Non-stationary deep lifting with application to acute brain infarct segmentation

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Abstract

We present a deep learning based method for segmenting acute brain infarcts in MRI images using a novel input enhancement strategy combined with a suitable non-stationary loss. The hybrid framework allows incorporating knowledge of clinicians to mimic the diagnostic patterns of experts. More specifically, our strategy consists of an interaction of non-local input transforms that highlight features which are additionally penalized by the non-stationary loss. For brain infarct segmentation, expert knowledge refers to the quasi-symmetry property of healthy brains, whereas in other applications one may include different anatomical priors. In addition, we use a network architecture merging information from the two complementary MRI maps DWI and ADC. We perform experiments on a dataset consisting of DWI and ADC images from 100 patients to demonstrate the applicability of proposed method.

Keywords: Deep learning, ischemic brain infarct segmentation, prior, input lifting

1. Introduction

Stroke is one of the leading causes of death and disability. Brain infarct volume has been shown to be a predictor of stroke outcome and may be a useful surrogate marker in clinical trials. Accurate delineation of brain lesions is, however, time consuming and prone to subjective errors. In this work, we incorporate expert knowledge of medical doctors to improve deep learning framework for brain infarct segmentation. As summarized in (Xie et al., 2021), incorporating knowledge of anatomical priors into deep learning models has been demonstrated to be an effective way for superior medical image segmentation. Previously, automated brain infarct segmentation models have been developed. Most of them, however, suffer from many false positives caused by the hyper-intensities present on DWI images. In this work, we utilize left and right hemisphere quasi-symmetry for lesion detection (Bao et al. (2021)), motivated by the numerous artifacts on DWI images, especially at the base of the brain, most of which show left-right hemisphere symmetry. This strategy helps in overcoming the aforementioned problem. To the best of our knowledge, this is the first work utilizing the interplay of certain non-local input transform and a corresponding loss term for that purpose.

2. Method

In this work, we add non-local prior information to the training process by lifting network inputs through a suitable transformation to a higher-dimensional space. For brain infarct segmentation the property of asymmetry that indicates pathological changes in the brain, is exploited. To this end, a symmetry transform is applied to the most important type of MRI image for stroke detection, namely the DWI image, which subsequently serves as an additional input channel for the input X. Together with the network architecture (Figure 2), which cleverly combines complementary information, and the loss term, which additionally penalizes symmetries, the problem of distinguishing between hyper-intensities caused by a brain infarct and those not attributable to a lesion, is addressed.

Let X and Y denote lifted input and ground truth respectively and $\Phi_\theta(X)$ the output of the model. Then, our proposed non-stationary loss function is of the form

$$\mathcal{L}_t^{\text{total}}(\Phi_\theta(X), Y) = \mathcal{L}^{\text{data}}(\Phi_\theta(X), Y) + \lambda(t) \cdot \mathcal{L}^{\text{prior}}(\Phi_\theta(X)). \tag{1}$$

Here, $\lambda(t)$ is the regularization parameter which is chosen depending on current epoch t and is increasing throughout the training process (in the numerical example we take $\lambda(t) = 0.0001 \cdot t^2$).

$$\mathcal{L}_t^{\text{data}}(\Phi_\theta(X), Y) \triangleq \alpha \, \text{BCE}_w(\Phi_\theta(X), Y) + (1 - \alpha) \, \text{DICE}(\Phi_\theta(X), Y).$$

Here, similar to (Taghanaki et al., 2019), BCE_w denotes the weighted binary cross-entropy, where we define w as the balancing factor between the number of lesion and background pixels, respectively. Further, α is the weighting parameter specifying the importance of BCE and DICE in the loss function which is set to 0.99 in our experiments. Both, the lifting and the non-stationary augmented loss are essential ingredients of our expert driven deep lifting framework.

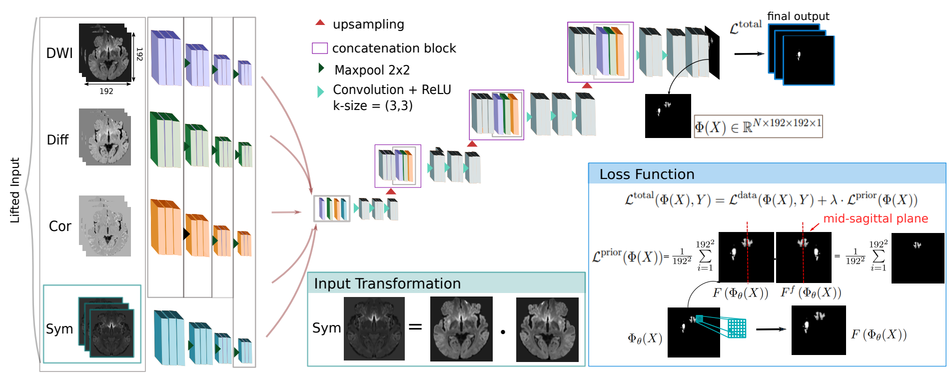

Figure 1: Visualization of the employed network architecture with corresponding input transforms (difference (DWI-ADC), correlation (DWI·ADC), symmetry-enhancement) and interacting prior term, where F defines a maxpooling.

3. Experiments and Results

We use data consisting of 100 MRI volumes (DWI and ADC) of acute brain infarcts originating from the local neuroradiology department. The MRI volumes were manually annotated and divided into training, validation and test sets.

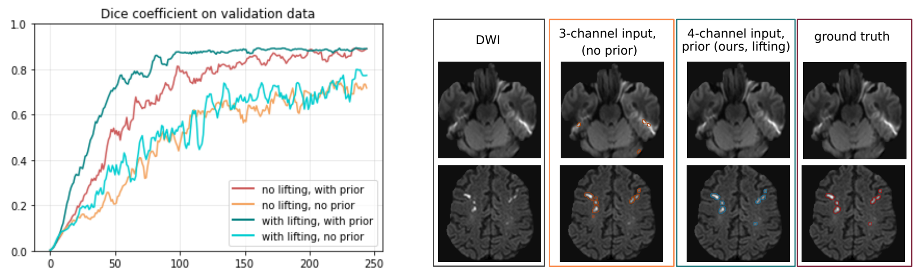

Figure 2: Visualization of the evolution of Dice coefficient (mean of two runs) on the validation set, and two selected examples of the segmentations on the test set.

Figure 2 shows the results we obtained. The curve corresponding to the combination of input transform and prior shows that the learning process is faster and more robust compared to the other strategies. We observed that adding the prior term alone already improves the performance of the model, while input lifting alone does not lead to performance improvements. A detailed evaluation of the proposed method will be carried out in future work.

4. Conclusion

Our results demonstrate that the application of a non-stationary prior term penalizing symmetries together with input lifting leads to improvements in the segmentation of brain infarcts. As a further step, we intend to apply the method to external datasets, as well as to extend the presented method. For example, we consider other non-local transforms (e.g., Hough transform) together with appropriate prior term to penalize certain properties or shapes that do not correspond to anatomical structures.

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