Two-stage Unsupervised Learning Method for Affine and Deformable Registration

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Introduction

Image registration aims to establish spatial correspondences between a pair of images. The process is typically formulated as an optimization problem which seeks spatial transformation φ by maximizing similarity of the fixed image F and moving image M.

$$\underset{\varphi}{\operatorname{argmin}}\,\Re(F,M,\varphi) = \underset{\varphi}{\operatorname{argmin}}\,(\underbrace{Sim(F,M(\varphi))}_{\text{Image similarity}} + \gamma \underbrace{Reg(\varphi)}_{\text{Regularization}})$$

Our goal: learn the global and local spatial transformation parameters in an unsupervised CNN model.

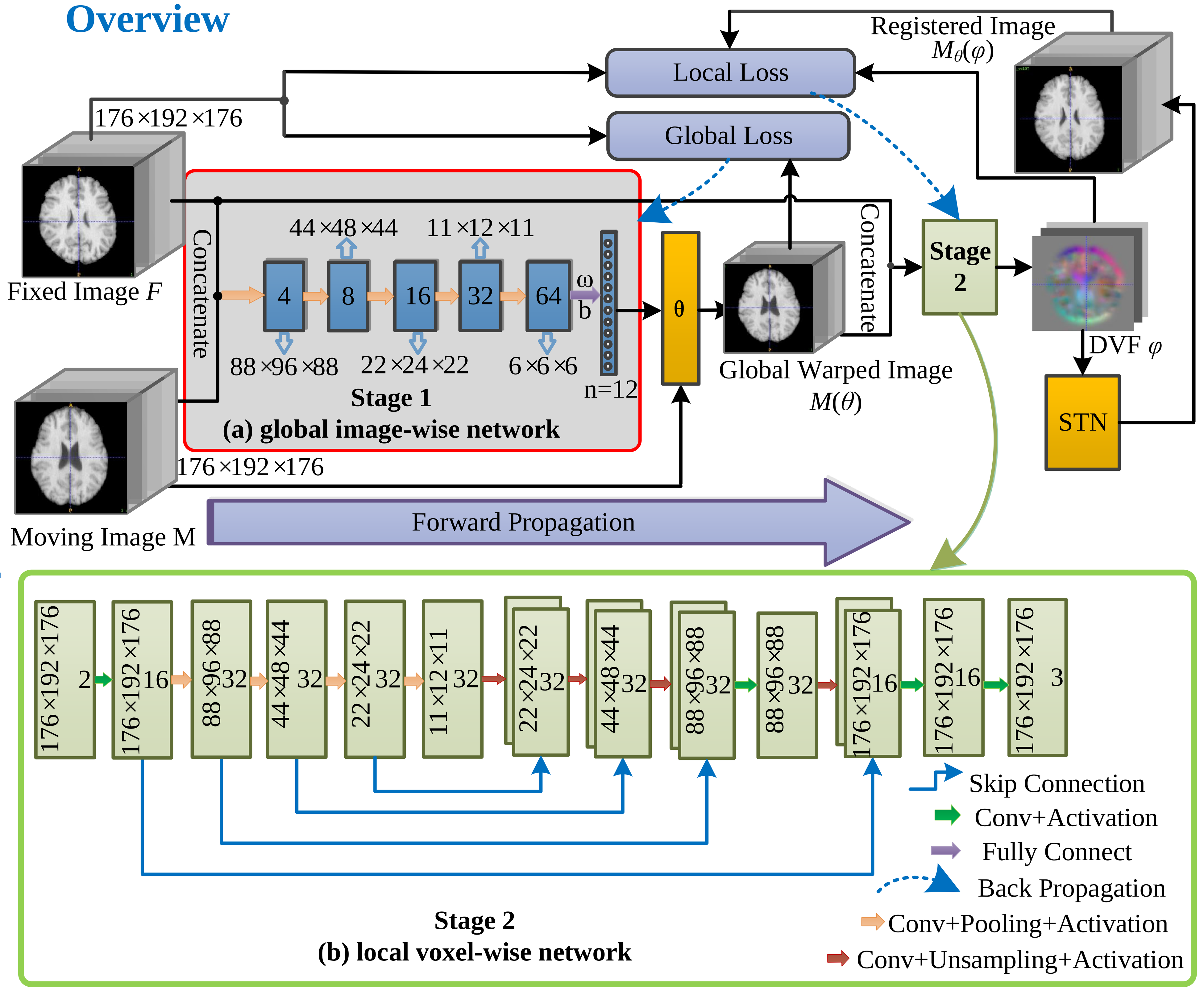
Problems and Solutions

- ➢ Iterative optimization methods are computationally expensive and time consuming. Registration performance is sensitive and requires user interaction to tune parameters.
- ✓ We model registration pipelines as an optimizable function parameterized by deep network weights which are learned in the training period.
- ➢ Preparing the supervised information for medical image registration is time consuming and requires specialized knowledge.
- ✓ We proposed a two-stage unsupervised learning method to find the global displacement map and local deformation field. The training does not need anatomical labels or ground-truth deformations fields. The fixed image is not restricted to a template image. The preprocess step does not need aligning images

Approach

- In the first stage, we learn a global image-wise affine map θ by a deep network. In the second stage, we learn a local voxel-wise deformation vector field φ by an encoder-decoder architecture.

Overview



Loss Functions

- The first stage measures NCC of the whole fixed image F and the moving image M to capture global information:

$$L_{global}(F,M,\theta) = -Ls_{im}(F,M(\theta))$$
$$= -\frac{\left(\sum_{x_i\in\Omega}(I_F(x_i)-\bar{I}_F)\,(I_{M_\theta}(x_i)-\bar{I}_{M_\theta})\right)^2}{\sum_{x_i\in\Omega}(I_F(x_i)-\bar{I}_F)^2\sum_{x_i\in\Omega}(I_{M_\theta}(x_i)-\bar{I}_{M_\theta})^2 + 1e^{-5}}$$

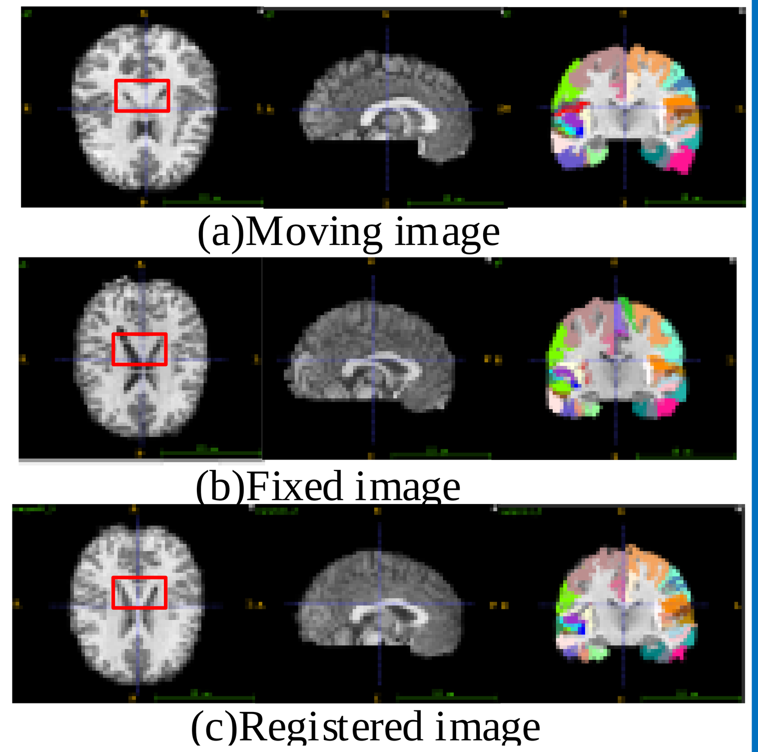
- In the second stage, loss function is defined as local NCC in addition with a regularization term (L_2 norm of φ on its gradients):

$$L_{local}(F,M_\theta,\varphi) = -Ls_{im}(F,M_\theta(\varphi)) + \gamma L_{r(\varphi)}$$
$$= -\sum_{k\in\Omega}\frac{\left(\sum_{x_i\in\Omega^k}(I_F(x_i)-\bar{I}_{Fk})\left(I_{M_{\theta(\varphi)}}(x_i)-\bar{I}_{M_{\theta(\varphi)}k}\right)\right)^2}{\sum_{x_i\in\Omega^k}(I_F(x_i)-\bar{I}_{Fk})\sum_{x_i}\left(I_{M_{\theta(\varphi)}}(x_i)-\bar{I}_{M_{\theta(\varphi)}k}\right)+1e^{-5}} + \gamma\sum_{k\in\Omega}\|\nabla\varphi(k)\|^2$$

Experimental Results

We used four public T1 weighted 3D brain MR images datasets: LPBA40, IBSR18, CUMC12 and MGH10, with 58-22 patient-level splits for training and testing.

Experiment results of MGH10 dataset



Mean DSCs (%) of 4 datasets by the two-stage network

Dataset	Original	Global	Registered
LPBA40	54.5	61.4	70.5
IBSR18	46.1	51.4	65.1
CUMC12	31.3	32.8	46.5
MGH10	40.6	41.4	43.9

Comparison with state-of-the-art methods(mean DSCs and standard deviations)

Dataset	Our method	Affine	BSpline	Fsf_ Demons	SyN	Voxel Morph
LPBA40	0.705 ±0.099	0.644 ±0.101	0.683 ±0.088	0.699 ±0.101	0.724 ±0.086	0.659 ±0.127
IBSR18	0.651 ±0.232	0.493 ±0.227	0.498 ±0.221	0.677 ±0.214	0.695 ±0.228	0.658 ±0.233
CUMC12	0.465 ±0.206	0.382 ±0.185	0.436 ±0.185	0.476 ±0.206	0.507 ±0.196	0.446 ±0.210
MGH10	0.439 ±0.185	0.402 ±0.176	0.399 ±0.169	0.406 ±0.180	0.236 ±0.178	0.436 ±0.184

The proposed approach outperforms several state-of-the-art methods in terms of accuracy and efficiency. It achieves promising results in volume overlap values and errors between fixed labels and warped moving labels.

Conclusions

The two-stage unsupervised CNN architecture can speed up 3D medical image registration pipelines. Anatomical labels or ground-truth deformation fields are not required. It can capture the global map and local deformation vector field. It can be tailored to different datasets without iteration and tuning parameters.