Pretraining Deformable Image Registration Networks with Random Images

Junyu Chen[1], Shuwen Wei[2], Yihao Liu[3], Aaron Carass[2], Yong Du[1]
[1]Department of Radiology and Radiological Science, Johns Hopkins University
[2]Department of Electrical and Computer Engineering, Johns Hopkins University
[3]Department of Electrical and Computer Engineering, Vanderbilt University

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Check out the source code on GitHub

Introduction

Background: Deep learning-based image registration methods typically require large domain-specific datasets for effective generalization. Recent research indicates that training on randomly generated images may effectively replace domain-specific pretraining [1], improving efficiency and reducing the amount of required labeled medical data.

Objective: This study proposes a novel pretraining strategy using registration between random images as a proxy task to train deformable registration networks, aiming to enhance generalizability, reduce reliance on domain-specific data, and accelerate convergence.

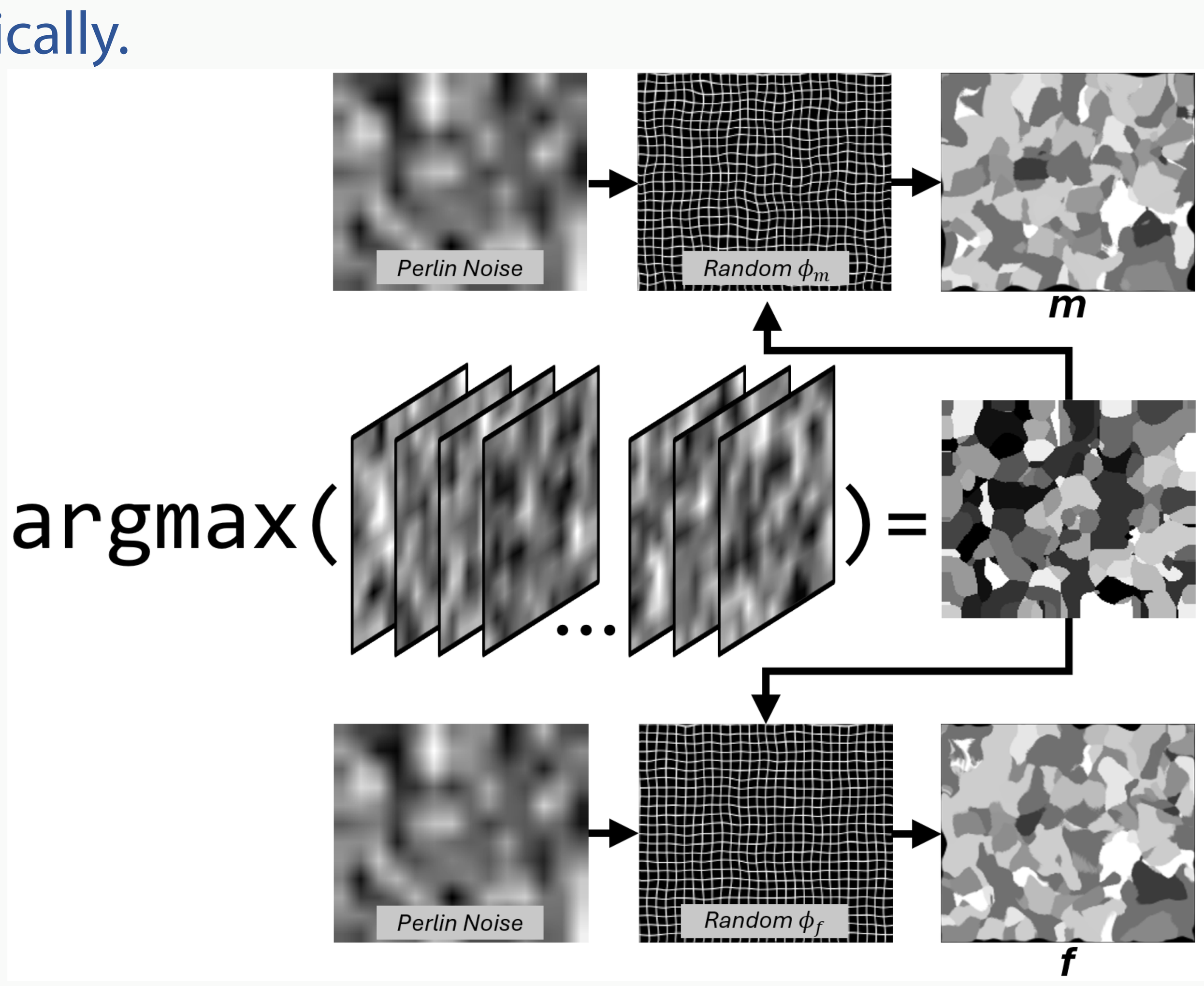
Methods

Proposed Pretraining Strategy:

Let ***m*** and ***f*** represent the moving and fixed images, respectively.

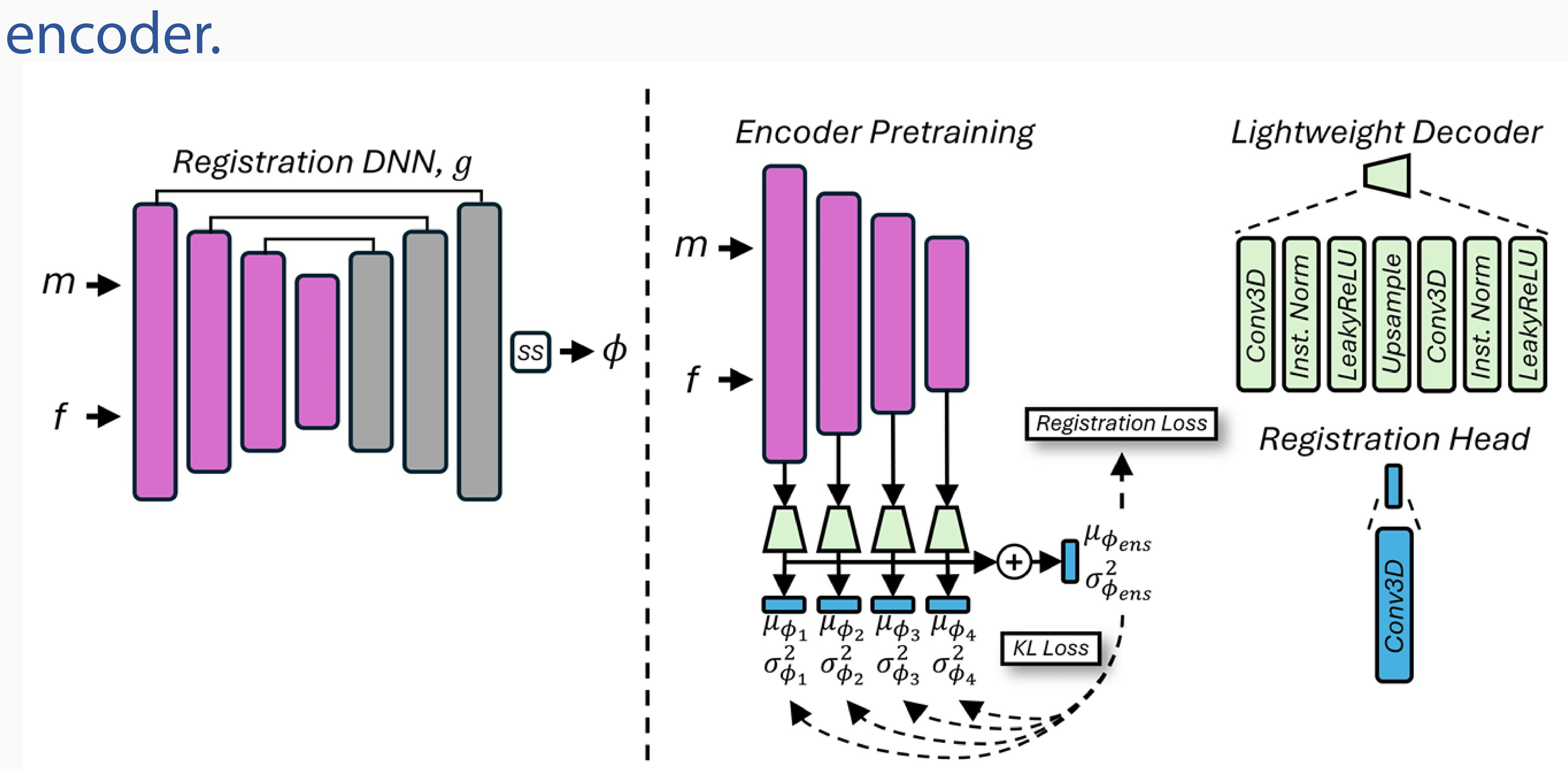
1. Random Image Generation:

Multi-channel Perlin noise-generated random shapes **without** additional Gaussian noise or bias fields; diffeomorphic deformation fields applied to create random image pairs dynamically.



2. Network Architecture:

We pretrain only the ***encoder*** of TransMorph [2] by pairing it with lightweight ***temporary decoders*** at multiple resolutions. These temporary decoders are discarded after pretraining. This asymmetric design, often used in computer vision [3], concentrates the learning of meaningful features within the encoder.



3. Self-Distillation Strategy:

Ensemble-based method using KL-divergence between decoder outputs to enhance consistency and representation learning across layers.

4. Loss Function for Pretraining:

Combines normalized cross-correlation (NCC) loss, diffusion regularizer, and KL-divergence-based self-distillation terms:

$$\mathcal{L}_{pretrain}(m, f) = \mathcal{L}_{NCC}(m \circ \mu_{\phi_{ens}}, f) + \lambda \|\nabla u_{ens}\|^2 + \eta \sum_{k\in K} \frac{1}{K} \mathcal{D}_{KL}(\mathcal{N}(\mu_{\phi_{ens}}, \sigma^2_{\phi_{ens}}) || \mathcal{N}(\mu_{\phi_k}, \sigma^2_{\phi_k})),$$

Methods (Cont.)

where the ensemble deformation field is represented by the mean $\mu_{\phi_{ens}}$ and variance $\sigma^2_{\phi_{ens}}$, while μ_{ϕ_k} and $\sigma^2_{\phi_k}$ are the estimates from the decoder at stage k.

Experimental Setup:

- Datasets: IXI brain MRI, comparison with deedsBCV [4], SynthMorph [1], and ConvexAdam [5].
- Training: Pretrained for 50 epochs, fine-tuning with 1·NCC+1·Diffusion Reg. for 250 epochs.

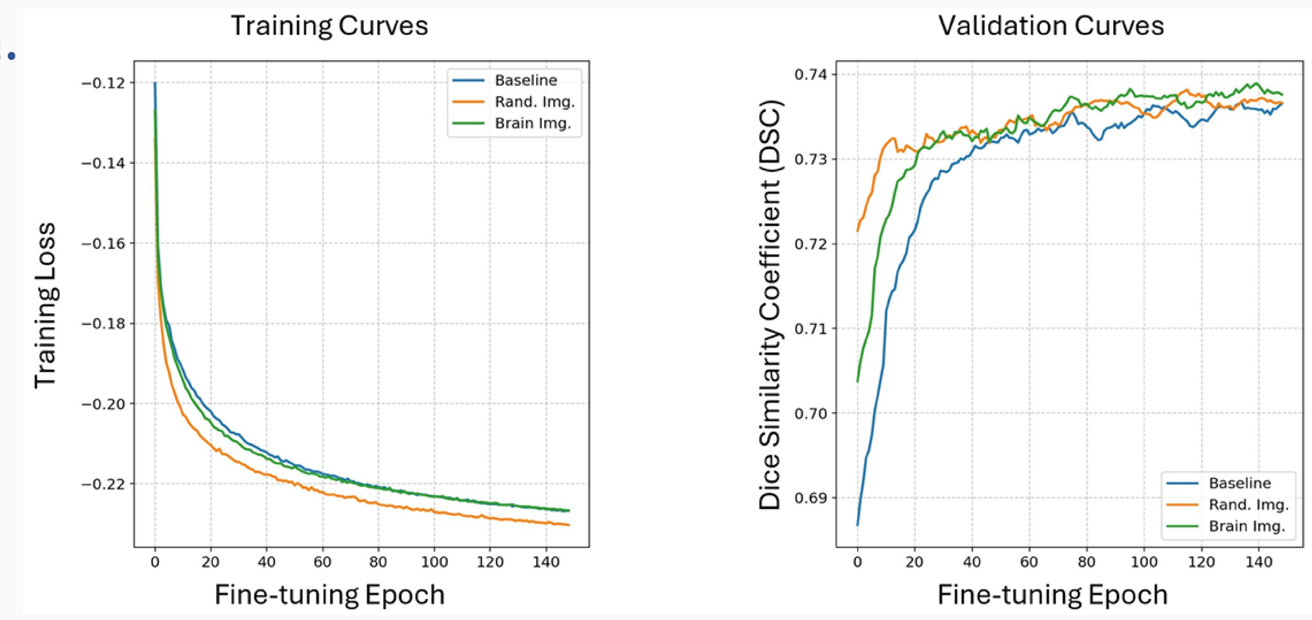
Results

Improved Registration Performance:

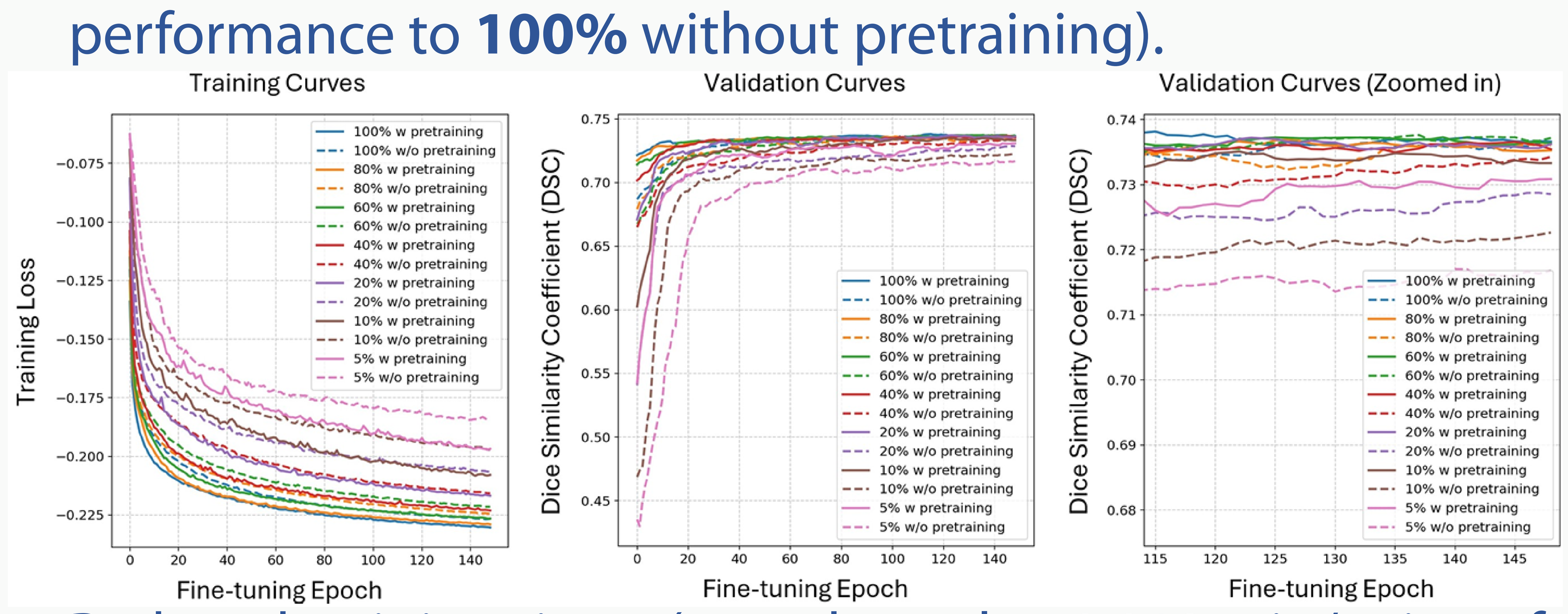
Pretrained models demonstrated **superior or equivalent performance** (*Dice score:* 0.751±0.122) compared to training-from-scratch (0.749±0.125) and baseline methods, including SynthMorph (0.688±0.152), deedsBCV (0.740 ± 0.127), and ConvexAdam (0.749 ± 0.126).

Efficiency and Data Reduction:

- Achieved accuracy on par with pretraining using in-domain data.



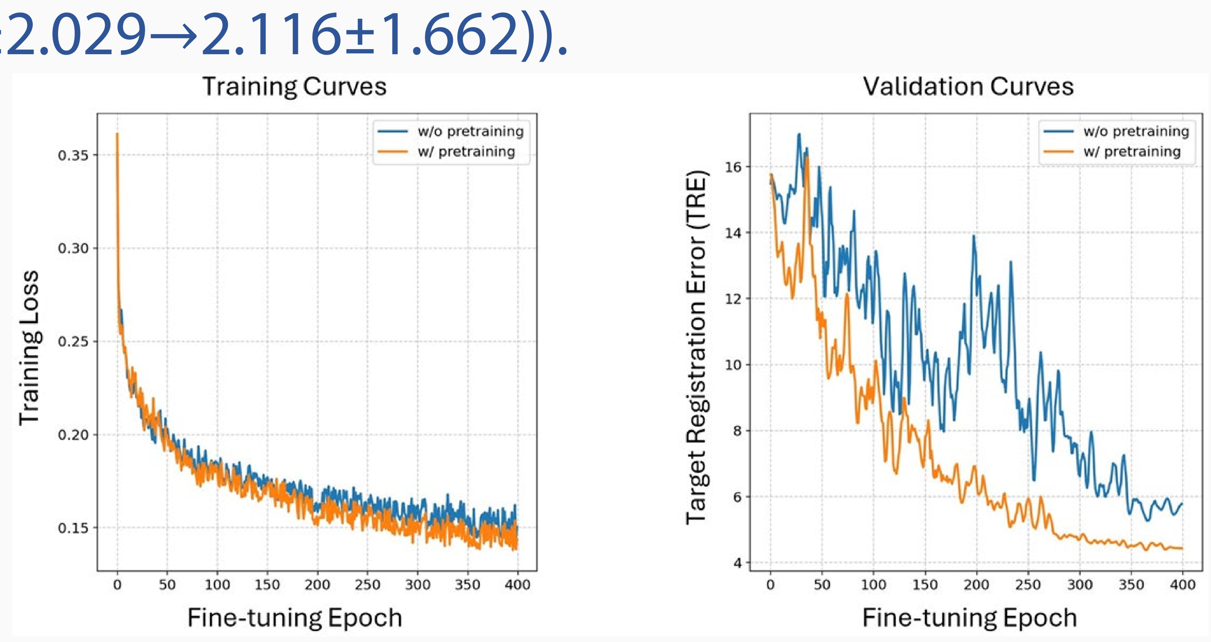
- Achieved competitive accuracy using substantially less labeled data (**10%** of training data achieved comparable performance to **100%** without pretraining).



- Reduced training times (encoder-only ~0.012 min/pair vs. full model ~0.022 min/pair).

Generalizability to Other Domains:

Demonstrated applicability to limited-data lung registration tasks (TRE significantly improved from not using pretraining (2.753±2.029→2.116±1.662)).



Reference

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5. Siebert, Hanna, et al. IEEE TMI 44.2 (2025): 738-748.

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