Combining Conventional Methods and Deep Learning
Unsupervised Models for Fast Intra-subject Registration of
Pediatric Brain MR Images

Andjela Dimitrijevic∗1,2, ANDJELA.DIMITRIJEVIC@POLYMTL.CA
1 NeuroPoly Lab, Institute of Biomedical Engineering, Polytechnique Montréal, Montréal, QC, Canada
2 Research Center, Ste-Justine Hospital University Centre, Montréal, QC, Canada

Benjamin De Leener∗1,2,3 BENJAMIN.DE-LEENER@POLYMTL.CA
3 Computer Engineering and Software Engineering, Polytechnique Montréal, Montréal, QC, Canada

Vincent Noblet∗4 VINCENT.NOBLET@UNISTRA.FR
4 ICube-UMR 7357, Télécom Physique Strasbourg, Strasbourg, France

Editors: Under Review for MIDL 2022

Abstract

Deep learning (DL) techniques have the potential of allowing fast deformable registration tasks. Studies around registration often focus on adult populations, while there is a need for pediatric research where less data and studies are being produced. In this work, we compared three methods for intra-subject registration on 434 pairs of publicly available pediatric Calgary Preschool dataset spanning 2-8 years old. NoReg method consists of going through a U-Net like CNN architecture without performing any prior registration task. On the other hand, RigidReg and RigidAffineReg methods are respectively rigidly and rigidly together with affine pre-network registered using ANTs. These combined approaches were robust given two different network input resolutions (1.5 and 2.0 mm isotropic). Indeed, the average Dice score values considering both resolutions for each method are 0.767±0.097 for NoReg, 0.923±0.048 for RigidReg and 0.923±0.047 for RigidAffineReg as well as all showing small median percentages of negative Jacobian determinant (JD) values. By achieving faster alignments, this tool for pediatric magnetic resonance imaging (MRI) scans could help proliferate larger scale population research in brain developmental studies.

Keywords: Learning-based image registration, pediatric, MRI.

1. Introduction

Registration consists of bringing a pair of images into spatial correspondence. There are hardly any registration methods dedicated to the pediatric brain, mainly because of the difficulties arising from major changes that occur during neurodevelopment. Conventional deformable registration involves estimating a deformation field by reducing it to an iterative optimization problem. This process is time consuming, but provides accurate results. Convolutional neural networks (CNN) can allow faster registrations by applying a learning-based approach. Hence, applying DL methods to pediatric brain scans could improve registration and future diagnostics for medical applications. Ultimately, it would be relevant to see if a combined scheme of both DL-based and conventional registration frameworks for pediatric populations could provide accurate results while being orders of magnitude faster.

∗ Contributed equally

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2. Methodology

The general objective of this study is to propose a DL framework which allows fast intra-subject deformable registrations after training on pediatric MRI scans. To do so, the non-rigid transformation is fragmented into its simpler parts. Pre-network rigid registration, RigidReg (RR) and rigid together with affine registration, RigidAffineReg (RAR) are performed on each intra-subject pair using ANTs (Avants et al., 2011). This is done to determine their respective impact on the network’s performance. Also, a third method called NoReg (NR) is investigated where no prior pre-registration task is done. The 434 pairs of moving/fixed 3D images were extracted from the longitudinal Calgary Preschool dataset (Reynolds et al., 2020) containing 247 T1-weighted images from 64 children aged 2-8 years old. These three methods are then trained using the DeepReg (Yunguan et al., 2020) toolkit by going through a U-Net like CNN architecture. Finally, the unsupervised networks are evaluated with obtained white matter (WM), gray matter (GM) and cerebrospinal fluid (CSF) segmentations considering the Dice score as a performance metric. The generated deformation fields are also regulated and then evaluated using the percentage of negative JD values indicating unwanted local foldings. The robustness of these DL techniques is assessed by using different input resolutions (1.5 versus 2.0 mm isotropic) for the same network architectures.

3. Experiments & Results

The preprocessing pipeline goes as follows, each image was N4 bias field corrected as well as non-linearly registered to MNI pediatric template for children 4.5–8.5 years old (Fonov et al., 2011). This non-linear registration was performed to obtain skull-stripped images and tissue segmentations for evaluation purposes. Also, a three-fold cross-validation technique is employed to train and evaluate all methods containing 123 pairs each. 65 pairs are used for test purposes. Below, presented results for the two evaluated resolutions in Table 1 and Figure 1 come from this unseen test set. The unsupervised network was trained on a GeForce RTX 2080 Ti GPU. Its U-Net architecture consists of a 3-layer encoder and decoder with 8, 16 and 32 channels each. As for the loss function, it is composed of a local normalized cross-correlation similarity measure and an L2-norm regularization factor to ensure realistic physical deformation fields. Local normalized cross-correlation is chosen for its robustness to local variations of intensities. Finally, the ADAM optimizer is used with a learning rate set to 1.0e-4.

<table>
<thead>
<tr>
<th>Methods</th>
<th>1.5 mm isotropic</th>
<th>2.0 mm isotropic</th>
<th>Native resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>NR</td>
<td>0.764 ± 0.105</td>
<td>0.770 ± 0.088</td>
<td>0s</td>
</tr>
<tr>
<td>RR</td>
<td>0.929 ± 0.045</td>
<td>0.916 ± 0.051</td>
<td>78.1s</td>
</tr>
<tr>
<td>RAR</td>
<td>0.924 ± 0.047</td>
<td>0.922 ± 0.047</td>
<td>365.8s</td>
</tr>
</tbody>
</table>

Table 1: Average Dice scores per resolution calculated over all regions and subjects using the test set for the three studied methods. Median percentages of negative JD values are given because of highly right-skewed distributed data. ANT pre-registration tasks are performed on the native resolution of 0.4492x0.4492x0.9 mm and using the available CPU implementation.
4. Discussion & Conclusion

As shown in Figure 1, all three methods benefited from passing through the neural network having higher Dice scores compared to their pre-network counterparts. NR was added to assess the performance of the network without pre-registration tasks performed. It was overshadowed by RR and RAR considering their higher mean Dice scores or smaller median percentage of negative JD values for both resolutions. Also, 1.5 mm isotropic resolution yields slightly better performances than 2.0 for RR and RAR at the cost of longer train and test times. Hence, hybrid schemes involving both unsupervised models and conventional intra-subject registration algorithms like RR and RAR were able to perceive neurodevelopmental changes from a large age range of 2-8 years old children.

Acknowledgments

This study was supported by Polytechnique Montréal, by the Canada First Research Excellence Fund, and by the TransMedTech Institute.

References


