Deep Learning Registration - A Survey

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Introduction

What is deep learning registration ?

- Image registration is a fundamental step in medical image analysis
  - to facilitate comparison between multiple subjects
  - to create average models of organs (atlas creation)
  - to monitor organ growth or deterioration
- Deep learning-based image registration is the use of deep learning methods to solve registration problems

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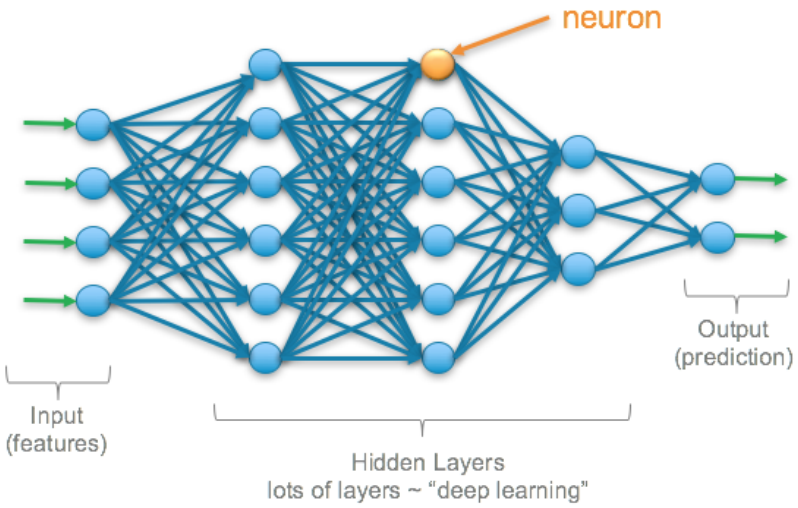

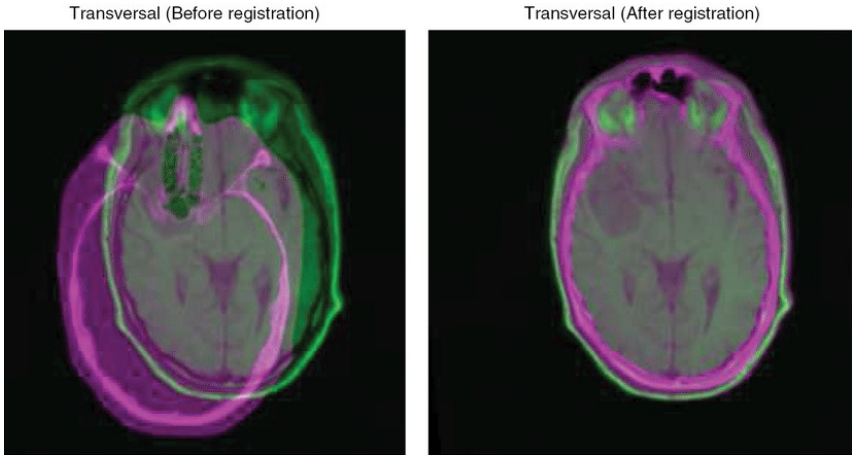

Introduction

Why use deep learning registration ?

- Faster registration
  - Once a model is trained and performing well, new pairs of images can be registered quickly
- Can learn a similarity measure
  - A deep learning model can be used to learn a similarity measure between multi-modal images

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How is deep learning registration done ?

- Deep Iterative Registration
  - Initially used to **augment the performance of iterative**, intensity based **registration**.
- Supervised Transformation Estimation
  - The need for **faster registration methods** motivated the development of deep learning based one-step **transformation estimation** techniques.
- Unsupervised Transformation Estimation
  - **No** need to collect **ground truth** data.

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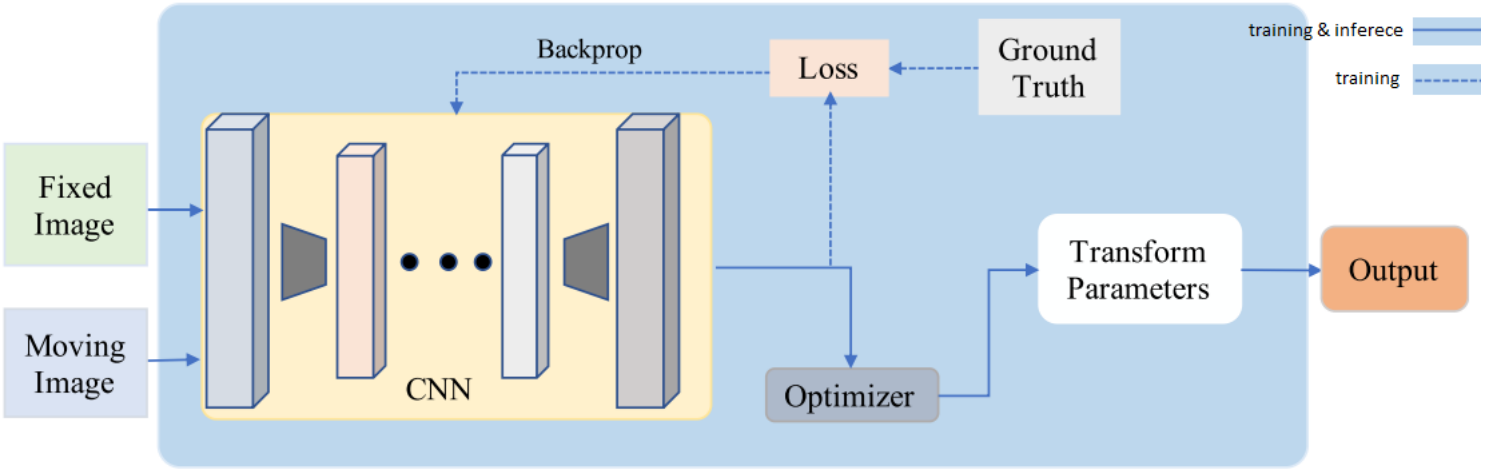
Deep Learning Registration Approaches

Deep Iterative Registration

- Deep similarity-based registration



A visualization of the registration pipeline for works that use deep learning to quantify image similarity in an intensity-based registration framework.

Authors : Grant Haskins et al. [link]

- Reinforcement learning based registration

Deep Learning Registration Approaches

Deep Iterative Registration

- Deep similarity-based registration
- Reinforcement learning based registration

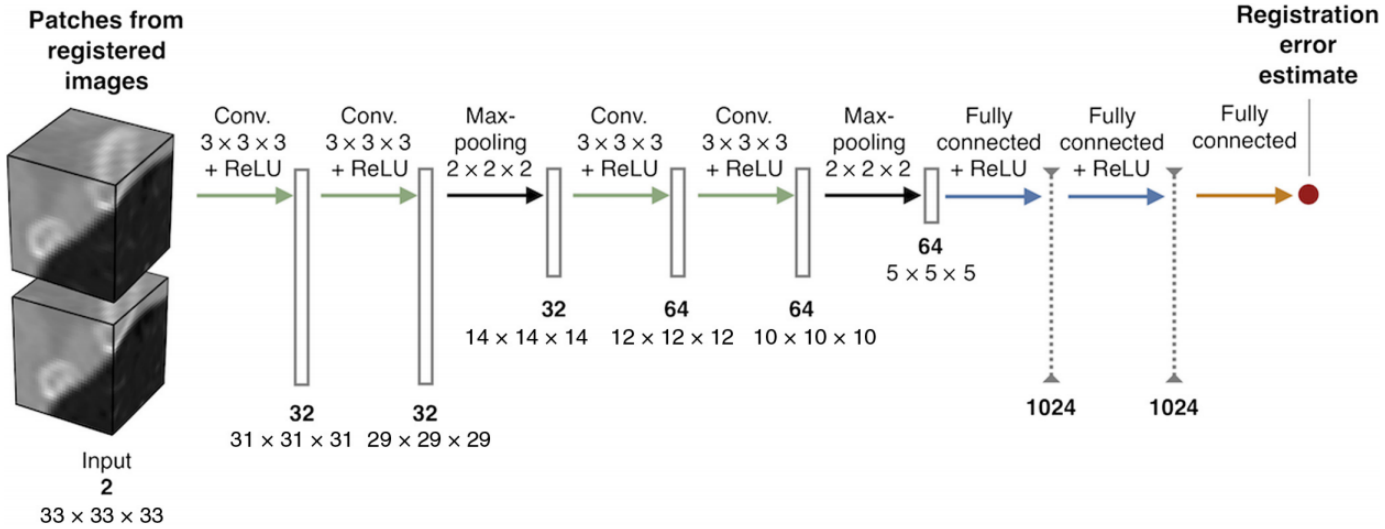


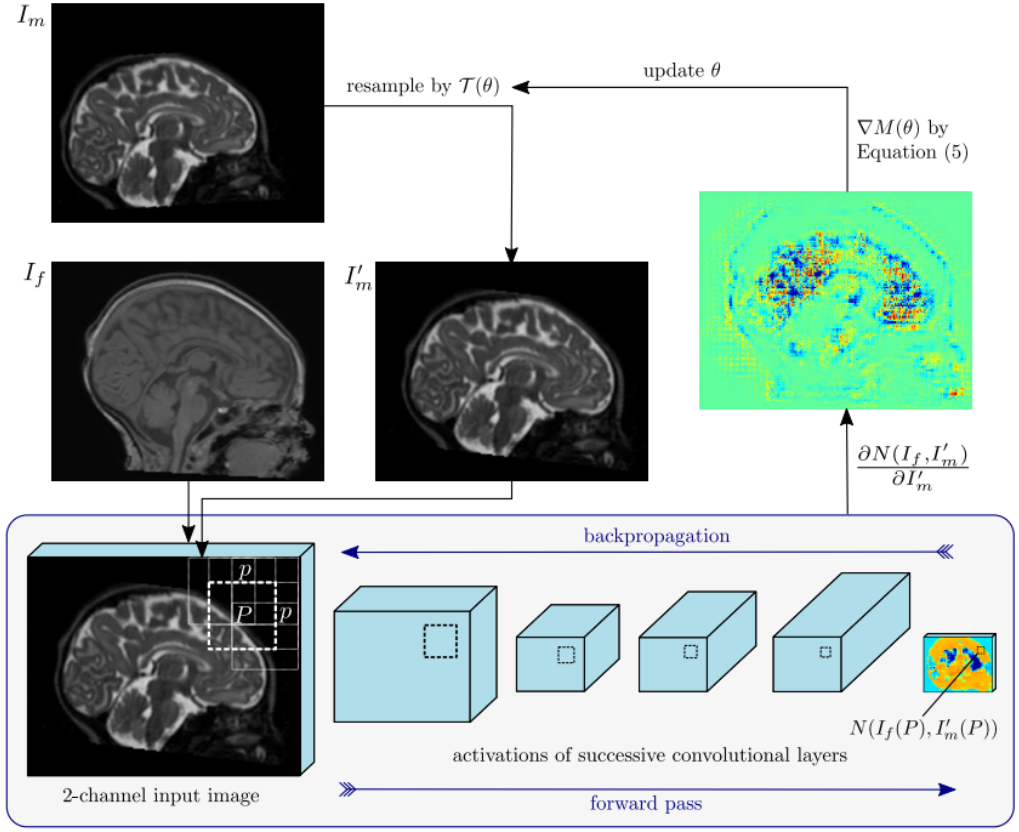
Fig. 2 The CNN architecture is comprised of two sequences of two convolutional layers and a pooling layer and followed by three fully connected layers that compute the error estimate.

Authors : Koen Eppenhof et al. [link]

Deep Learning Registration Approaches

Deep Iterative Registration

- Deep similarity-based registration
- Reinforcement learning based registration

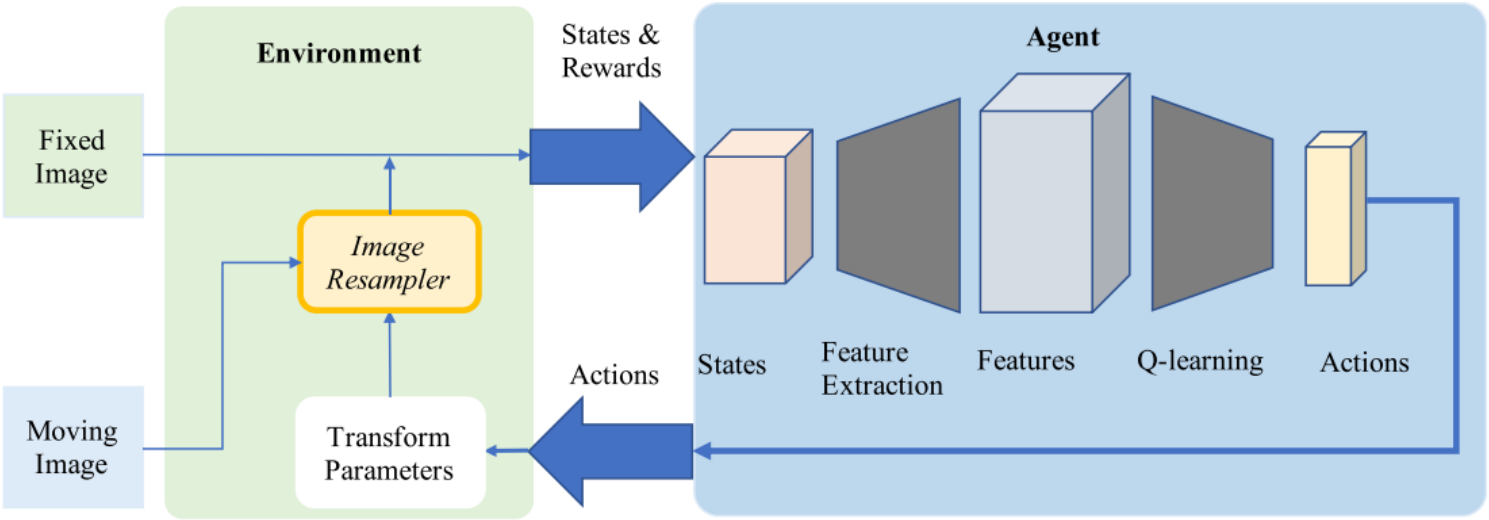


Authors : Martin Simonovsky et al. [link]

Deep Learning Registration Approaches

Deep Iterative Registration

- Deep similarity-based registration
- Reinforcement learning based registration



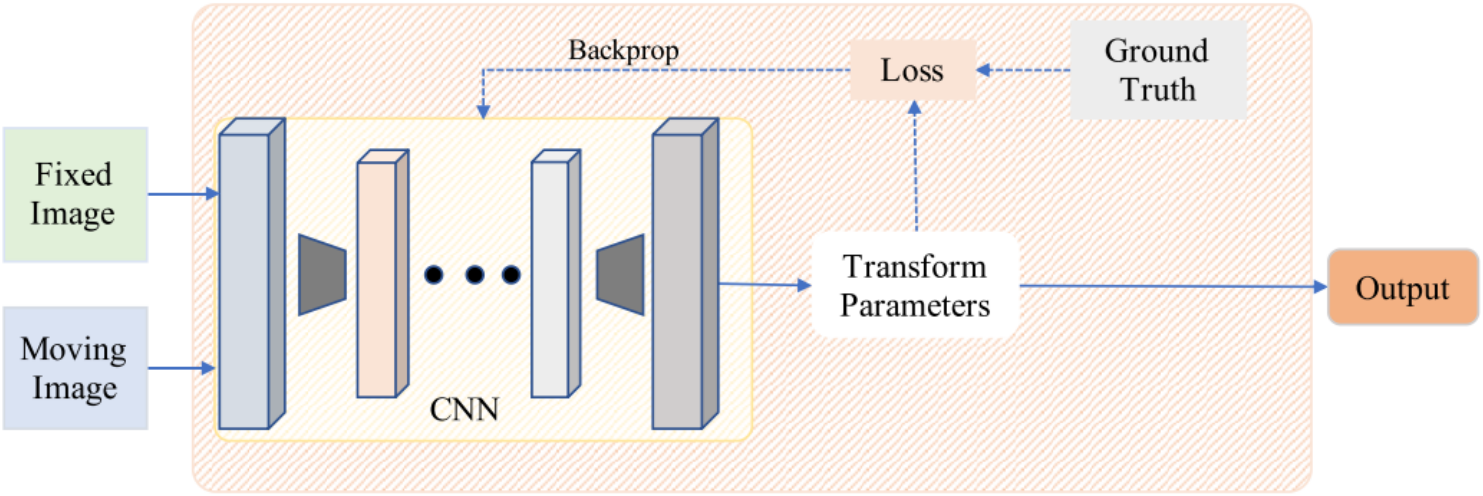
A visualization of the registration pipeline for works that use deep reinforcement learning to implicitly quantify image similarity for image registration. Here, an agent learns to map states to actions based on rewards that it receives from the environment.

Authors : Grant Haskins et al. [link]

Deep Learning Registration Approaches

Supervised Transformation Estimation

- Full supervision



A visualization of supervised single step registration.

Authors : Grant Haskins et al. [link]

- Dual/Weak supervision

Deep Learning Registration Approaches

Supervised Transformation Estimation

- Full supervision
- Dual/Weak supervision

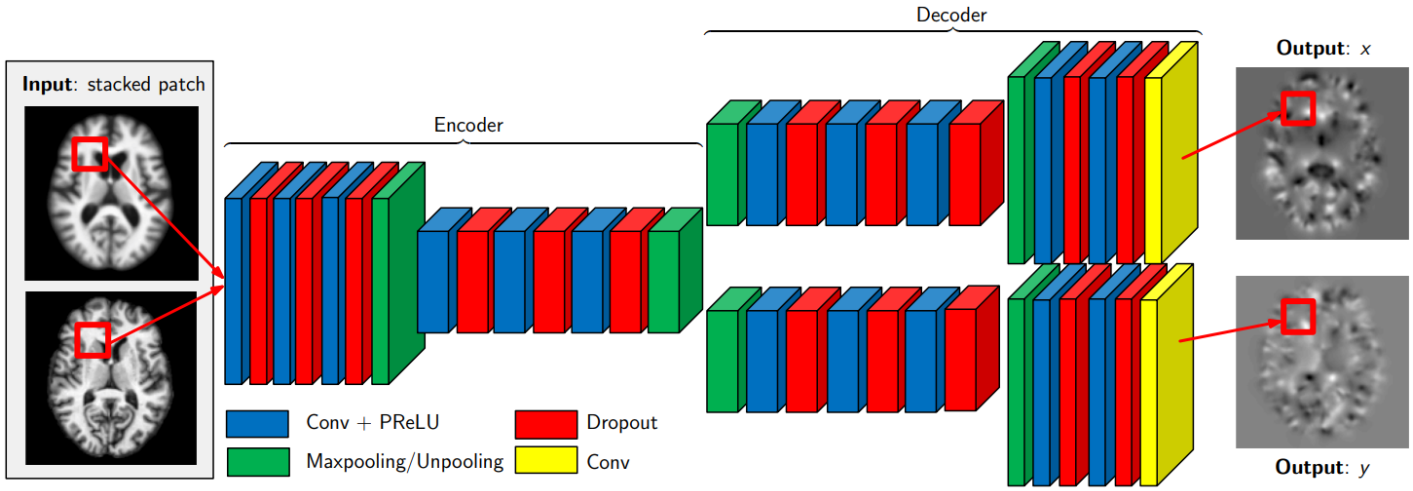


Fig. 1: Bayesian probabilistic network structure (for 2D images): The inputs are 2-layer stacked patches from the moving image and fixed image at the same location. The output is the initial momentum prediction of the patches in x and y spatial directions. For a deterministic version of the network, we simply remove all dropout layers. For a 3D image network we increase the number of decoders to 3 and use volumetric layers.

Authors : Yang et al. [link]

Deep Learning Registration Approaches

Supervised Transformation Estimation

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- Dual/Weak supervision

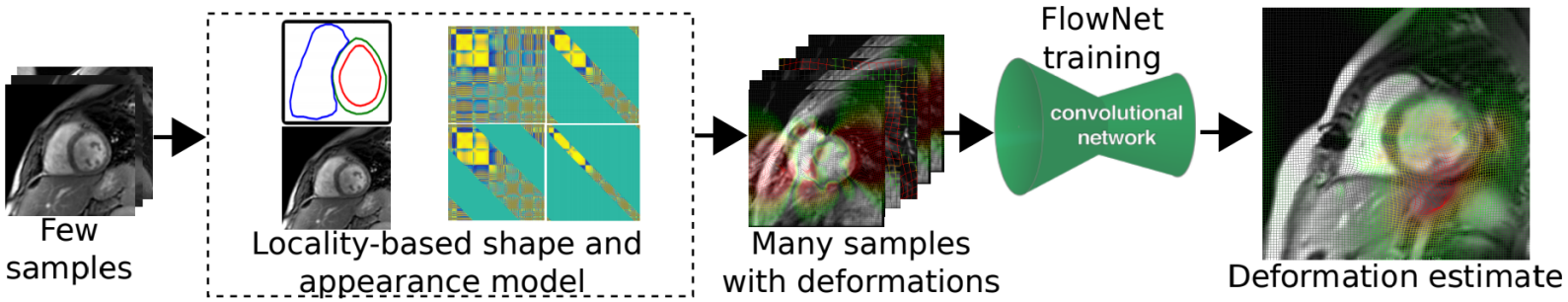

Fig. 1. Overview of the proposed model-based data augmentation approach.

Authors : Uzunova et al. [link]

Deep Learning Registration Approaches

Supervised Transformation Estimation

- Full supervision
- Dual/Weak supervision

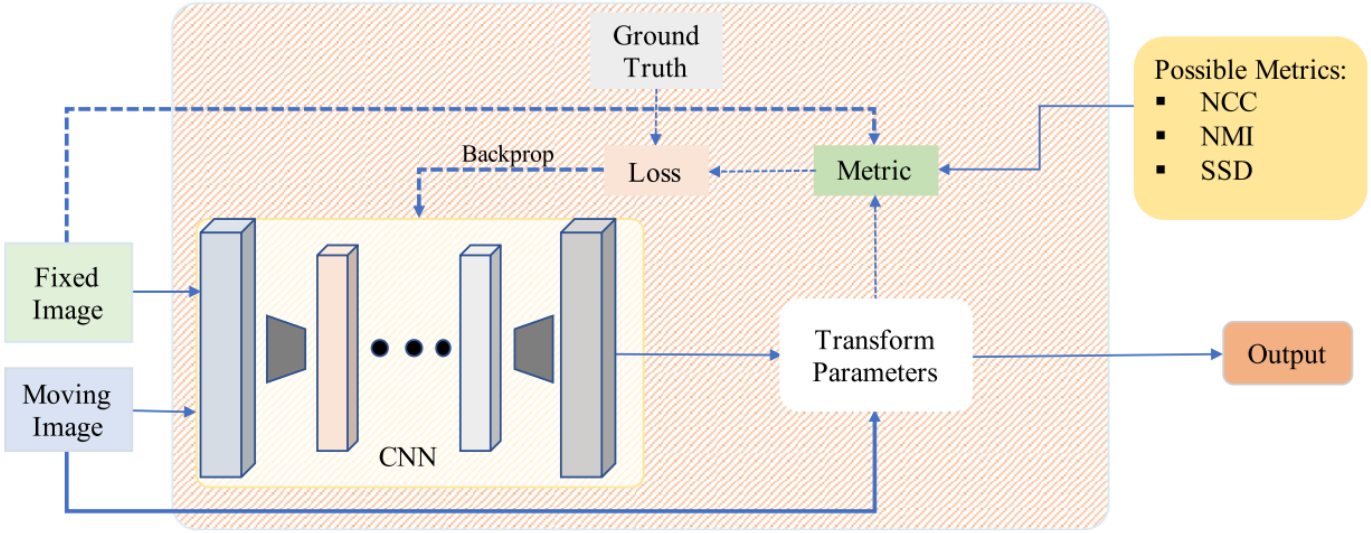

Fig. 6 A visualization of deep single step registration where the agent is trained using dual supervision. The loss function is determined using both a metric that quantifies image similarity and ground truth data.

Authors : Grant Haskins et al. [link]

Deep Learning Registration Approaches

Supervised Transformation Estimation

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- Dual/Weak supervision

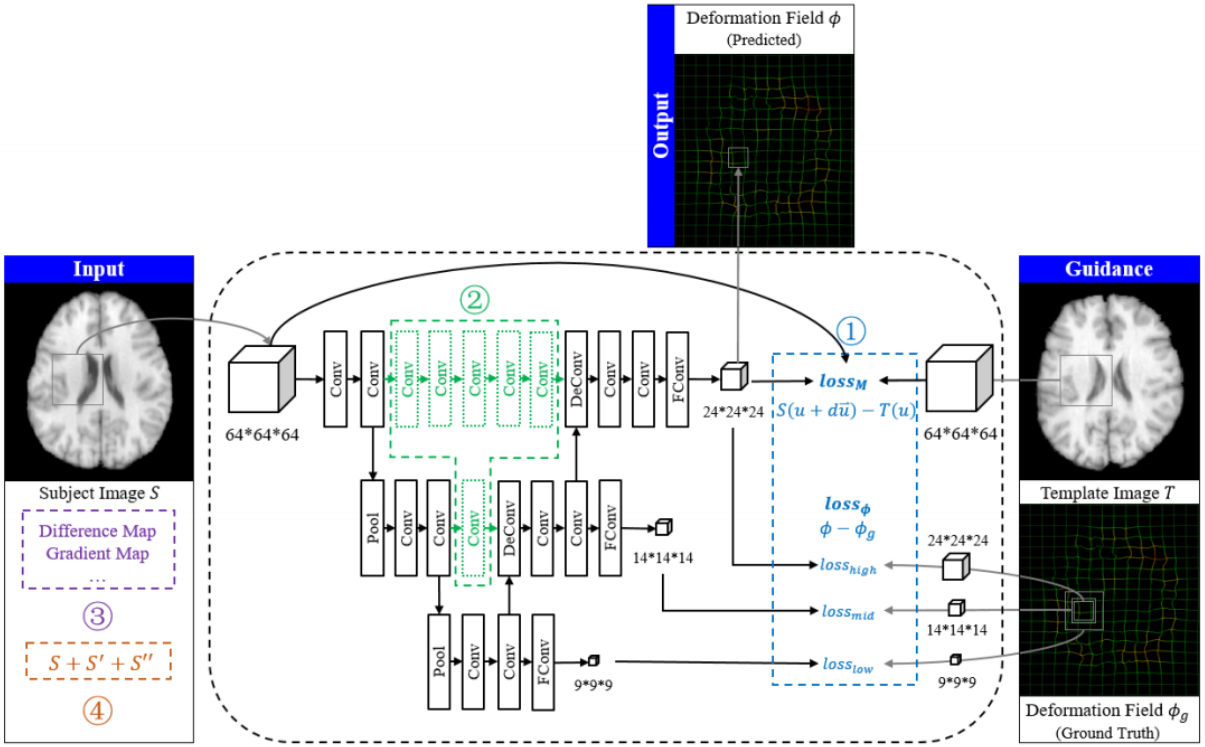


Fig. 1. Overview of our proposed method.

Authors : Fan et al. [link]

Deep Learning Registration Approaches

Supervised Transformation Estimation

- Full supervision
- Dual/Weak supervision

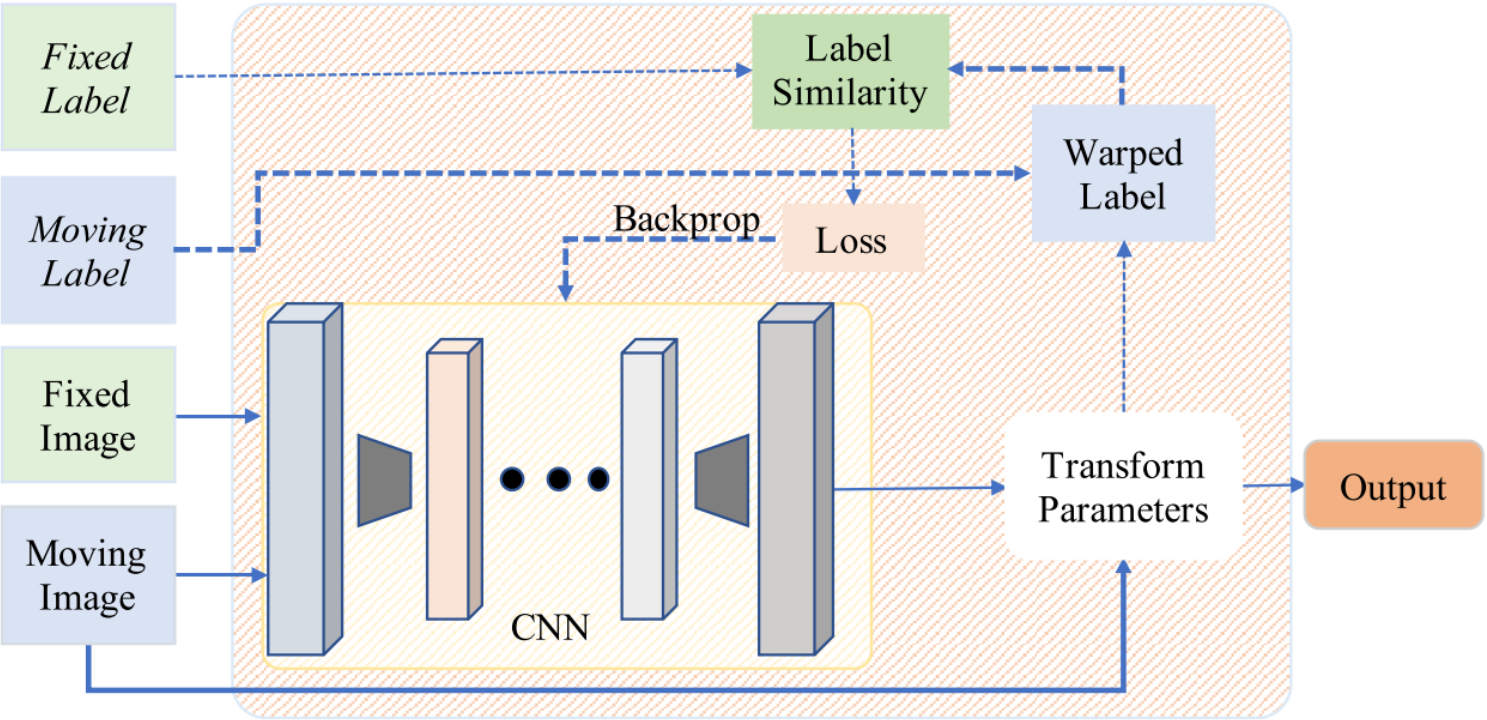


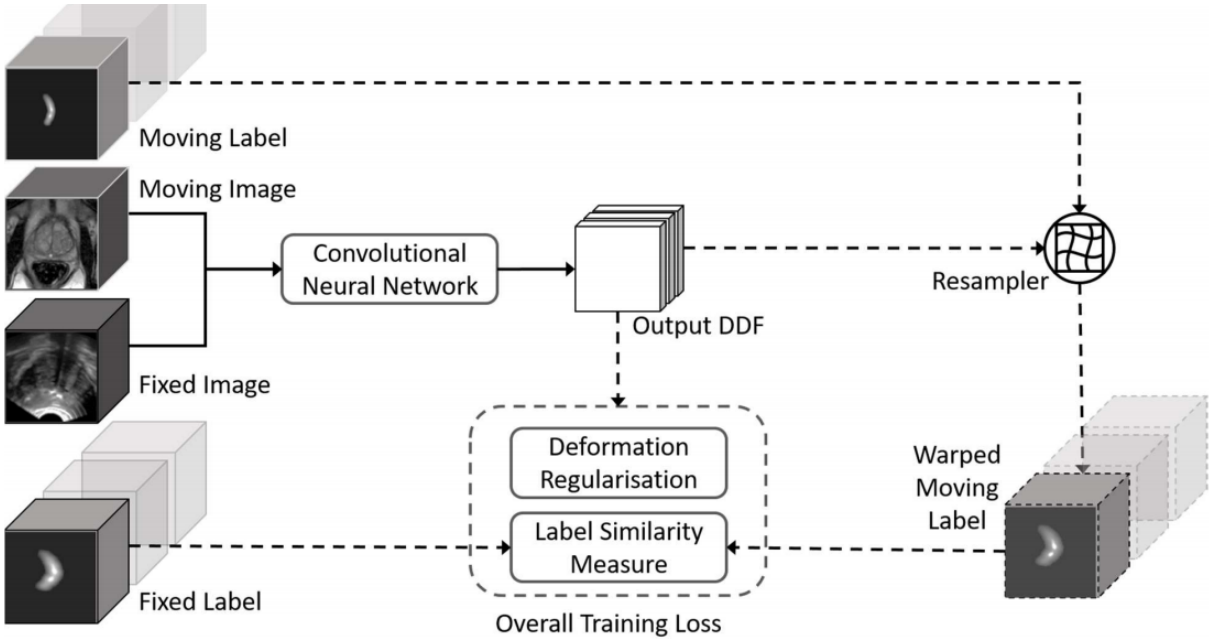
Fig. 8 A visualization of deep single step registration where the agent is trained using label similarity (i.e weak supervision). Manually annotated data (segmentations) are used to define the loss function used to train the network.

Authors : Grant Haskins et al. [link]

Deep Learning Registration Approaches

Supervised Transformation Estimation

- Full supervision
- Dual/Weak supervision



Authors : Hu et al. [link]

Deep Learning Registration Approaches

Unsupervised Transformation Estimation

- Similarity Metric based Unsupervised Transformation Estimation

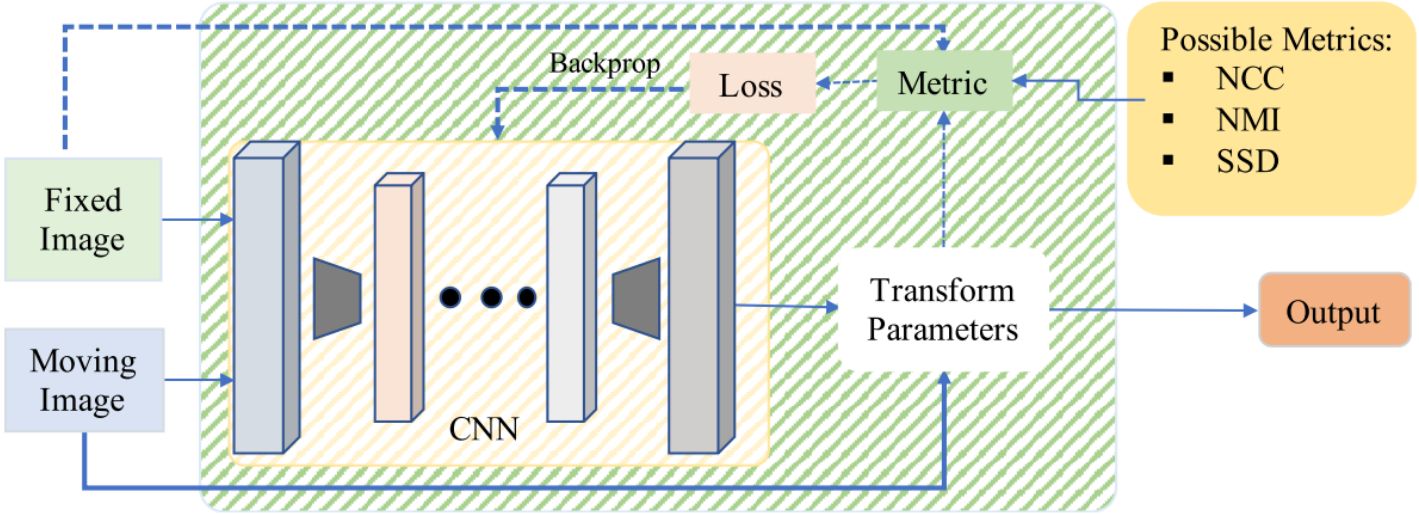


Fig. 9 A visualization of deep single step registration where the network is trained using a metric that quantifies image similarity. Therefore, the approach is unsupervised.

Authors : Grant Haskins et al. [link]

- Feature based Unsupervised Transformation Estimation

Deep Learning Registration Approaches

Unsupervised Transformation Estimation

- Similarity Metric based Unsupervised Transformation Estimation
- Feature based Unsupervised Transformation Estimation

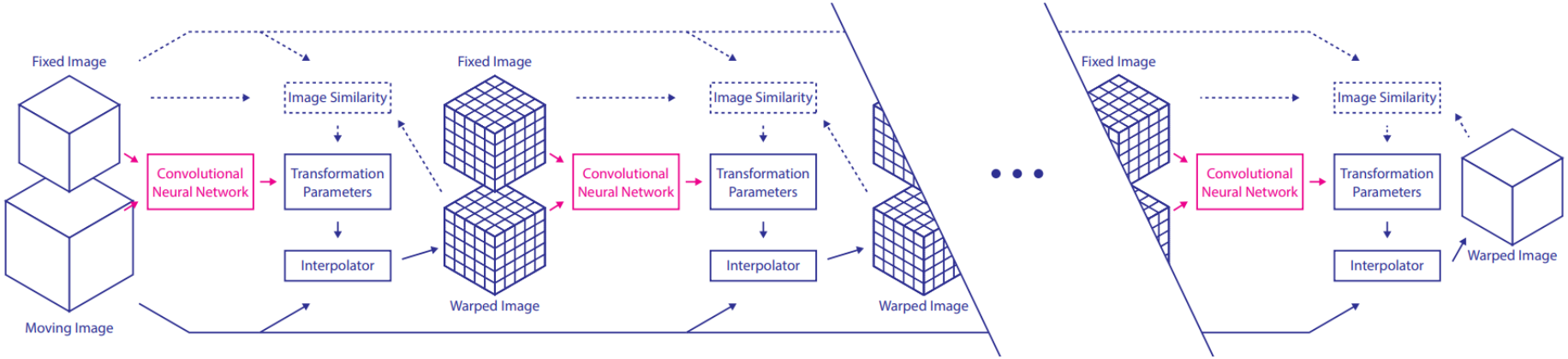


Figure 4: Schematic representation of the DLIR framework applied for hierarchical training of a multi-stage ConvNet for multi-resolution and multi-level image registration. The first stage performs affine registration of an image pair and the subsequent stages perform coarse-to-fine deformable image registration. The ConvNet in each stage is trained for its specific registration task by optimizing image similarity. The weights of the preceding ConvNets are fixed during training. This procedure prevents exploding gradients and conserves memory. Transformation parameters are passed through the network and combined at each stage to create a warped image. The warped image is passed to the subsequent stage and is used as the moving image input.

Authors : de Vos et al. [link]

Deep Learning Registration Approaches

Unsupervised Transformation Estimation

- Similarity Metric based Unsupervised Transformation Estimation
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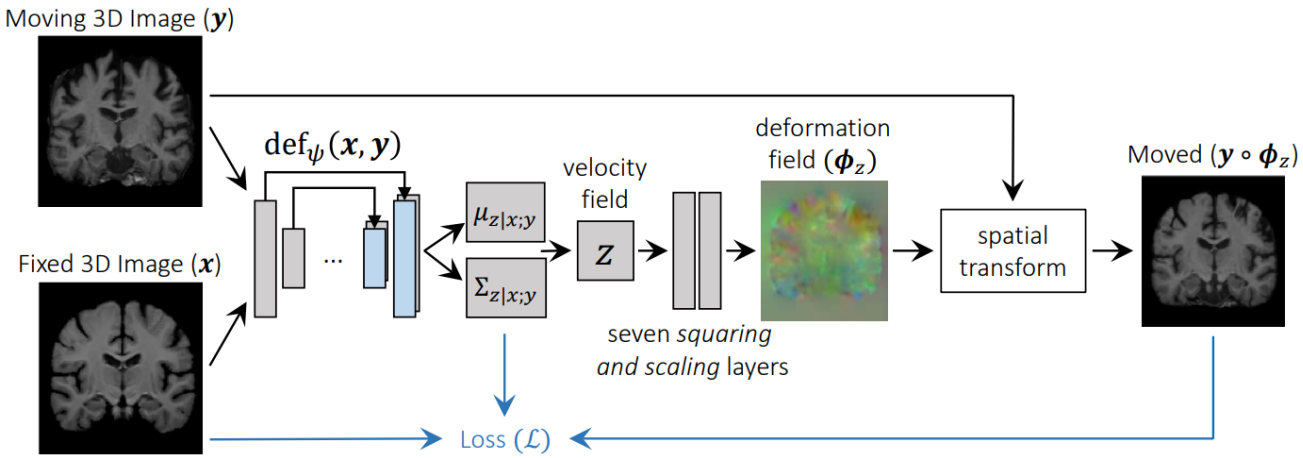

Fig. 1. Overview of end-to-end unsupervised architecture. The first part of the network, $\text{def}_\psi(\boldsymbol{x}, \boldsymbol{y})$ takes the input images and outputs the approximate posterior probability parameters representing the velocity field mean, $\boldsymbol{\mu}_{z|x;y}$, and variance, $\boldsymbol{\Sigma}_{z|x;y}$. A velocity field $\boldsymbol{z}$ is sampled and transformed to a diffeomorphic deformation field $\boldsymbol{\phi}_z$ using novel differentiable *squaring and scaling* layers. Finally, a spatial transform warps $\boldsymbol{y}$ to obtain $\boldsymbol{y} \circ \boldsymbol{\phi}_z$.

Authors : Dalca et al. [link]

Deep Learning Registration Approaches

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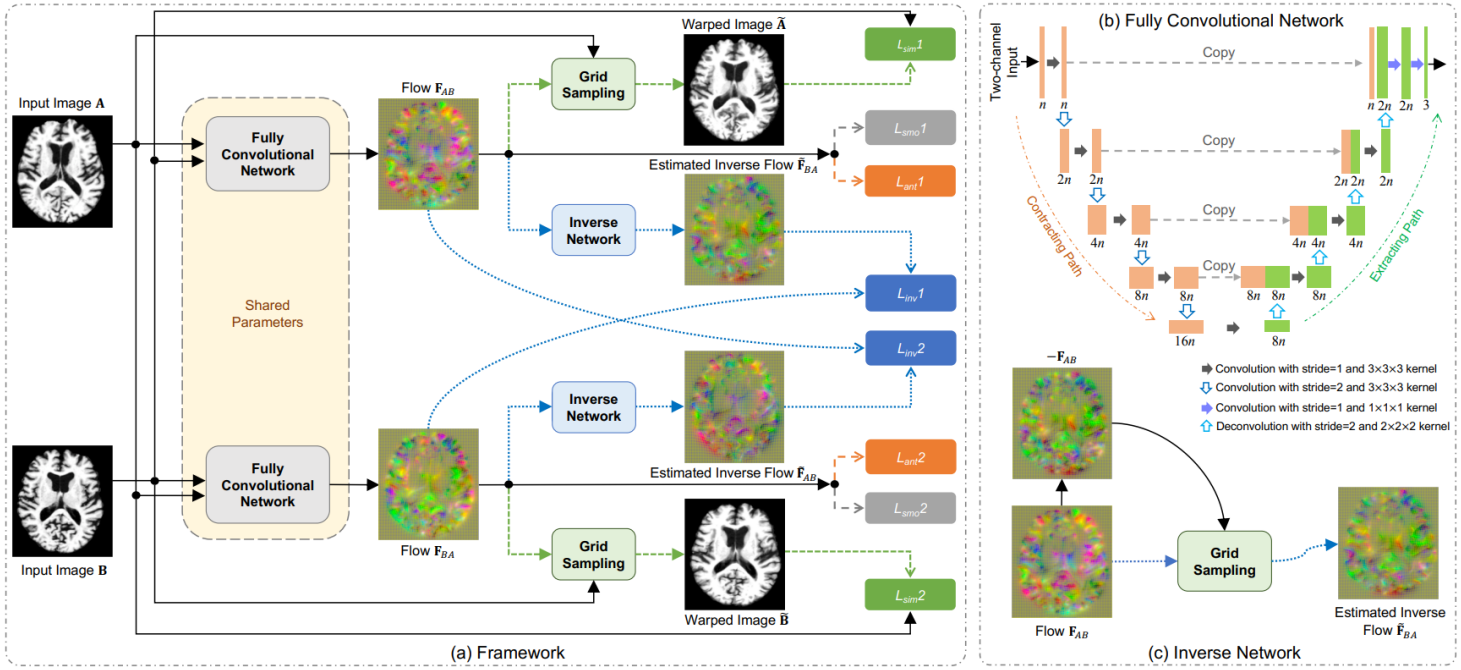

Fig. 2. Pipeline of the proposed Inverse-Consistent deep neural Network (ICNet) for unsupervised deformable image registration, which takes a pair of images as input. (a) Framework of ICNet, (b) architecture of fully convolutional network (FCN), and (c) illustration of the inverse network. The term n in (b) denotes the number of starting convolutional channels in FCN.

Authors : Jun Zhang [link]

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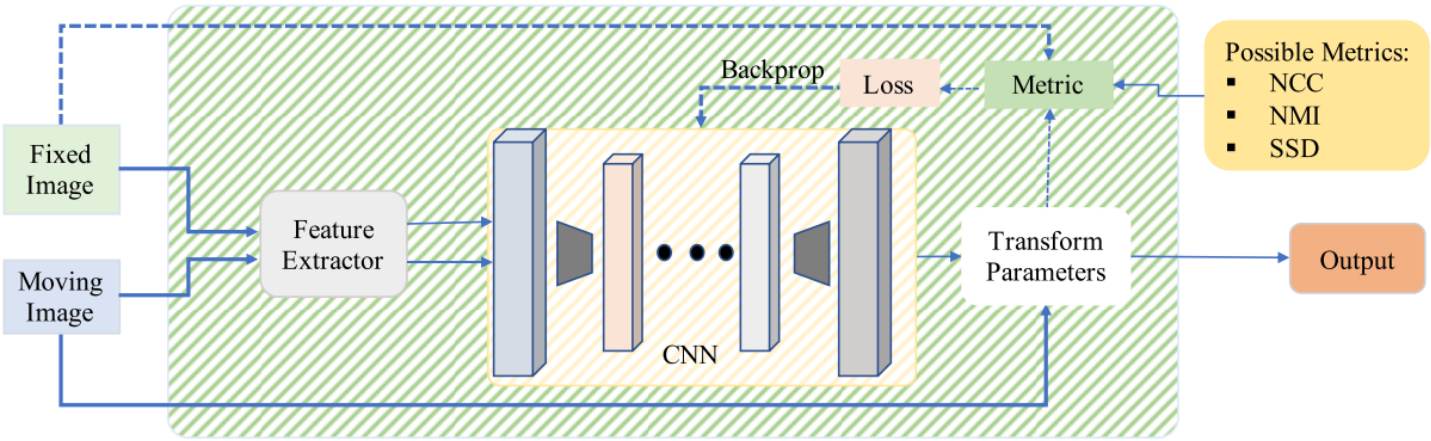

Fig. 10 A visualization of feature based unsupervised image registration. Here, a feature extractor is used to map inputted images to a feature space to facilitate the prediction of transformation parameters.

Authors : Grant Haskins et al. [link]

Deep Learning Registration Approaches

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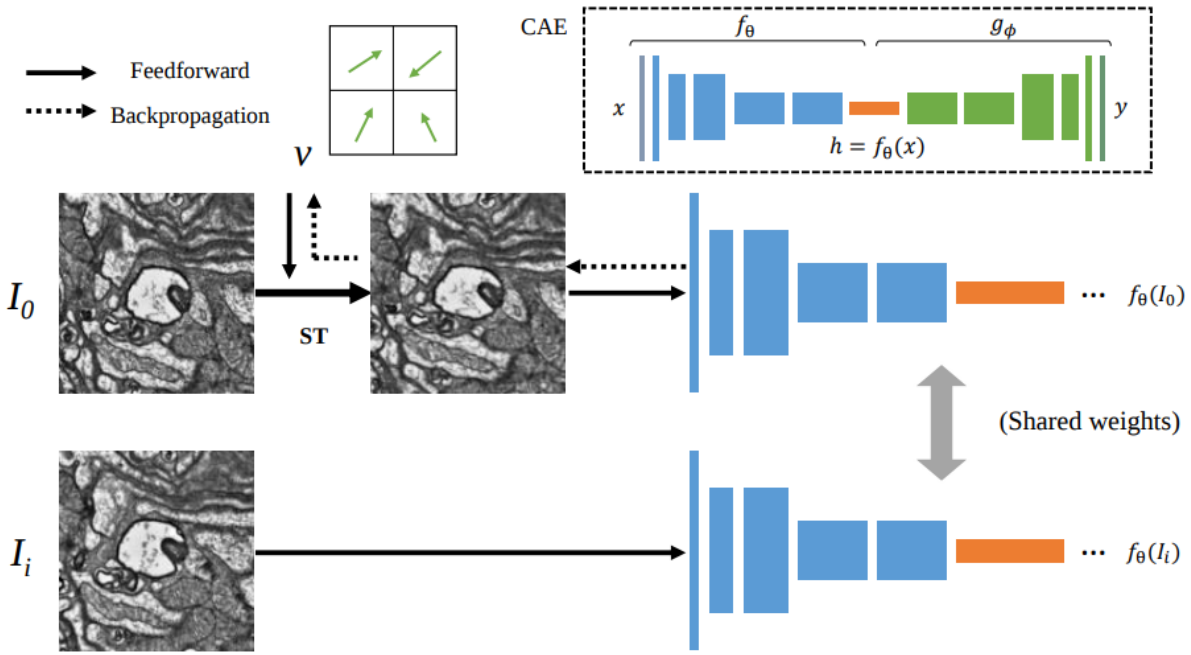

Fig. 2. The overview of our method. The upper right dashed box represents the pre-trained convolution autoencoder (CAE). The alignment is processed by backpropagation with loss of autoencoder features.

Authors : Yoo et al. [link]

Deep Learning Registration Approaches

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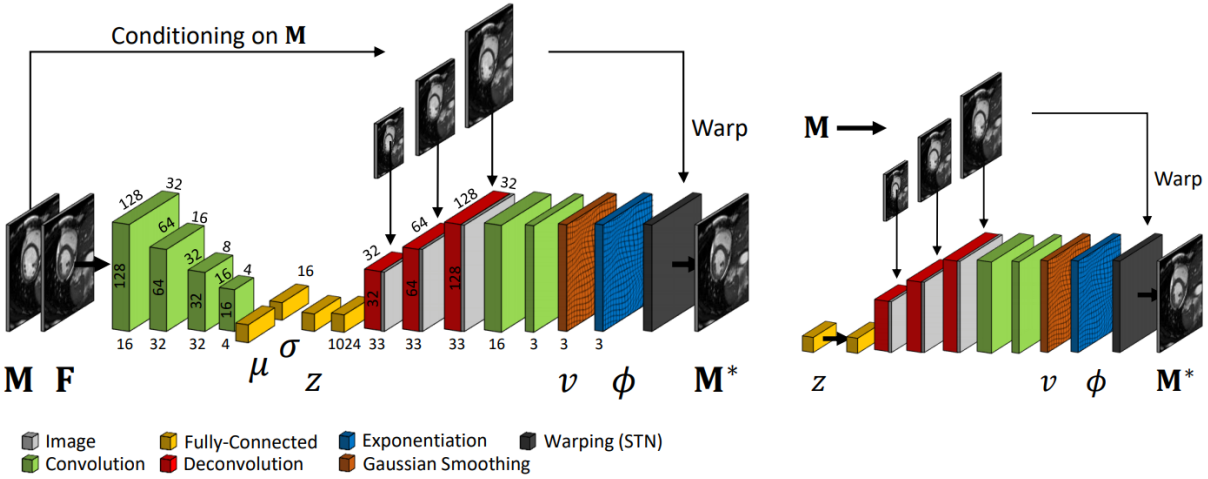


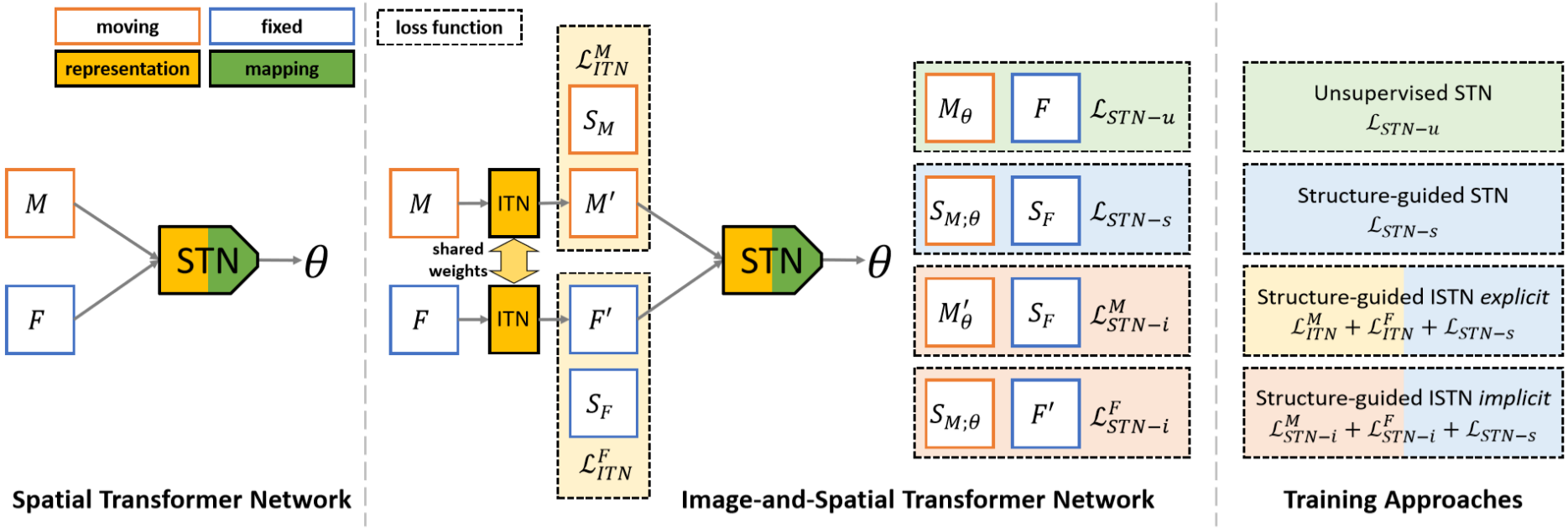
Fig. 1: (a) CVAE registration network during training and registration including diffeomorphic layer (exponentiation). Deformations are encoded in z from which velocities are decoded while being conditioned on the moving image. (b) Decoder network for sampling and deformation transport: Apply z-code conditioned on any new image $\mathbf{M}$.

Authors : Krebs et al. [link]

State-of-the-art Approaches (A couple of MICCAI 2019 papers)

State-of-the-art Approaches

Image-and-Spatial Transformer Networks for Structure-Guided Image Registration



Authors : Lee et al. [link]

State-of-the-art Approaches

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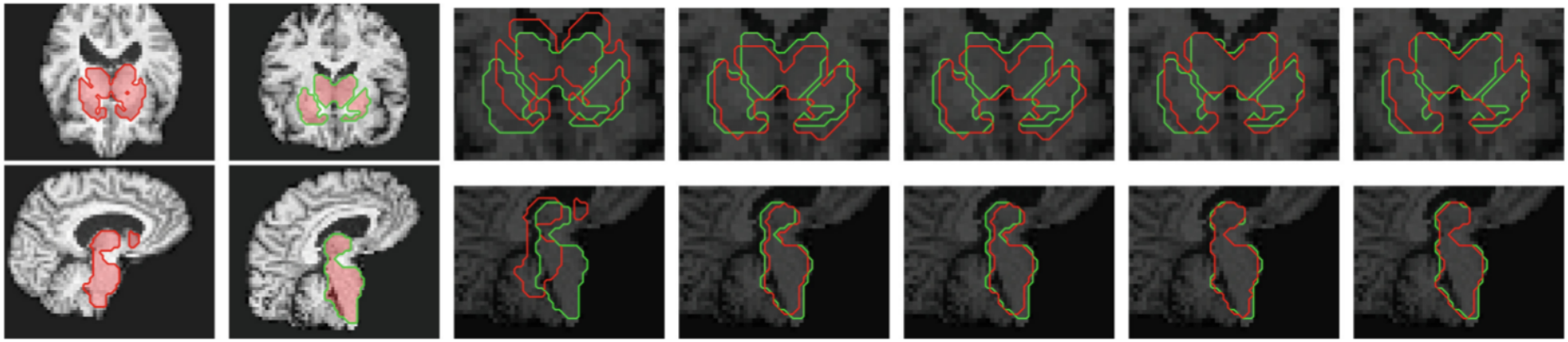
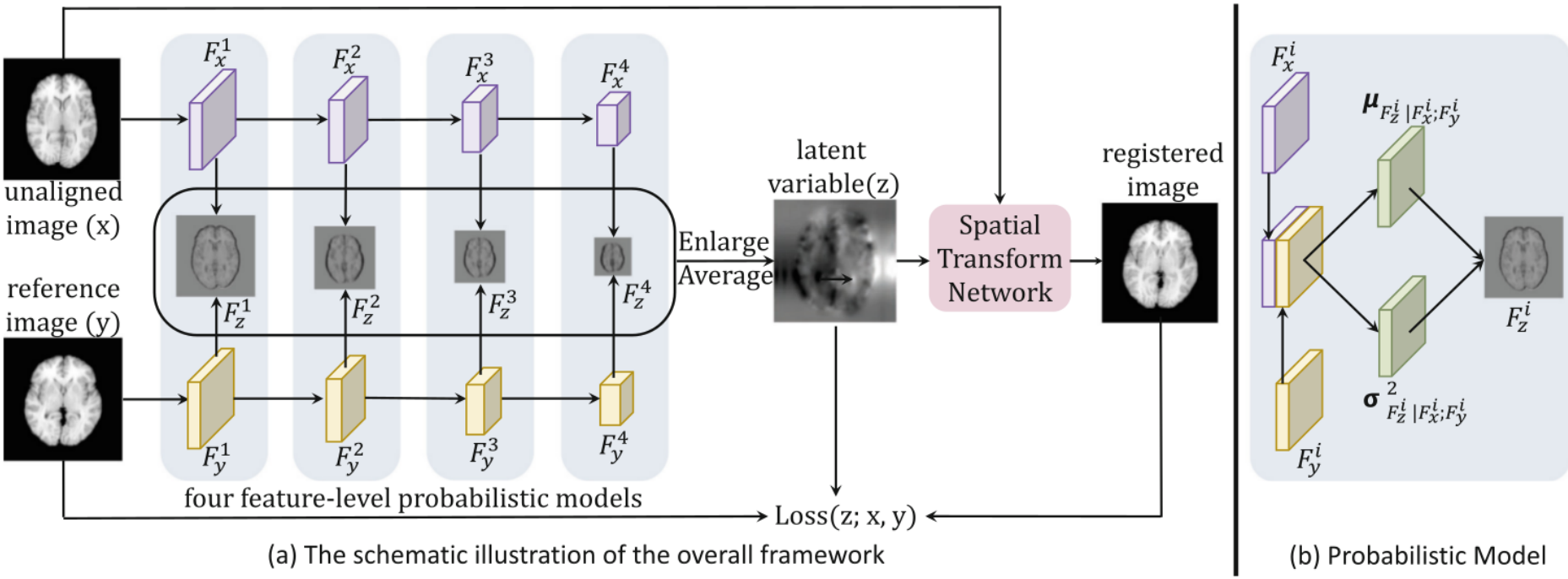


Visual results for affine registration with SoI overlaid in red (moving), and green (fixed). On the left : the input images before registration. Close-ups from left to right : initial alignment, STN-u, STN-s, ISTN-e, ISTN-i.

Authors : Lee et al. [link]

State-of-the-art Approaches

Probabilistic Multilayer Regularization Network for Unsupervised 3D Brain Image Registration



(a) The schematic illustration of the overall framework

(b) Probabilistic Model

Authors : Liu et al. [link]

State-of-the-art Approaches

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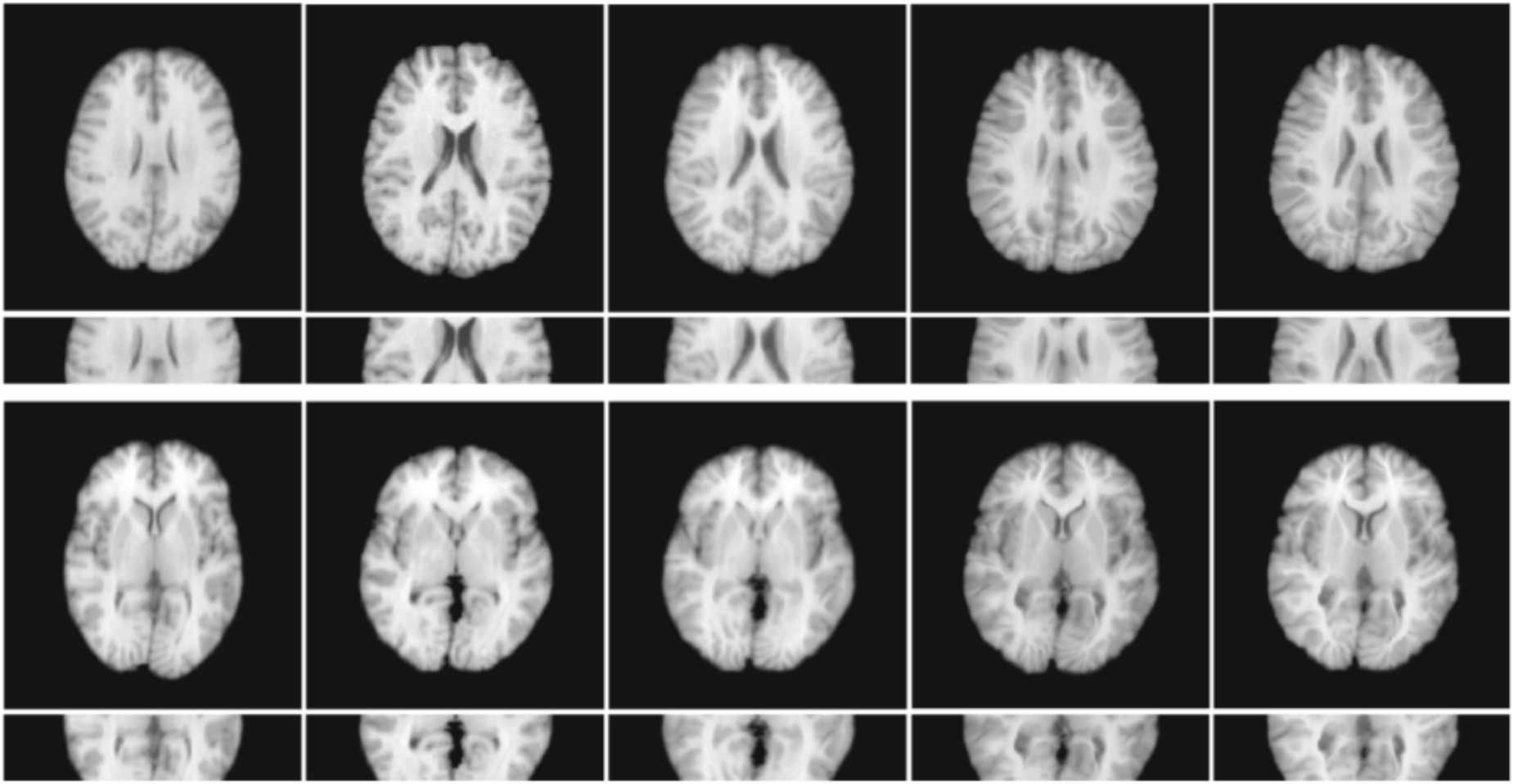
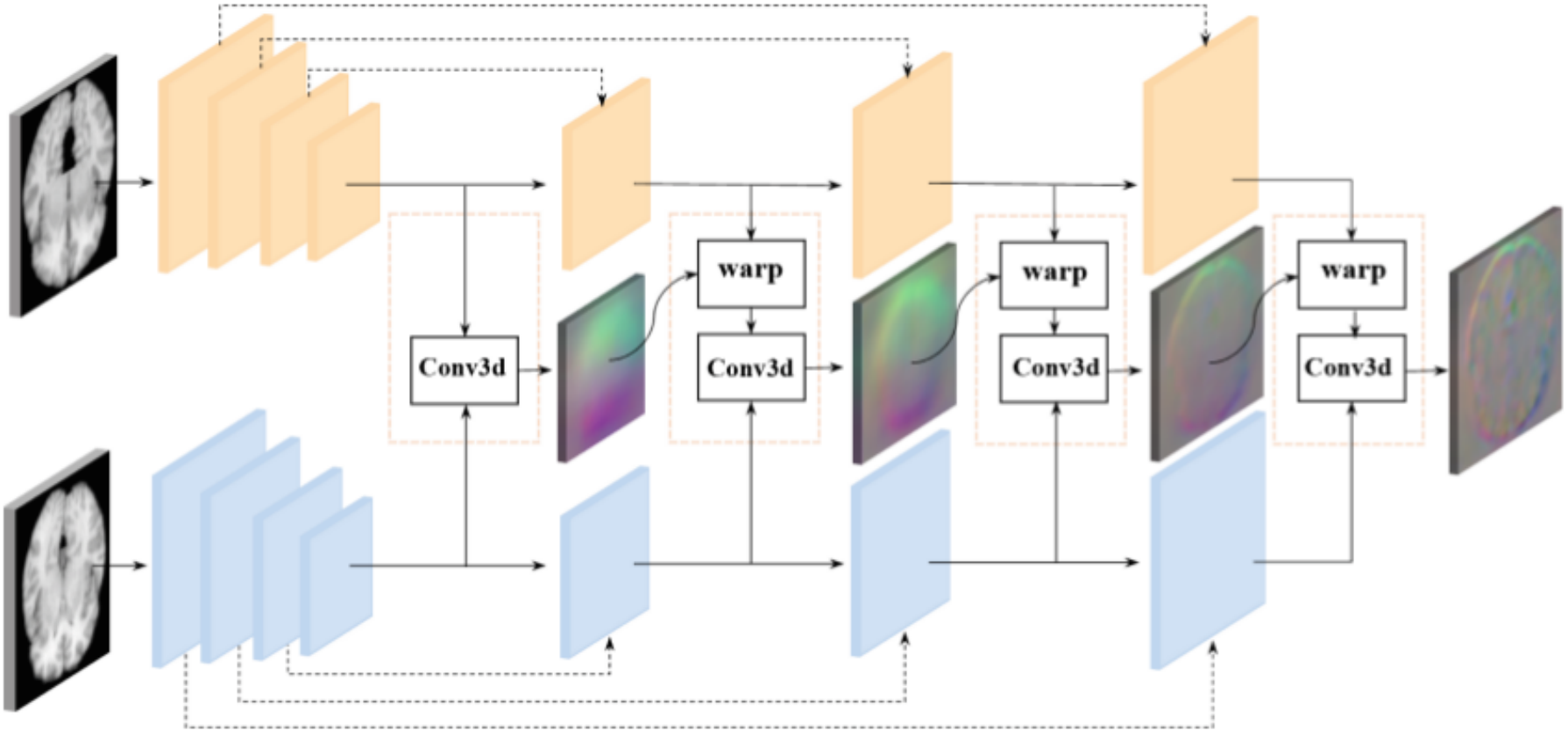


(a) unaligned image (b) reference image (c) our result (d) VoxelMorph (e) FAIM

Authors : Liu et al. [link]

State-of-the-art Approaches

Dual-Stream Pyramid Registration Network



Authors : Hu et al. [link]

State-of-the-art Approaches

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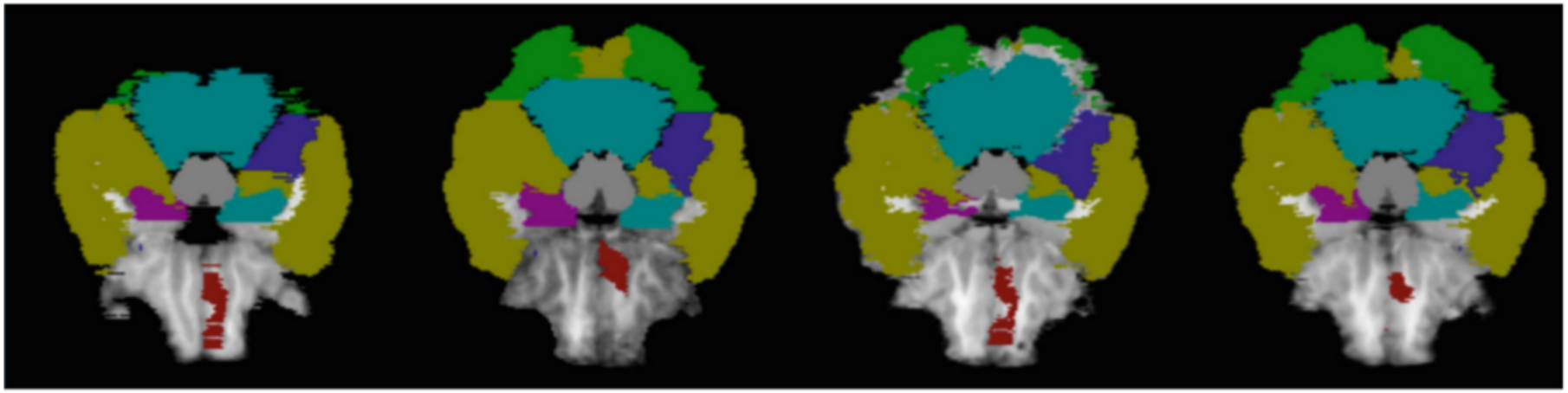
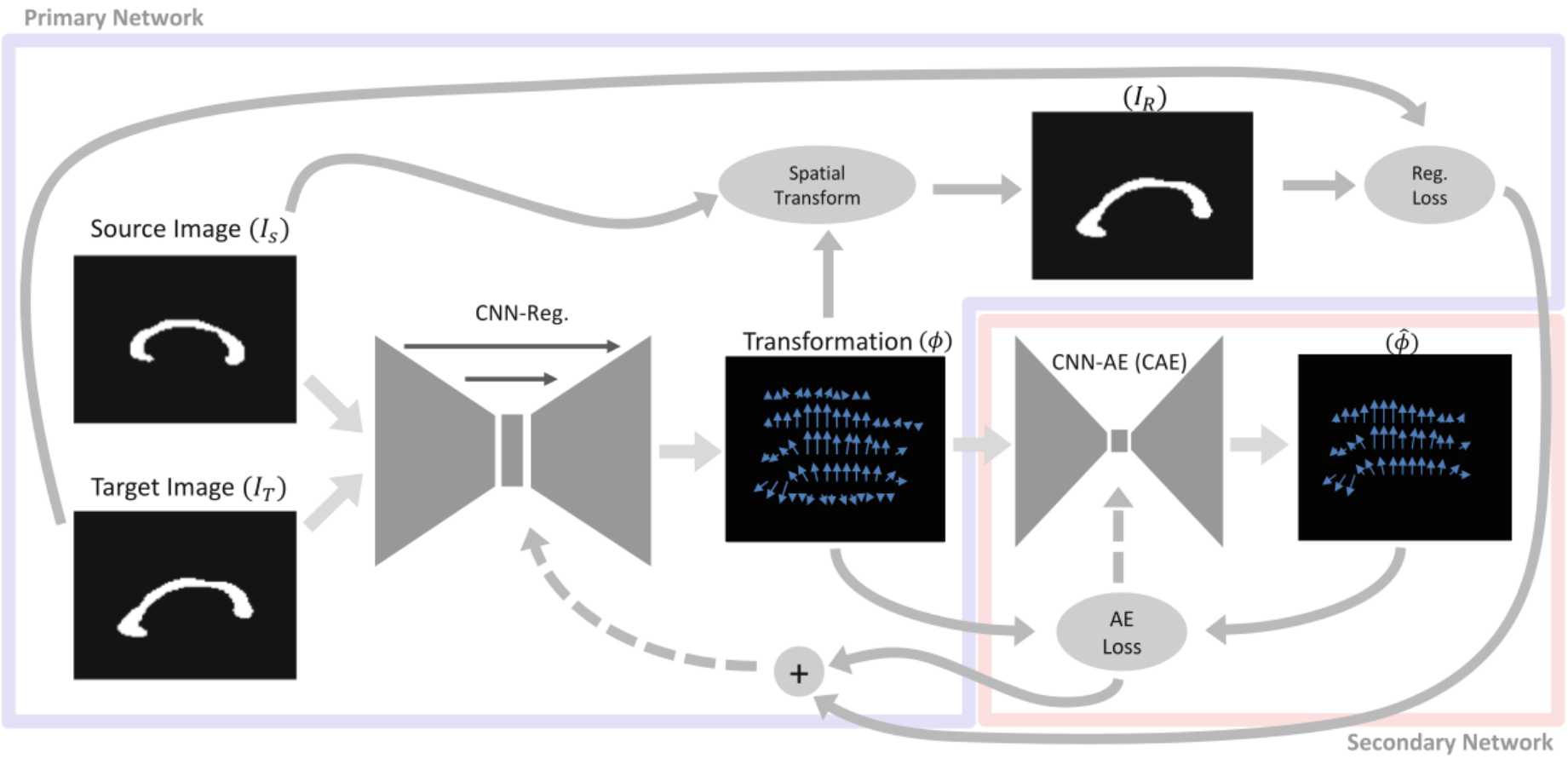


Fig. 3. Registration results on large displacements. From left to right: the moving image, the fixed image, results of VoxelMorph and Dual-PRNet. (Color figure online)

Authors : Hu et al. [link]

State-of-the-art Approaches

A Cooperative Autoencoder for Population-Based Regularization of CNN Image Registration



Authors : Bhalodia et al. [link]

State-of-the-art Approaches

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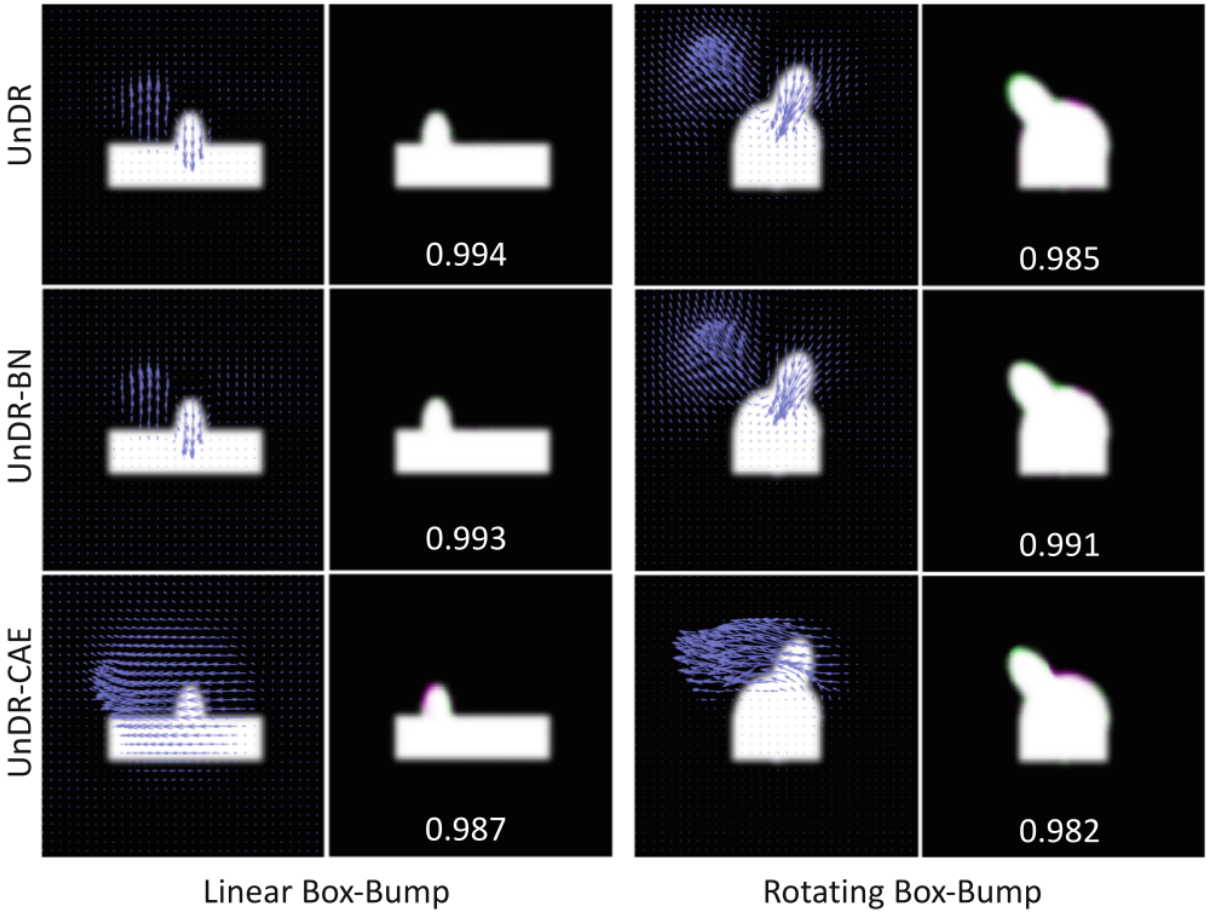
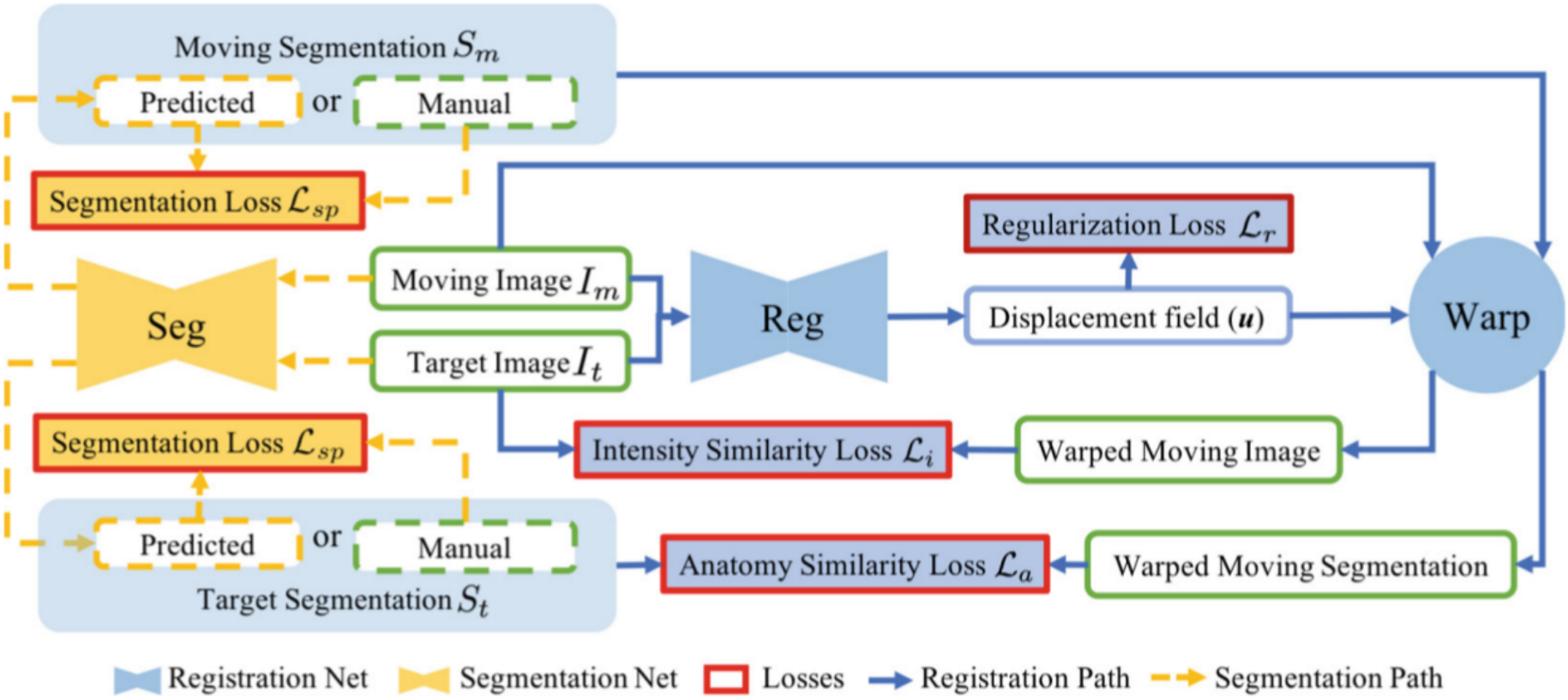


Authors : Bhalodia et al. [link]

State-of-the-art Approaches

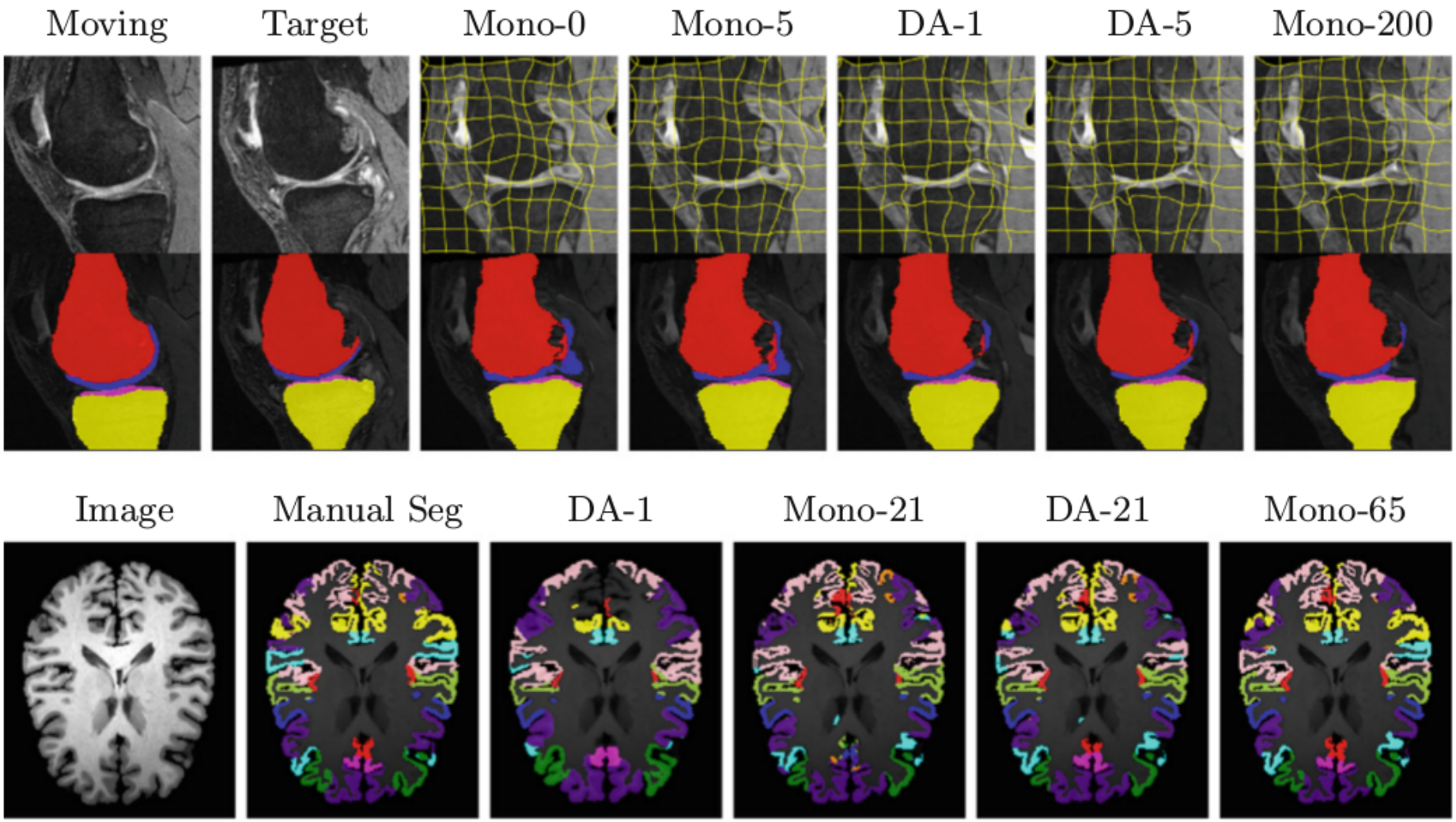
DeepAtlas : Joint Semi-supervised Learning of Image Registration and Segmentation



Authors : Xu et al. [link]

State-of-the-art Approaches

DeepAtlas : Joint Semi-supervised Learning of Image Registration and Segmentation



Authors : Xu et al. [link]

Conclusions and Future Directions

Conclusions

- Deep learning can be used to perform faster registrations
- Deep learning can be used to learn a similarity measure

Future Directions

- Incorporating different tasks into the pipeline : (registration+segmentation)
- Using raw image domain data