Unsupervised Non-Correspondence Detection in Medical Images Using an Image Registration Convolutional Neural Network

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1 Introduction

Medical image registration allows comparing images from different patients, modalities or time-points, but often suffers from missing correspondences due to pathologies and inter-patient variations. The handling of non-corresponding regions has been tackled with several approaches in the literature. For evolving processes, metamorphoses models have been used that model both spatial and appearance offsets to align images from different time-points [1, 2]. Other approaches mask out [3] or weight down [4, 5] the image distance measure in non-corresponding regions based on outlier detection [3], estimation of matching uniqueness [4] or correspondence probabilities [5].

Our recently published paper "Deep learning-based simultaneous registration and unsupervised non-correspondence segmentation of medical images with pathologies" [6] proposes a convolutional neural network (CNN) for joint image registration and detection of non-corresponding regions. As in previous iterative approaches [3], non-correspondences are considered as outliers in the image distance measure and are masked out. The conversion to a deep learning-based approach allows a two-step training procedure that results in better separation of spatial displacement and non-correspondence segmentation. Network training does not require manual segmentations of non-correspondences that are found in a single run, overcoming limitations of other CNN-based approaches [7–10].

2 Materials and Methods

The joint non-correspondence detection and image registration network (NCR-Net) is inspired by the U-Net [11] but follows a Y-shaped architecture with one encoder and two separate decoders. The decoders output a diffeomorphic deformation field ϕ and a non-correspondence segmentation S, respectively. Both decoders are connected to the encoder with skip connections. Moving image M and fixed image F serve as network input and outputs are generated on three resolution levels. At each resolution level, the loss function is computed to enable in-depth supervision of the network, with finer resolution levels being given more weight.

Segmentation and registration performances of NCR-Net are extensively evaluated on two datasets. The first dataset consists of longitudinal OCT images from 40 patients suffering from age-related macular degeneration. Three boundary segmentations, but no pathological labels are given for these data. The second dataset is the LPBA40 dataset, containing 40 whole-head MRI volumes from healthy probands and manual segmentations of 56 anatomical regions. To introduce known non-correspondences into the images, we simulate four different stroke lesions, two of which are quite large and the other two are smaller.

The network training takes place in two phases. First, the encoding part of the network as well as the deformation decoder are pre-trained with the "standard" objective function for image registration

$$\mathcal{L}_{\mathrm{Reg}}(\theta; \mathrm{M}, \mathrm{F}) = \sum_{\mathbf{x} \in \Omega} \mathcal{D}\big[\mathrm{F}, \phi \circ \mathrm{M}\big] + \alpha \mathcal{R}_{\phi} + \lambda \, \mathcal{L}_{\mathrm{opt}} \tag{1}$$

consisting of image distance measure $\mathcal{D}$ and regularization of the deformation $\mathcal{R}_{\phi}$. The last term $\mathcal{L}_{\mathrm{opt}}$ is optional and may be used to provide supervision to the registration or segmentation task. In this work, we use the Dice loss comparing brain masks for MRI and retinal masks for OCT data in moving and fixed images to support the registration task. In the second training phase, the entire CNN is updated using

$$\mathcal{L}(\theta; \mathrm{M}, \mathrm{F}) = \sum_{\mathbf{x} \in \Omega} \big(1 - S\big) \cdot \mathcal{D}\big[\mathrm{F}, \phi \circ \mathrm{M}\big] + \alpha \mathcal{R}_{\phi} + \beta \mathcal{R}_{S} + \lambda \, \mathcal{L}_{\mathrm{opt}} \tag{2}$$

as loss function. Here, the image distance is evaluated in corresponding regions only and the segmentation S is regularized with $\mathcal{R}_S$ consisting of segmentation volume and perimeter.

3 Results

In a first experiment, ablation studies are performed on the OCT data, comparing supervised and unsupervised versions of NCR-Net, i.e. versions trained with and without $\mathcal{L}_{\mathrm{opt}}$, as well as versions trained with the proposed two-phase training or with loss function (2) from scratch. Two main results arise from this experiment. First, unsupervised and supervised NCR-Net perform comparably, allowing its use even for datasets without any given annotations. Second, the two-phase training scheme significantly improves Hausdorff and average surface distance of all three segmented retinal boundaries, indicating better disentanglement of spatial deformation and non-correspondence segmentation.

The registration performance of NCR-Net is further evaluated on the LPBA40 data by calculating average Jaccard indices of the given anatomical labels and

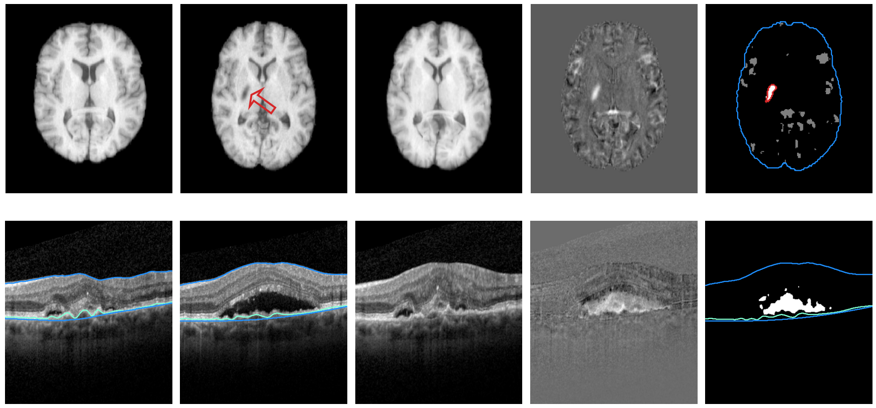

Fig. 1. Exemplary results for MRI (top row) and OCT (bottom row) data. Shown are moving, fixed, warped moving and the difference image after registration as well as the generated non-correspondence maps. Manually segmented retinal borders and automatically generated brain masks are given in blue. For the MRI data, segmentation results before and after region-growing are displayed in gray and white, respectively. The ground truth lesion is outlined in red.

comparing NCR-Net to state-of-the-art registration algorithms in 2D and 3D. NCR-Net significantly outperforms the competitive methods in the presence of large pathologies and performs comparable for images with small or no lesion. Network training with small and large simulated lesions leads to improved robustness against non-correspondences.

Finally, we evaluate the non-correspondence detection and segmentation performance of NCR-Net using the MRI data. The generated segmentations are compared to the ground truth lesion masks in two ways, first directly and second after applying region growing inside the lesions. In 2D, mean Dice scores of 0.871, 0.870, 0.630 and 0.880 are achieved for the four lesion types considered. Even though the segmentation performance in 3D is inferior, lesion detection rates are still high with 83.7 % for the worst performing lesion type.

4 Discussion

Our NCR-Net closes the gap between deep learning and iterative approaches for joint image registration and non-correspondence detection. The proposed network achieves state-of-the-art and robust registration of pathological images while additionally segmenting non-correspondent areas. With a two-step training scheme, the disentanglement of spatial deformations and non-correspondence segmentation is improved. Manual annotations may provide more supervision to the registration task, but can also be omitted without much performance loss. The simulated stroke lesions are detected as non-correspondent regions by NCR-Net very reliably and the generated segmentations are shown to be usable for unsupervised lesion segmentation and for the monitoring of evolving diseases.

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