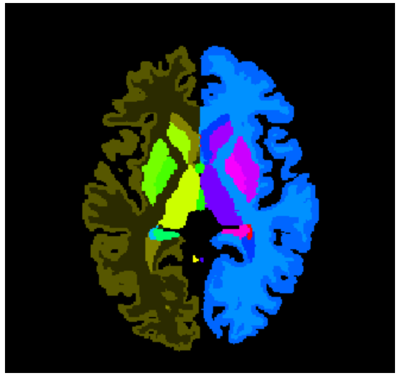
Training Strategies

- Half-resolution (80 x 96 x 112)



Anatomical segmentation maps (35 classes)

MR Brain Inter-patient Registration



<u>Anatomical segmentation maps (35 classes)</u>

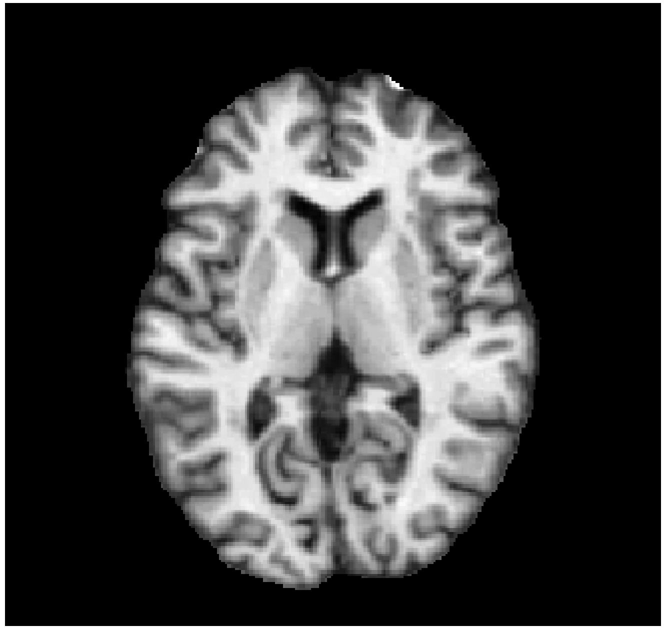
Result on the validation set

- Dice: Dice similarity coefficient of segmentations (35 classes)
- HD95: 95% percentile of Hausdorff distance of segmentations
- SDlogJ: standard deviation of log Jacobian determinant of the deformation field
- NMI: Normalized mutual information

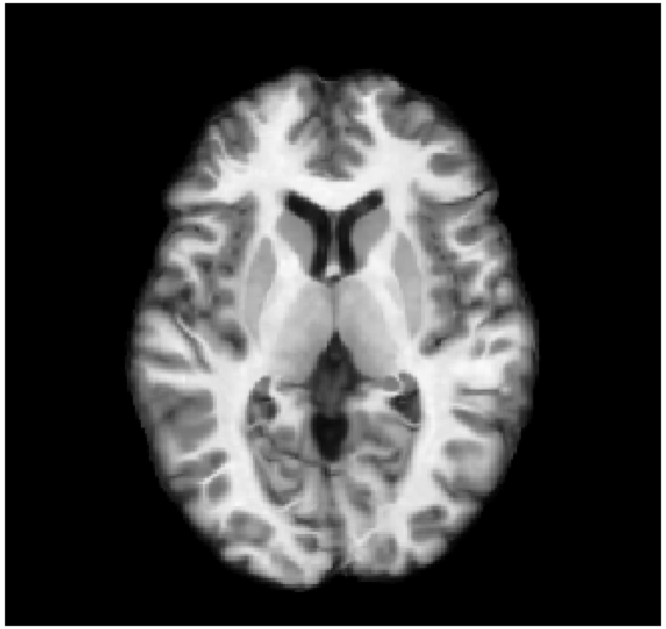
Method	Dice	HD95	SdlogJ
VoxelMorph (Leaderboard: mattiaspaul)	0.7871	2.0460	0.0642
Unsupervised c-LapIRN	0.8146	1.8523	0.0771
c-LapIRN + Dice ($\lambda_{dice} = 0.3$)	0.8563	1.5667	0.0772
c-LapIRN + Dice ($\lambda_{dice} = 1.0$)	0.8610	1.5139	0.0721

Qualitative Results

Moving image (CT)



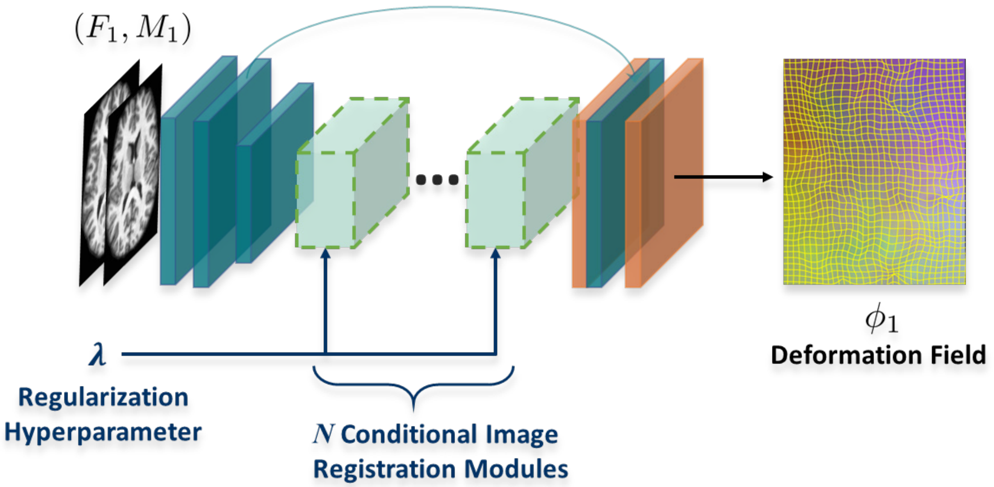
Fixed image (MR)

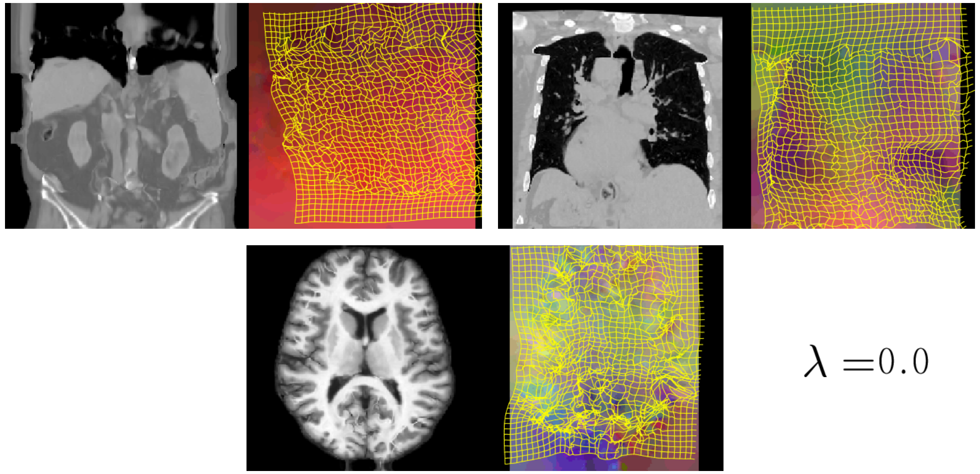


Warped moving image

Summary

- **Conditional Deformable Image Registration Method**
  - Enable rapid hyperparameter tuning for deep learning-based methods
  - Achieve controllable smoothness regularization of the deformation field
- **Generic Image Registration Method**
  - CT-MR thorax-abdomen intra-patient registration
  - CT lung inspiration-expiration registration
  - MR brain inter-patient registration
- **Modularized Design**
  - Can be easily transferred to existing CNN-based image registration approaches





$\lambda = 0.0$

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