Corpus Callosum Segmentation using UNET and Transfer Learning

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Abstract

The Corpus Callosum is an important brain structure, whose function is to interconnect the brain's hemispheres. The segmentation of this structure is very challenging, but nowadays several automatic strategies to achieve this goal already exist. In this paper it will be presented a deep learning algorithm for the Corpus Callosum segmentation, using a U-Net model. Also, in this work, a transfer learning approach was performed, where the network was trained to execute the cerebellum segmentation, and the net weights were stored to apply them to the Corpus Callosum segmentation task.

The obtained results were very satisfying, achieving an average dice score of 62.51% and 81.62% for the control and the autistic patients group, respectively, making this methodology very interesting for Corpus Callosum segmentation in diagnosis tasks, for example.

1 Introduction

The Corpus Callosum (CC) is a brain structure composed of white matter, which connects the left and right brain hemispheres, being responsible for the communication between them. This structure can reach approximately 10 cm of length and 1 cm of width, containing about 200 million axonal projections [1]. Structural features of CC, like size and shape, are correlated to neurological diseases, such as epilepsy, autism, schizophrenia, and dyslexia, for example. Thus, automatic and precise segmentation can be advantageous for the diagnosis of these diseases, based on quantitative CC features [2].

When compared to manual segmentation, an automatic approach is easier to perform, saving time, and the segmentation result is independent of errors inherent to human performance. Manual segmentation of the CC is difficult by the fact that the fornix and the nervous tissue's intensity around the CC on MRI (Magnetic Resonance Imaging) images is very similar to the CC's intensity [2].

The U-Net is a convolutional neural network used recently for biomedical images segmentation purposes. This specific network is composed by a contracting (down sampling) and an expanding (up sampling) path, symmetrically placed. The first one has the architecture of a common convolutional network, composed by repeated perform of two 3x3 convolutions, each pursued by a ReLU (Rectified Linear Unit) and a 2x2 max pooling operation, responsible for the input images down sampling. The function pooling has 2 as stride. In the down sampling path, the quantity of feature channels is doubled at each step. On the other hand, the expansive path is responsible for the up sampling of the feature map at each stage followed by 2x2 convolution that reduces the feature channels to half. The convolution output is concatenated with the correspondent feature map on the same level in the descent path, reincluding the localization information, and two 3x3 convolutions are processed, each one followed by a ReLU. In the final layer a 1x1 convolution is applied to map the resulting feature vector, formed by 64 components [3].

The U-Net is a good option for segmentation goals because it is capable of combining localized and contextual information, given by the down sampling and the up sampling paths, respectively, making this network more precise when compared with others, and doesn't need a large amount of data for the training task, making use of data augmentation. Also, the use of a weighted loss function allows an accurate diagnosis separating efficiently two objects of interest, since in the training task the network gives more weight to the pixels between the objects as the distance between them decreases [3].

In this work, transfer learning was used to facilitate the learning process for the CC's segmentation, obtaining a more accurate and faster segmentation. Transfer learning approaches allow the use of less labelled training data. Succinctly, a network is previously trained for a different segmentation task, in this paper the U-Net was trained with cerebellum images, well segmented by the VolBrain platform [4], and then the knowledge (features, weights) acquired are used on the contracting path, only being necessary the training of the expanding path for the final goal, the CC's segmentation in this specific case. Some of the obtained images using this approach can be seen in Figure 1.

2 Methodology

The U-Net described in the introduction was trained using images from ABIDE dataset [5]. More specifically 32 images from the California Institute of Technology were used for training, of which 19 were of autistic patients and the rest were from control cases and 6 were used for validation of the model. The datasets partitions for training and validation were chosen randomly. For testing the trained network, 5 images of normal and 5 of autistic patients were randomly used, from the Carnegie Mellon University image repository.

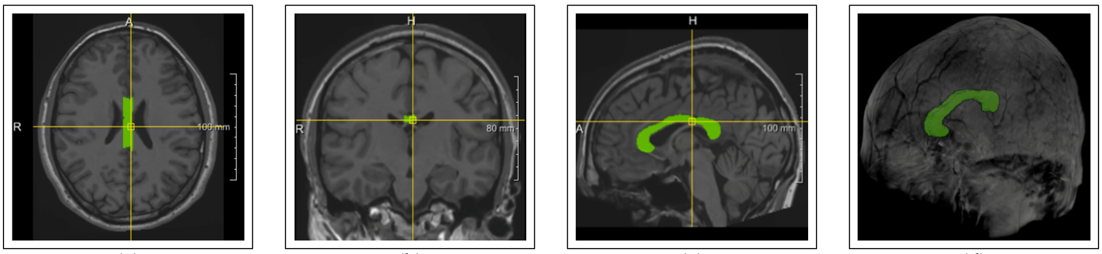
The images were all passed through the VolBrain MRI image pipeline [4] to obtain MRI scans all on the same position and to obtain cerebellum segmentations. To achieve CC segmentation, that will be used for model optimization, the software ITK-SNAP [6] was used to segment each image manually, since VolBrain does not segment this structure. Each slice of the processed volumes was padded with zeros to reach a dimension of 256x256 pixels in width and length. This last procedure was necessary to conform to the dimension requirements of the input image to the U-Net.

The training of the network was carried out in two stages. In the first one the model was fed MRI images slices as an input and cerebellum segmentations as an output, as a way to train the encoder of the model. After completion of the first stage, the weights of the encoder's layers were locked to speed up training of the following part. On the second stage, the model was trained using the same MRI images, as an input, and CC segmentations as the desired output. Cerebellum segmentations were chosen for this transfer learning method, because they represent a task that is similar to the CC segmentation (same domain).

Each stage was trained using an Adam optimizer with a learning rate of 0.0001 and a binary cross-entropy function. The training was constituted by 10 epochs, which were carried out in each stage of training. The data fed to the network was augmented through random rotation operations (in a range of 10 degrees), random horizontal and vertical flips and random shifts (in a range 0.1*image size) in the original image.

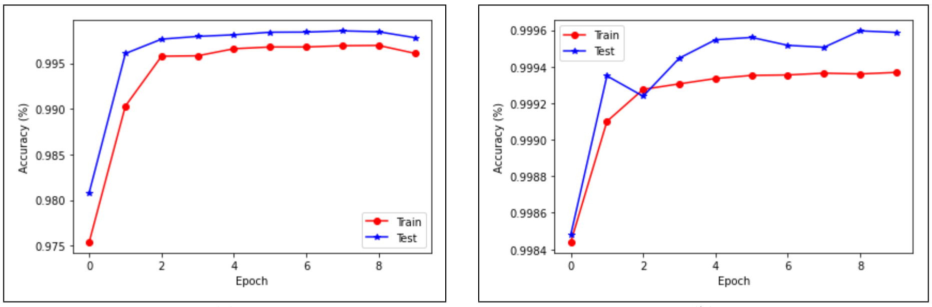
3 Results and Discussion

The training of this type of networks usually is performed using GPU. However, it was ran in CPU, due to hardware limitations, taking more time to execute the training task. For the cerebellum segmentation, the 10 epochs were performed in 21 hours and 53 minutes. For the CC segmentation, the 10 epochs were performed in 22 hours and 35 minutes. The accuracy per epoch obtained in training of both phases can be observed



(a) (b) (c) (d)

Figure 1: CC segmentation in the anatomical planes: (a) axial; (b) coronal; (c) sagittal; (d) 3D representation;



(a) (b)

Figure 2: Voxelwise accuracy evolution in the training task through epochs: (a) cerebellum segmentation; (b) CC segmentation;

on Figure 2. After training, the automatic segmentation of each volume could be completed within 45 seconds average.

Anyone seeking to reproduce the obtained results in this article should try to use a GPU for training, since the process should become much more time efficient, making it possible to run more epochs for a better understanding of the model. However, from the training history it is possible to understand that both steps of training stabilize the segmentation accuracy after 4 epochs for the training and testing datasets. This is not verified on the testing dataset of the CC segmentation, where the accuracy fluctuates a bit, approximately 0.0002%, so it was considered irrelevant. Such a phenomenon may be explained by the random errors performed in manual segmentation, that make it harder for the model to properly adapt, which can also explain why the second stage of segmentation took longer than the first one. With the use of transfer learning to segment the CC it is possible to achieve higher accuracy values in less epochs, as can be seen in Figure 2 (b), due to the fact that most of the training was already done with the cerebellum segmentation dataset.

To evaluate the network performance, 5 MRIs of normal patients and 5 MRIs of autistic patients were automatically segmented, being one example of this procedure represented in Figure 1, and compared against the manual ones. To analyze the match of both segmentation a dice score evaluation metric was used, due to its relevance in segmentation tasks. The mean results for this metric was 62.51% for the control group and 81.62% for the autistic patients group.

The achieved results for dice score were satisfactory for both groups, however the algorithm was more successful in the segmentation of brains of autistic patients. The differences may be explained by different factors. The first one is related to the fact that the CC segmentation were done manually by an untrained researcher, and as a result they are bound to have many small random mistakes in them. In fact, in some separate cases, the automatic segmentation seems better than the manual one, meaning that the poor dice score achieved is not a good measurement of the quality of segmentation. The second one is related to poor MRI image quality after VolBrain treatment. Specifically one of the images used in the control group was distorted, which caused the algorithm to falsely label a region as CC, causing the drop in the mean dice score. Perhaps more vast image augmentation procedures could be applied, to ensure that the process remains robust, even when faced with this type of problems. On other note, the training accuracy was significantly higher than in these test volumes because the metric used was different due to the limitations of the algorithm used.

4 Conclusion and Final Remarks

This algorithm was able to perform a good CC segmentation, obtaining satisfactory results in the dice score evaluation metric. However, some improvements can be done in the training task, like the execution of a manual segmentation of CC by a specialist of the area, and the application of more image augmentation procedures to increase the robustness of the algorithm, leading to better dice score results.

The use of transfer learning had various advantages along this work. First, this methodology was able to perform a good CC segmentation even with the presence of some errors in the ground truth, since it was executed by an untrained individual. Second, by using this methodology it is possible to achieve accurate segmentations of the desired anatomical structure within few epochs. If a bigger dataset is used in the initial phase, it should be possible to achieve even better results, easing the training for the end user, allowing him to obtain a segmentation tool with a smaller dataset and in shorter time.

The obtention of CC segmentation by an automatic system, like the one that was described in this paper, can be used to support diagnosis tasks, like the diagnostic of Autism Spectrum Disorder. Also, this algorithm can be used to obtain an automatic segmentation of diverse structures, giving the possibility to obtain batches of data, which can be used to study relevant properties (texture, edges, volume, etc.) of those structures, allowing the progress of several science fields.

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