Automated Segmentation of Lacunes in brain MRI scans

Lacunes of presumed vascular origin are small cavities in the brain filled with cerebrospinal fluid (CSF). The presence of lacunes is an important neuroimaging biomarker for cerebral small vessel disease (CSVD). Manual segmentation of this biomarker is cumbersome and subject to observer bias as it is difficult to distinguish lacunes from other similar looking structures, e.g. enlarged perivascular spaces [1-3]. An automated method for lacune segmentation would facilitate research on these lesions as well as research on CSVD. The aim of this project is to develop an automated method for lacune segmentation using a convolutional neural network (CNN). The method will be developed on data from the Rotterdam Scan Study, which is a large population-based imaging study [4,5]. A common approach for medical image segmentation is by using a U-Net [6] architecture and DICE as loss function. This could be a starting point. Ghafoorian et al. [7] proposed a method using CNNs for lacune segmentation with a patch-wise approach. In this project the objective is to develop an image-level approach, which can potentially be compared to the method of Ghafoorian et al. [7].

There are several important challenges that can be addressed during the project. Firstly, the dataset is highly imbalanced. Of the approximately 4000 scans of the Rotterdam Scan Study, about 733 scans contain a lacune or occasionally multiple lacunes. Additionally, lacunes are very small, so only an extremely small portion of the voxels in the image are labeled as lacune. This imbalance will likely pose a serious challenge during the optimization of the CNN as well as during evaluation, as many metrics are affected by class imbalance. Furthermore, due to the limited resolution of MRI scans partial volume effects occur, making it difficult to discern exact boundaries. As lacunes are extremely small, this is a very relevant challenge, as a large portion of the total volume of the lacune could be uncertain. Investigating how this reliability in the segmentations can be taken into account during training of the CNN would be extremely interesting. Lastly, when a CNN trained on a particular dataset is applied on another dataset with different acquisition parameters the performance often drops considerably or can even crash completely. Once the method works on the Rotterdam Scan Study data, it could be applied to another dataset with available lacune annotations, e.g. the Heart-Brain Connection Study dataset. The difference in performance on this dataset could be analyzed and another interesting challenge would be to adapt the method so performance on the new dataset is upheld as much as possible.

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