INFANT BRAIN MRI SEGMENTATION WITH DILATED CONVOLUTION PYRAMID DOWNSAMPLING AND SELF-ATTENTION

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ABSTRACT

In this paper, we propose a dual aggregation network to adaptively aggregate different information in infant brain MRI segmentation. More precisely, we added two modules based on 3D-U-Net to better model information at different levels and locations. The dilated convolution pyramid downsampling module is mainly to solve the problem of loss of spatial information on the downsampling process, and it can effectively save details while reducing the resolution. The self-attention module can integrate the remote dependence on the feature maps in two dimensions of spatial and channel, effectively improving the representation ability and discriminating ability of the model. Our results are compared to the winners of iseg2017's first evaluation, the DICE ratio of WM and GM increased by 0.7%, and CSF is comparable. In the latest evaluation of the iseg-2019 cross-dataset challenge, we achieve the first place in the DICE of WM and GM, and the DICE of CSF is second.

Index Terms— Infant brain MR images, brain tissue segmentation, multimodality data, 3D deep learning

1. INTRODUCTION

In brain research, brain tissue segmentation is an important part. The accurate segmentation of infant brain tissue MR images is the key to studying early brain development. In recent years, deep convolutional neural networks have shown great potential for medical image analysis. Many models based on FCN [1], U-Net [2], and DeepLab [3] have achieved remarkable results in the field of medical segmentation. Multitudes of scholars have made great efforts to accurately segment brain MR images of infants in isointense stage (approximately 6-8 months of age). Nonetheless, gray matter(GM) and white matter(WM) in brain tissue of infants in isointense stage show similar intensity in magnetic resonance images. At the same time, the brain images of infants also has the problem of blurred tissue boundaries, a lot of noise and too few samples, which all limit the further improvement of the performance of the algorithm.

In order to make better use of the characteristics of medical imaging, more and more algorithms began to adopt brain multimodality data for joint analysis. We utilize the combination of other algorithms to use multimodality data, combine the T1 and T2 modal brain MR images, and then exploit the complementary information to accurately segment brain structures. In the meantime, we have made corresponding improvements to its
defects based on the 3D-UNet network [4], thus form the final network structure which can effectively improve the performance of the network.

The 3D-U-Net network is a very powerful structure, and previous work [6,7,8] has demonstrated that this kind of encoding-decoding network structure can perform better in brain tissue segmentation. But there are also two problems: (1) Continuous downsampling in the encoding phase will cause spatial information loss, which results in the network unable to accurately locate the category of each voxel. (2) The network decoding phase cannot totally consider the global information, which is not conducive to the network to predict the pixel categories.

To solve the first problem, many works use an atrous convolution pyramid structure to construct multi-scale features. DeepLab [9] proposed an atrous pyramid pooling module (ASPP) based on atrous convolution, which adopted parallel-cavity convolution layers with different dilation rates to capture multi-scale information. DenseASPP [10] introduced Dense Connect on the basis of ASPP, which connected multiple sizes of ASPP intensively to generate denser spatial sampling and features on a larger scale. Different from other methods, we propose an improved dilated convolution pyramid structure to form the downsampling module. By using the dilated convolution [11] of different dilation rates, the features are extracted from multiple scales before downsampling, avoiding the loss of detailed information on the downsampling stage. Specifically, we use four different convolutions to construct four levels of features, which are then combined to form the final feature for downsampling. This allows each downsampling to be performed on four different features, which preserves different features of the next level of features. Our proposed dilated convolution pyramid downsampling module can provide multi-scale features, so that the semantic information can be extracted in the encoding phase without a lot of details being lost.

For the second problem, many network structures use self-attention mechanism to explicitly encode remote information. Traditional 3D-U-Net used deconvolution to upsample and then reuse convolution operations to emphasize remote dependencies. However, deconvolution applies the same local kernel to scan each location without taking into account global information. The early attention mechanism application in computer vision is Spatial Transformer Networks [12]. This article adopted the attention mechanism to transform the spatial information in the original image into another space and retains the key information. Based on the non-local attention method [13], the position self-attention block in the decoding phase is used to calculate the output of one position by paying attention to each position of the input. And the image feature map information is aggregated on the
position with distinguishing features. In the channel attention module, the channel attention feature maps are generated by using the relationship between the channels on the feature maps. In the previous paper [14,15], the channel attention mechanism algorithm often used the average pooling for space compression, and it was considered that the pooling can effectively learn the scope of the target object. We propose a 3D-based improved dual-channel attention module that combines channel attention module and spatial attention module, and ultimately combines the information that is focused on both by concat operations. Unlike the previous work, we are using the attention mechanism on the 3D medical image and increasing channel attention which can effectively models long semantic dependencies, so we can use the edge information and details of the image more effectively.

The contribution of our work can be summarized as follows: (I) We utilize the spatial convolution structure of the spatial pyramid based on the downsampling of Res-Net, and utilize the convolution of different dilation rates to capture multi-scale information and can effectively expand the receptive field of the convolution kernel. (II) A self-attention based on 3D medical images is proposed. The attention method we proposed can not only effectively encode the wider context information into local features, but also mine the interdependencies between channel maps and improve the feature representation of specific semantics. (III) Our model has achieved very effective results through experimental demonstrations. In the iseg2019 cross-dataset competition, several indicators win the first place, proving that our model has significant generalization performance.

2. PROPOSED METHOD

2.1 Multi-scale information and dilated convolution

In the convolutional layer of a deep network, the size of the convolution kernel determines the size of the receptive field, that is, the size of the learning feature [16]. In the case of different convolution kernel sizes, features of different scales can be features are of great significance to improve the segmentation performance of deep networks, that is, multi-scale features. The proposed architecture is illustrated in Fig.1. If a large convolution kernel is used to obtain the receptive field, the training parameters will be too complicated, and the problem of over-fitting will be caused. For the conflict of large-scale features and computational cost, two methods are used to solve this problem.

One approach is to utilize a superimposed convolution layer with a small kernel so that large-scale features can be obtained. Another method is to apply dilated convolution. Dilated convolution is a special convolution operation that achieves large-scale features without adding too many parameters and computational costs. And we can get multi-scale features by changing the size of the dilation rate. In this paper, the use of dilated convolution in the encoding part is very helpful for extracting and aggregating multi-scale features, and favorable experimental results are obtained.

2.2 Res-Net combine dilated convolution

Existing research [17] showed that the residual network can improve the training of deep learning models to some extent. We use a residual-network-based structure in downsampling.

We cancel the pooling layer and replace the commonly used pooling layer with a convolution with a stride of 2. The left side is a convolution of $1 \times 1 \times 1$ with a stride of 2. The right side contains a dila-block module and an activated convolutional layer with a convolution kernel size of $3 \times 3 \times 3$ and a stride of 2.

About this dila-block. The structure is shown in the Fig.2, including a pre-activation layer with four dilations convolutions in the middle. The convolution kernel has a size of $3 \times 3 \times 3$ and the first three dilation rates are 1, 2, 4, respectively, the last one is a $1 \times 1 \times 1$ convolution. After the convolution, the four blocks are concated together and then connected to the convolution layer of the next stage.

2.3 Dual-attention

Fig.1. Illustration of our structure

Fig.2. Illustration of dila-block.
A common example is a self-attention block used in decoding phase that computes the output of a position by focusing on each position of the input. These studies [18,19,20] were all used to capture long-range dependencies, that is, to aggregate the information of feature graphs.

We also add a self-focus module to the decoder part of the 3D-Unet network, similar to DA-Net [21]. The difference is that we add a self-attention mechanism module to the 3D image. Most of the previous studies were based on two-dimensional research. Compared to two-dimensional, we need to process the 3D images into 2-dimensional vectors when processing the data. The spatial-attention structure is shown in Fig.3.

![Image](image.png)

**Fig.3. Illustration of spatial-attention.**

We first represent a $D \ast W \ast H$ cube of the 3D image as a vector of $D \ast W \ast H \ast C$, after the flatten operation, these vectors are folded into a matrix of size of $(D \ast W \ast H) \ast C$. For each vector generated by 3D cube $B$, we multiply it by the transpose of $C$, then get a feature map $F$ through a softmax. $F$ is defined as:

$$F = \text{Softmax}(\frac{BC^T}{\sqrt{C}})$$

where $F \in R^{(D \ast W \ast H) \ast (D \ast W \ast H)}$. We multiply the obtained feature map to finally obtain the vector $V$ of the same size as the $B$ generation vector.

$$V = Q_B \ast F \tag{2}$$

After we have calculated each vector generated by (2), then we superimpose them together to produce the final output. In order to better integrate the sub-module into the network, we pass a 1*1*1 convolutional layer and then send it to the network. Finally, we get the same output as the original image:

$$O = \text{Conv}(\text{restore}(\)) \tag{3}$$

where $\text{restore}(\)$ is the reverse operation of the previous reduce operation. This module enhances their presentation capabilities by encoding a wider range of contextual information into local features.

Channel Attention Module (Fig.4): As mentioned in the DA-Net, the channel map for each high-level feature can be thought of as a class-specific response, with different semantic responses associated with each other. We can mine the interdependencies between channel maps to emphasize interdependent feature mapping. Therefore, we have built a channel attention module to explicitly model the dependencies between channels.

![Image](image.png)

**Fig.4. Illustration of channel-attention.**

Different from the spatial attention, we calculate the channel characteristics directly in the input image. After we perform the flatten operation on the input image, it becomes $(D \ast W \ast H) \ast C$. We will multiply it and get a new channel feature map $F_C \in R^{D\ast W\ast C}$. Finally, we will multiply the original image to obtain $K_C$:

$$K_C = Q_C \ast F_C \tag{4}$$

which is the same size as the image after flatten, and finally we perform the same operation as the positional attention to restore the original image size. The final feature of each channel is the weighted sum of all channel features and the original features, modeling the long semantic dependencies between the feature maps, which helps to improve feature discrimination.

Finally, we connect the dual-attention module in parallel and use it in the decoder part. This module effectively utilizes the spatial attention and channel attention information to model the long-term semantic dependence of the feature map, which effectively improves the representation ability and discriminative ability of the model.

### 3. EXPERIMENTS

In this section, we evaluate our results through several public datasets: iseg2017 [22] is from the Baby Connection Project, where UNC and UMN researchers conduct a four-year safe, non-invasive multimodality for 500 normally-developed children aged 0-5 years. A total of 10 training sets and 13 test sets are included. The annotations for the data set labels consist of gray matter, white matter and Cerebrospinal fluid. In the iseg2019 cross-dataset, the test set contains samples of three other datasets. For preprocessing, these images have been resampled into $1 \times 1 \times 1$ mm3 to eliminate the effect of resolution, and employed the same tools for skull stripping and intensity inhomogeneity correction.

#### 3.1 Experimental setup

We use cross-validation to train, taking 9 samples from the training set as the training set, and the remaining one as the validation. In the test process, we use the tenth sample as our verification sample. We use the initial learning rate setting of $3.3e^{-3}$, the patch-size size is set to $32*32*32$, and the
batch-size is 5. We have referenced other parameter settings based on paper [23].

We use 3D-Unet as our baseline model, and we make some changes compared to the structure we proposed in the paper. The depth of the baseline model is 3, and the encoding and decoding stages use the Res-Net structure. This structure has been shown to have good results in biomedical image segmentation [24]. Our evaluation indicators use DICE, MHD and ASD.

3.2 Performance study

We test our model on the iseg2017 dataset and compare these results with the results of all the methods in the first round of the iseg2017 Challenge. Of the 9 indicators, 7 achieve the best performance. We also have advanced precision compared to other papers that have been published but not evaluated. The results in Table 1 shows that our model achieves the advanced accuracy in this task.

In the iseg2019 cross-dataset segmentation competition (Team:QL111111), ranking first in five indicators of GM and WM, and the gap between us and the first in CSF is very small. Moreover, we have an obvious lead in WM segmentation results, the DICE value is 1.4% higher than the second.

Table 1. Comparison of our results with other methods.

| Method          | CSF DSC | ASD  | WM DSC | ASD  | GM DSC | ASD  |
|-----------------|---------|------|--------|------|--------|------|
| Msk_SKKU        | 95.8    | 0.116| 90.1   | 0.391| 91.9   | 0.330|
| LIVIA[25]       | 95.7    | 0.138| 89.7   | 0.376| 91.9   | 0.338|
| Bern_IPMI       | 95.4    | 0.127| 89.6   | 0.398| 91.6   | 0.341|
| TU/eIMAG        | 94.7    | 0.150| 89.0   | 0.433| 91.0   | 0.375|
| Hyper[26]       | 95.6    | 0.120| 90.1   | 0.382| 92.0   | 0.329|
| Ours            | 95.9    | 0.114| 90.8   | 0.353| 92.6   | 0.307|

Table 2. The results of cross-dataset segmentation.

| Method | CSF DSC | ASD  | WM DSC | ASD  | GM DSC | ASD  |
|--------|---------|------|--------|------|--------|------|
| TAO    | 83.5    | 0.526| 86.0   | 0.515| 83.0   | 0.543|
| Xfzl   | 82.6    | 0.556| 86.1   | 0.522| 82.5   | 0.558|
| Fight  | 82.6    | 0.570| 86.3   | 0.523| 82.9   | 0.561|
| WYF    | 82.9    | 0.546| 85.0   | 0.547| 82.6   | 0.568|
| Ours   | 83.4    | 0.553| 87.7   | 0.474| 83.5   | 0.513|

3.3 Ablation experiments

The result of our baseline is in the 10th sample, that is, the first 9 samples are used for training, and the 10th is used as the validation set. The results of CSF and GM on the DICE are 3% higher than the base model, and the WM is increased by 5.4%. See that our model has a very significant effect on it.

Fig.5 shows the results of our final segmentation visualization in iseg2017. From left to right are ground truth, baseline and our model respectively. Fig.5 (a) shows the results of WM on the gold standard, baseline, and our model. We clearly see that the edge of the baseline is not smooth and has many parts outside the boundary, while our model has achieved relatively excellent results in most areas (in red circle). The baseline in the GM of Fig.5 (b) is not clear in gurus structure. In contrast, the results of our model can clearly see the gurus (in blue circle), which is inseparable for the improvement of DICE and MHD values.

In order to verify the effectiveness of each part of our experiment and determine whether this structure is conducive to the final effect, we perform the following 2 ablation experiments:

Model-1: In this ablation experiment, we validate the effectiveness of the proposed self-attention model, which remove the self-attention module based on our model.

Model-2: The downsampling part is removed from the proposed model to verify its effectiveness.

From the Table 3, we can see that each module of our proposed model is very helpful for our final result, and it has a big improvement compared with the baseline.

Table 3. Ablation experiment results.

| Model   | CSF DSC | ASD  | WM DSC | ASD  | GM DSC | ASD  |
|---------|---------|------|--------|------|--------|------|
| Model-1 | 95.3    | 87.0 | 91.6   | 91.6 |
| Model-2 | 94.6    | 86.3 | 90.8   | 90.6 |
| Baseline| 92.3    | 84.6 | 89.8   | 88.3 |
| Ours    | 95.3    | 91.3 | 92.4   | 92.9 |

4. CONCLUSION

In this paper, we present a dual aggregation network based on pyramid structure and self-attention mechanism in multimodality MRI segmentation of infants. Existing 3D-Unet segmentation methods can easily cause global information loss during the downsampling phase. In the decoder part, the deconvolution cannot recover all necessary information during the upsampling process, which reduces the accuracy of image segmentation. Our proposed spatial pyramid-based downsampling and self-attention mechanisms minimize image loss during image convolution. At the same time, our model also has excellent performance in the segmentation of cross-dataset competition, indicating its excellent generalization performance. It can be said that our model has excellent performance in brain tissue segmentation tasks.

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