Abstract – Corpus Callosum (CC), the largest white matter structure, is connector between the two cerebral hemispheres in human brain. Structural features of CC such as shape and size have been used to study various neurological diseases. Robust segmentation of CC in midsagittal plane is critical in the qualitative studies. In this paper, we introduced a convolutional neural networks (CNN) with anatomical information for CC segmentation. Our method showed better segmentation performance (mean Dice index: 95.44±0.9859) than other methods (mean Dice index: 95.22±1.2532). We concluded that anatomical information integrated in CNN improve the segmentation performance significantly.

Keywords: Corpus Callosum, Segmentation, Convolutional Neural Networks, Anatomical Information

1 Introduction

Corpus Callosum (CC) is the largest white matter structure in human brain. It is connector between right and left cerebral hemispheres. Abnormal structural features of CC have been known to be associated with various neurological diseases such as autism [1], and Alzheimer’s disease [2]. Robust segmentation of CC from brain magnetic resonance (MR) image plays an important role in detecting abnormal structural features of CC. CC in midsagittal plane has been widely used because it has relatively explicit boundaries and reflects characteristic of overall CC.

Manual segmentation of CC is labor intensive and time consuming approach, not suitable for studying large-scale data. The results of manual segmentations also have inter- and intra- variation, leading to flexible segmentation results. Various automatic methods for CC segmentation have been proposed to avoid problems of manual segmentation. Active contour model (ACM) is one of the successful approaches in the segmentation of CC [3, 4]. While ACM has been applied to various segmentation methods and shown good results, initialization of contour is difficult because it is sensitive to noise and alteration of target structure. Furthermore, ACM has difficulty in segmenting the detailed parts of target structure with severe variation because of internal energy.

Recently, convolutional neural networks (CNN) has shown excellent performance in medical image segmentation field [5]. We used CNN to overcome the issues in CC segmentation and integrated anatomical information in CNN training stage for improvement of CC segmentation. The anatomical information used in this study was intensity distribution and coordinates of target structure. Since brain MR image was generally analyzed in the standard image space (e.g. MNI152 space), the coordinates themselves are closely related to the location information of the target structure. Furthermore, intensity distribution in brain MR image (specifically, T1-weighted image) is closely related to the brain tissue types such as gray matter, white matter and cerebrospinal fluid.

In this paper, we introduced a novel method for CC segmentation using CNN with anatomical information such as intensity distribution and coordinates. We compared the four training methods of CNN as following: (1) training without any anatomical information; (2) training with coordinates information; (3) training with intensity distribution; and (4) training with coordinates and intensity distribution information.

2 Methods

2.1 Data acquisition

The training and test data were selected from Open Access Series of Imaging Studies (OASIS) database (www.oasis-brain.org). The cross-sectional data of OASIS consists of T1-weighted brain MR image of 416 subjects. 50 normal subjects were randomly selected from 416 subjects. Demographic information of the selected subjects was as following: 19 males, age range = 18-38 years, mean age = 23.7 years and standard deviation = 4.5 years.

2.2 Pre-processing

All T1-weighted images were pre-processed. First, the non-uniform intensity distributions of the images were corrected. Second, the corrected images were aligned with standard space, MN152 space. Third, the intensities of the aligned images were normalized, ranging from 0 to 1. Finally,
the normalized images were cropped to rectangular region containing CC in midsagittal plane.

2.3 Training stage of CNN

2.3.1 Training without any anatomical information

The foreground, i.e. CC, and background patches were extracted from the cropped training images. The input image was 21x21 gray scale patches in training stage. The architecture of CNN used in this study was as following: Three convolution layers (all filter size: 3x3, stride: 1, zero padding); two max-pooling layers (all pooling size: 2x2, stride: 2); one fully connected layer (1024 channels); output layer (two labels); rectification unit as activation function; cross-entropy as cost function; mini-batch gradient descent using back-propagation algorithm as optimizer (batch size: 200, maximum iteration: 1000 thousand – the accuracy of all training methods saturated); apply dropout (ratio: 0.5).

2.3.2 Training with coordinates information

The coordinates of aligned images in the MNI152 space were used as anatomical information because they have meaningful information about location of the target structure. The coordinates were normalized, ranging from 0 to 1 and used as input image on each voxel consisting of the patch, i.e. three channel input image including intensity image, x-axis coordinates plane and y-axis coordinates plane.

2.3.3 Training with intensity distribution information

CC is white matter having a brightest intensity distribution in T1-weighted MR image. We included the patch whose center voxel intensity exceeded a threshold value only in the training stage based on the intensity distribution of the CCs of the training images. It has the effect of minimizing the training of the obvious parts and maximizing the training of the ambiguous parts.

2.3.4 Training with coordinates and intensity distribution information

Coordinates information and intensity distribution information were used together for training.

2.4 Validation

The segmentation performance was evaluated using 5-fold cross validation, i.e. 5 iteration with 40 training subjects and 10 test subjects. Dice index was used for quantitative measurement of segmentation performance. The closer the measurement is to 100%, the better the spatial agreement between two images. The manual CC segmentation images by an expert were used as ground truth for performance evaluation.

3 Results

Table 1. showed means and standard deviations of Dice indexes between ground truth and each segmentation result for test images. Training with coordinates and intensity distribution showed better segmentation performance than the other methods (Table 1).

<table>
<thead>
<tr>
<th>Methods</th>
<th>Dice index Mean</th>
<th>Standard deviation</th>
</tr>
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<tbody>
<tr>
<td>Normal</td>
<td>95.22</td>
<td>1.2532</td>
</tr>
<tr>
<td>Coordinate</td>
<td>95.11</td>
<td>1.1556</td>
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<tr>
<td>Intensity</td>
<td>95.34</td>
<td>0.9315</td>
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<tr>
<td>Coordinate and Intensity</td>
<td>95.44</td>
<td>0.9859</td>
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</tbody>
</table>

4 Conclusions

In this paper, we introduced the novel method for segmentation of CC in midsagittal plane using CNN with anatomical information. Coordinates and intensity distribution of training images were used as anatomical information. Training with coordinates and intensity information showed better segmentation performance than the other methods.

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5 References