Multi-Planar Segmentation for Left Atrial MR Image in a Few Seconds Using 3D-like Fully Convolutional Network and Transfer Learning

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Abstract

Precisely segmenting left atrium in 3D MR images can benefit the ablation procedure of atrial fibrillation. However, traditional automated solutions often fail in relieving experts from the labor-intensive manual labeling. In this paper, we propose an automated segmentation method based on multi-planar segmentation network with a 3D fusion strategy, able to use complementary information from different axes of the 3D scans. First, we use 3 successive 2D slices in MR volume as input (3D-like) and VGG-16 pre-trained on ImageNet for natural image classification as base network of fully convolutional network (FCN). Compared to fully 3D FCN, the 3D-like method can be trained quickly and do not have memory limit problems. Then, this base network is trained on axial, coronal, and sagittal axis. 3D fusion strategy is used by combining the segmentation results of each axis. Finally, we evaluate the proposed method with 5-fold-cross-validation on the MICCAI 2018 atrial segmentation challenge dataset, and obtain a average dice index of 0.904 on validation set.

Keywords: Deep learning, Atrial segmentation, Fully convolutional network

1. Introduction

In order to precisely segment left atrium in 3D MR images, numerous segmentation methods have been tested by world-wide researchers. Among these methods, the most common method is atlas-based, which has a good accuracy for heart segmentation, but it often lack efficiency due to heavy computations on the registration algorithm. Recently, methods based on deep learning are replacing the conventional methods in medical image segmentation fields, especially in cardiac field. For example, in (Mortazi et al., 2018, 2017), a multi-planar segmentation network has been applied to segment left atrium, but they method only utilize 2D information. Our previous work (Xu et al., 2017; Puybareau et al., 2018) can obtain good segmentation results for brain and heart segmentation, but only relies on single planar information. It also been successfully applied to the segmentation of pelvic vessels (Virzi et al., 2018). To combine advantages of multi-planar information and 3D-like method, we construct a network structure similar to our previous work for training on several axes, which can take advantage of the information coming from the different axes and the 3D-like information.
2. Proposed Method

2.1. Data description

Left atrial dataset used for this work was provided by the MICCAI 2018 Atrial Segmentation Challenge. It contains 154 3D MRIs, among which 100 patient data are annotated. In the experiments, we only rely on the 100 training data: 80 patient for training and 20 for testing.

2.2. Pre-processing

Images are cropped to keep the center of the volume and rescaled to [0,255]. We apply grain filter (Carlinet and Géraud, 2015) of size 9 to remove noise. Because the input of pre-trained VGG-16 must be RGB image, we propose a 3D-like method that stacks 3 successive 2D slices: to segment the \(n\)th slice, we use the \(n\)th slice of the MR volume, and its neighboring \((n-1)\)th and \((n+1)\)th slices, as the green, red and blue channels, respectively.

2.3. Network architecture

The proposed network architecture takes 3D MR scans as an input and parses it to three perpendicular planes: axial, coronal, and sagittal. For each plane, a 3D-like segmentation Network is trained to label pixels. After training each network separately, fusion strategy is used by combining the segmentation results of each of the 3D-like segmentation network.

Segmentation Network. We apply the VGG-16 network (Simonyan and Zisserman, 2014) to feature extraction, which is pre-trained on millions of natural images of ImageNet for image classification (Krizhevsky et al., 2012), and discard its fully connected layers to keep only the 5 stages of convolutional parts called “base network” composed of convolutional layers, Rectified Linear Unit (ReLU) layers, and max-pooling layers between two successive stages. The four max-pooling layers divide the base network into five stages of fine to coarse feature maps. Inspired by the work in (Long et al., 2015; Maninis et al., 2016), we add specialized convolutional layers (with a \(3 \times 3\) kernel size) with \(K\) (e.g. \(K = 16\)) feature maps after the convolutional layers at the end of each stage. All the specialized layers are then rescaled to the original image size, and concatenated together. We add a last convolutional layer with kernel size \(1 \times 1\) at the end. This last layer combine linearly the fine to coarse feature maps in the concatenated specialized layers, and provide the final segmentation result. The proposed network architecture is illustrated in Fig. 1.

3D Fusion method. After training, we obtain 3D segmentation results on coronal, sagittal and axial, respectively, and transpose segmentation results on coronal and sagittal to axial. To merge these 3D segmentation results, the voting method is used, for example, if \(a+b+c\geq 2\) (with \(a\): 3D segmentation results on axial; \(b\): 3D segmentation results on coronal are transposed to axial; \(c\): 3D segmentation results on sagittal are transposed to axial.), the predicted result is positive.

2.4. Post-processing

After merging, we keep only the largest component (6-connectivity). We smooth the 3D segmentation results using a 5x5x5 3D median filter.
Figure 1: Architecture of the proposed network. Note that each input RGB image is built from the slice \( n \) and its neighboring slices \( n - 1 \) and \( n + 1 \)

Table 1: Quantitative evaluation of our proposed framework

<table>
<thead>
<tr>
<th>Dataset</th>
<th>0~19</th>
<th>20~39</th>
<th>40~59</th>
<th>60~79</th>
<th>80~99</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dice_axial</td>
<td>0.902</td>
<td>0.896</td>
<td>0.902</td>
<td>0.866</td>
<td>0.908</td>
<td>0.895</td>
</tr>
<tr>
<td>Dice_coronal</td>
<td>0.877</td>
<td>0.903</td>
<td>0.889</td>
<td>0.844</td>
<td>0.890</td>
<td>0.881</td>
</tr>
<tr>
<td>Dice_sagittal</td>
<td>0.885</td>
<td>0.904</td>
<td>0.895</td>
<td>0.857</td>
<td>0.889</td>
<td>0.886</td>
</tr>
<tr>
<td>Dice_fusion</td>
<td>0.911</td>
<td>0.918</td>
<td>0.909</td>
<td>0.864</td>
<td>0.917</td>
<td>0.904</td>
</tr>
</tbody>
</table>

3. Results

Implementation details: We implement all results with Keras using NVIDIA Quadro P6000 GPUs. We update the weights of network with an Adam optimizer (batch size=12, \( \beta_1=0.9, \beta_2=0.999, \) epsilon=0.001, learning rate=0.002,) and we did not use learning rate decay. We trained the network for 10 epochs.

Results: We have evaluated the proposed method with 5-fold-cross-validation on the MICCAI 2018 atrial segmentation challenge dataset. To segment an entire 3D volume, the runtime is less than 2.5 seconds. The evaluation results are showed in table 1. From the table, we can make the conclusion that the segmentation results using multi-axes information is more stable than single-axis. We obtain a average dice index of 0.904 on validation set.

4. Conclusion

The proposed method provides promising results for cardiac segmentation utilizing multi-axes information and a 3D-like method. We achieved the better results in terms of the dice index. However, the fusion result mainly depends on the training accuracy of the different axes. Therefore, to relieve its impact, in the future, we will add the fusion strategy as one layer of network. We will also try to concatenate low-level features of the heart from different axes, for example, by concatenating the output of the third 'MaxPooling2D' layer of VGG16 based on axial, coronal, and sagittal.
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References


