다중 확장된 컨볼루션 U-Net 을 사용한 간 영역 분할

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Liver Segmentation using Multi-dilated U-Net

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Abstract

This paper proposes a novel automated liver segmentation using Multi-Dilated U-Nets. The proposed multi-dilation segmentation model has the advantage of considering both local and global shapes of the liver image. We use the CT images subject-wise, every 2D image is concatenated to 3D to calculate the IOU score and DICE score. The experimental results on Jeonbuk National University hospital dataset achieves better performance than the conventional U-Net.

1. Introduction

The human organ liver being the body's largest internal organ performs many essential functions like making proteins, bile production etc. Liver disease still leads to heavy deaths worldwide. Liver cancer happens to one of the most common diseases that causes death every year. The goal of liver segmentation is to provide an overview of the targeted liver segmentation areas to radiologists and other health professionals [5,6,7,8]. As manual segmentation can be time-consuming, automated segmentation can save time. Liver segmentation in CT image sequences is a difficult task because of the different shape and sizes of liver in different people [6].

Classical computer vision-based image segmentation methods were used to segment liver before the popularity of deep learning. 3D region growing segmentation method was used to segment the liver [1].

Deep learning's performance on natural images have proven to be a great success and image segmentation using deep networks performs well [2,3]. U-Net [4] consists of contracting path to capture the context and expanding path that enables precise location.

Yanbo Feng et al. [5] used a multiscale approach to segment cancer area in liver which shows better scores compared to the state of the art. Wendong Xu et al. [6] proposed a ResUNet based liver segmentation in CT images which further uses 3D probabilistic and geometric post process and got state of the art performance in LiTS dataset. Supriti Mulay et al. [7] used HED-Mask R-CNN on Multimodal images purpose. Han et al. [8] developed an automatic liver lesion segmentation using deep neural networks.

This paper proposes a framework for liver segmentation in CT images with a multi dilated network to segment liver. The proposed model has the advantage of considering both local and global shapes of the liver image. Experiment results are given which shows the efficiency of the proposed system.

The paper is organized as follows. Section 2, the proposed method in detail. Section 3 consists of the experiments conducted. The conclusion is given in Section 4.

2. Method

A. Problem Description

The CT image is a 3-D volume where each pixel is indexed by (x,y,z), z being the depth and (x,y) being a spatial coordinate. The segmentation results of the liver is marked with a curve as shown in Fig.3.

B. Proposed Multi-Dilated U-Net

The standard convolutional kernel is optimized to single scale, so it cannot properly cope with both the small and large parts of object. To remedy this limitation, we propose a multi-dilated convolutional kernels in which large dilation kernel treats large parts and a small dilation kernel treats small parts.

The structure of the proposed multi-dilated U-Net is shown is Fig. 1 In this paper all the convolutional layers have the kernel size 3x3. Dilation is added to the input layer like 3, 20, and 1 and the average is used. For multi-dilated U-Net we add max-pooling layer to the down sampling layer. We construct a multi-dilated U-Net with 3 blocks of up sampling and down sampling. The segmentation results are same size of the input image.

We also use the ensemble method to boost the segmentation performance. In this method, three different sizes of the image are input to independent multi-dilated U-Net and the outputs are averaged.

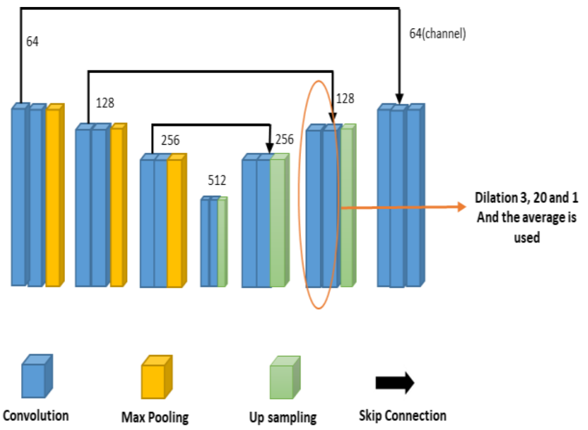

Fig.1 Multi-dilated convolutional neural network.

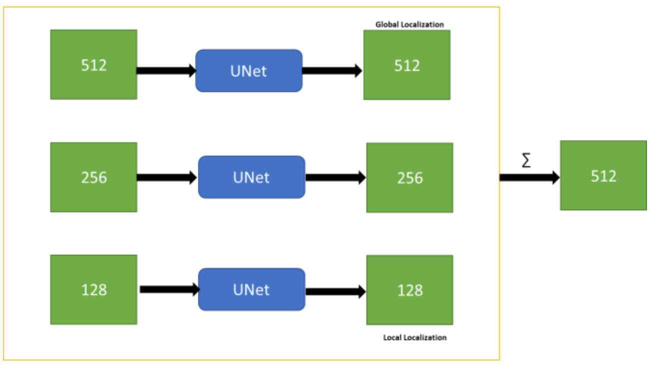

Fig. 2 Ensemble Classifier used to boost the performance (U-Net used is same as the Fig. 1)

C. *L2 Loss Function*

L2-norm loss function is also known as least squares error (LSE). It is minimizing the sum of the square of the differences(S) between the target value (Y_i) and the estimated value (f(xi)):

$$S = \sum_{i=1}^{n} (y_i - f(x_i))^2$$

3. Experiments and Results

A. *Dataset and Experiment Setting*

We evaluated our proposed framework on Jeonbuk National University Hospital dataset which includes total number of 791 CT scans from 50 patients where they are divided into 40 subjects for training and 10 subjects for testing as shown in Table 1.

Dataset	Number of patients/subjects
Training set	40
Testing set	10

Table 1. The train and test set of the used dataset

We designed a framework for liver segmentation where each image was 512x512 on which augmentation like rotation, random contrast and horizontal flip was applied. The dataset was passed forward and backward through the network for 500 epochs. The Adam optimizer was used.

B. *Results*

IOU and DICE scores were calculated to evaluate the accuracy of the liver segmentation. Table 2 shows the performance for U-Net, the proposed multi-dilated U-Net, and ensemble. The multi-dilated U-Net is better than U-Net, and ensemble is better than single multi-dilated U-Net in terms of both IOU and DICE metric. Fig.3 illustrates sample segmentation results.

Model	IOU	DICE
U-Net	0.8828	0.9376
Multi-DU-Net	0.9061	0.9507
Ensemble Classifier	0.9183	0.9573

Table 2. Performance comparison of the segmentation models.

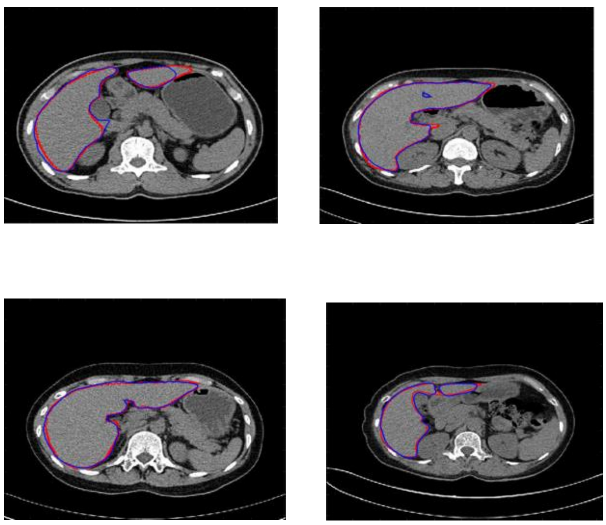

Fig. 3 Sample of the segmentation results. Here Red represents the Ground Truth and Blue represents the deep learning results.

4. Conclusion

This paper proposed an automatic liver segmentation framework using multi-dilated U-Net with L2 loss function. The ensemble was also tested. The proposed framework obtained an efficient performance on the dataset used. We believe that the dilated convolution operated well for both the local and global shape. In a future work, more organs such as pancreas and stomach will be tested for segmentation using the proposed models.

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