Towards Segmentation and Spatial Alignment of the Human Embryonic Brain Using Deep Learning for Atlas-based Registration

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Aim Automatic segmentation and spatial alignment of the human embryonic brain in first trimester 3D ultrasound.

Method Two CNN's trained unsupervised and end-to-end using the loss (Eq. 1), designed for this problem

Conclusion Based on the results presented here, we conclude that our method is a promising approach.

Results synthetic 2D data

- Image I generated as: $I \coloneqq A(\phi_a^{gt} \circ \phi_d^{gt}\ (x))$.
- We evaluated the results using the Target Registration Error (TRE).
- Row 1 and 2 of figure 1 show the need for two networks.
- Row 3 of figure 1 shows the benefit or regularizing scaling.

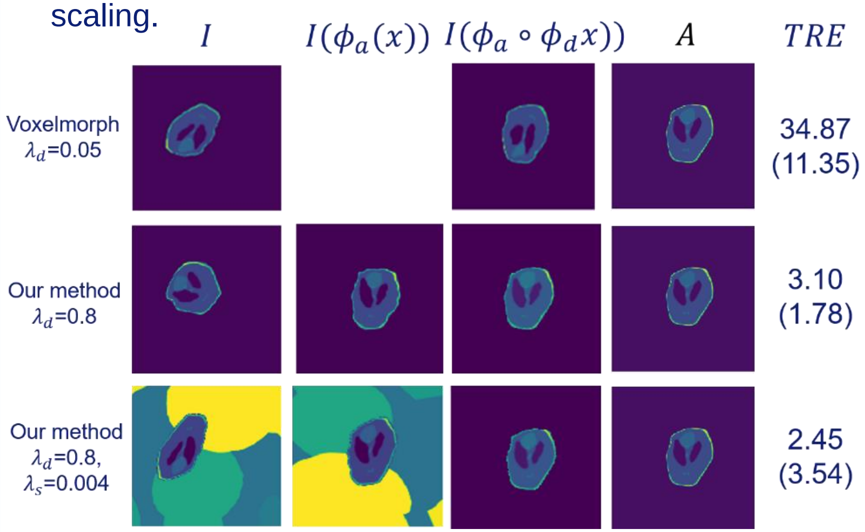

Fig 1. Visual result for the experiments on synthetic data. The TRE is the mean over the validation set with the standard deviation between brackets.

Results 3D US data

- We applied our framework on 3D ultrasound acquired in the 9th week of pregnancy[1].
- Only in 26% of the validation set alignment was achieved.

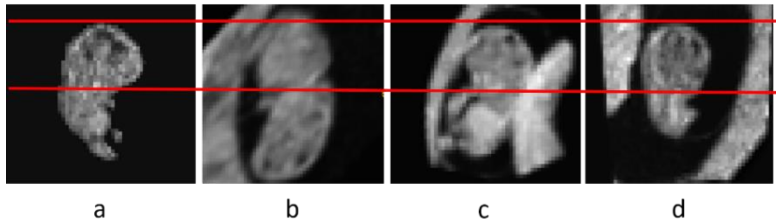

Fig 2. Visual result for the experiments on 3D ultrasound data. A) Atlas image. B) example of the body of the embryo aligned to the brain. C) Example of embryo where the head is matched correctly, but the orientation is 180 degrees off. D) example of correct alignment of the embryonic brain.

Future work

To improve results on 3D ultrasound data the following was done:

- Train both networks separate instead of end-to-end.
- Minimal supervision for affine alignment using the Crown and Rump landmarks.
- Presented at the PIPPI workshop at MICCAI 2020: https://youtu.be/CKQvJK-S2bQ

Framework

Given **Atlas $\mathbf{A}$**, segmented and put in standard orientation. Our aim is to find an affine transformation $\boldsymbol{\phi_a}$ and nonrigid deformation $\boldsymbol{\phi_d}$ such that for every **image $\mathbf{I}$** we obtain:

$$A(x) \approx I(\phi_a \circ \phi_d\ (x))$$

Loss function

$$\mathcal{L}(A, I, \phi_d, \phi_a) = \mathcal{L}_{sim}(A, I(\phi_a \circ \phi_d\ (x)) + \lambda_d \mathcal{L}_{diffusion}(\phi_d) + \lambda_s \mathcal{L}_{scaling}(\phi_a)$$

Network architecture

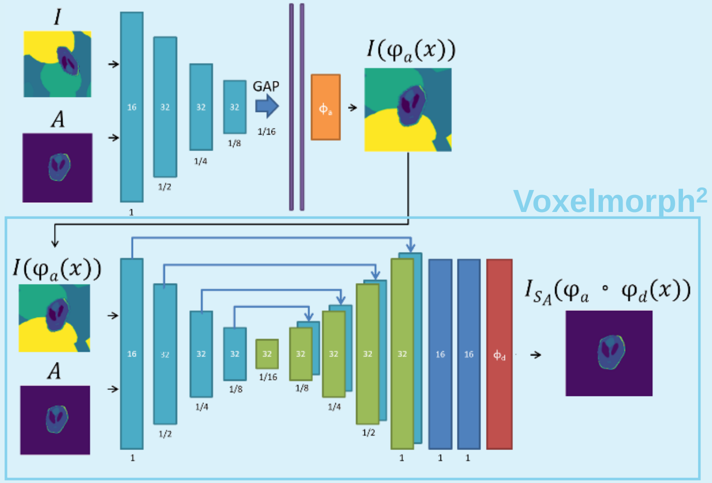

Fig. 3. Architecture of our network, where the nonrigid part is based on voxelmorph[2].

[1]*Steegers-Theunissen, R., et al. Int J Epi 45, 374-381 (2016)*

[2]*Balakrishnan, G., et al. IEEE Trans med Imaging 38(8), 1788-1800 (2019)*