Full-automated lung lobe segmentation on volumetric chest CT with 3D U-Net

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Abstract

The lung function analyses based on pulmonary lobe segmentation are vital in the clinical environment, because lobe is considered as a functional unit and lung disease preferentially influences at the spatial lobe. In this regard, we presented a method for fully automated lung lobe segmentation by using 3D U-Net with convolutional neural net on the volumetric chest CT. CT scans of 352 COPD patients were divided into 252 cases for training, 40 cases for validation and 20 cases for testing. CT data was resampled into $160\times160\times128$ for input of 3D U-Net. Dice similarity coefficient and Jaccard index were 95.6 ± 1.8 and 91.6 ± 3.1, respectively. It took 21.48 ± 3.08 and 29.89 ± 4.61 seconds for left and right lobe segmentation, respectively. This method showed good accuracies without any interaction of operators and could be applied to the clinical environment.

1 Introduction

The human lung is divided into five distinct pulmonary anatomical compartments called lobes. We call the boundary surface between the pulmonary lobes as lobar fissure. Lung lobe segmentation in CT could be useful for image-based analysis of lung function and disease evaluation, planning for surgery and leading to additional image segmentation of sub-lobes, airways and vessels. However, manual lung lobe segmentation is time consuming for routine clinical applications. Various automatic pulmonary lobe segmentations, therefore, have been developed [1], which has been regarded very difficult due to severe anatomic and disease variations. Recently, adopting deep learning technique to medical image segmentation showed great performance even in the COPD patients [2]. However, fully automatic pulmonary lobe segmentation has been considered as challenging, since most human have more than one incomplete and/or fake fissures and diseased lung such as infiltrative lung

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disease, which leads to difficult recognition on fissure and lobar fissure. Consequently, it was almost impossible to develop full-automated pulmonary lobe segmentation with conventional methods. In this paper, we proposed fully automated pulmonary lobe segmentation using 3D U-Net without lobar fissure detection in COPD patients.

2 Methodology

2.1 Subjects

We divided CT scans of 332 COPD patients with full inspiration and full expiration into 3 groups: 272 cases for training, 40 cases for validation and 20 cases for testing. 206 cases were scanned using Somatom Sensation 16 MDCT (Siemens Healthcare, Erlangen, Germany) with scan parameters including 140kVp, 100effmAs, 0.75mm thickness and B30f convolution kernel. 126 cases were scanned using Philips Brilliance 40 MDCT (Philips Healthcare, Nederland) with scan parameters including 140kVp, 110mAs, 0.8mm thickness, B convolution kernel. Dynamic range of both CT scans is -1024 3075 HU. We gained gold standard of our data through the cooperation with a thoracic radiologist who worked more than 5 years in this field.

2.2 segmentation using 3D U-Net

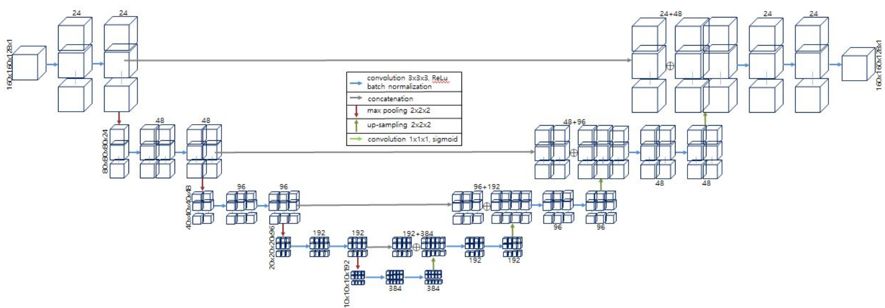

Figure 1: Illustration of 3D U-Net architecture

We trained volumetric chest CT using 3D U-Net [3], since the 3D spatial information is very important for pulmonary lobe segmentation. 3D U-Net is generally used in volumetric image segmentation, and it consist of four steps including analysis and synthesis paths. Analysis path for dimension reduction has layers including two steps of $3\times3\times3$ convolutions by a rectified linear unit (ReLu) [4] and $2\times2\times2$ max pooling with strides of two. Synthesis path for extension of original dimension consist of each layer including an up-convolution of $2\times2\times2$ by strides of two, followed by two $3\times3\times3$ convolutions by a ReLu. The advantage is 3D U-Net have the connection from left to right side using concatenation which prevents from loss of information at the deeper layers. We used input matrix size of $160\times160\times128$, since the GPU memory is not enough and size of input image must be unify. We trained using cropped 3D lung images with lung segmentation, left and right lung separation, image cropping, resizing and normalization. Our model was implemented in Keras by using Theano and the loss function for calculate error was used Dice similarity coefficient (DSC). We used cuDNN convolution layer implementation for managing memory efficiently, since the 3D volume data was too big. This model was trained using Ubuntu 14.04 GPU server with CUDA 8.0/cuDNN, keras, TensorFlow, CNTK, Theano and DARKNET platform [5], [6]. The GPU server has three 1080TI, 11GB and one Titan XP, 12GB.

2.3 Evaluation Metric and Statistical Comparison

We used DSC, Jaccard similarity coefficient (JSC), Mean surface distance (MSD), Hausdorff surface distance (HSD) [7] to evaluate the accuracy of pulmonary lobe segmentation, since DSC and JSC are shown as a high value in case of large objects.

Table 1: Accuracy of lobe segmentation method with four kinds of evaluation metrics

N=40	LtLower	LtUpper	RtLower	RtMiddle	RtUpper	Overall
DSC%	95.9 $\pm$ 0.6	96.5 $\pm$ 0.7	96.1 $\pm$ 1.8	93.4 $\pm$ 2.3	96.0 $\pm$ 0.7	95.6 $\pm$ 1.8
JSC%	92.2 $\pm$ 1.2	93.3 $\pm$ 12.8	92.4 $\pm$ 1.3	87.7 $\pm$ 4.0	92.6 $\pm$ 3.1	91.6 $\pm$ 3.1
MSD	1.00 $\pm$ 0.16	0.99 $\pm$ 0.28	1.01 $\pm$ 0.21	1.47 $\pm$ 0.82	1.25 $\pm$ 0.88	1.15 $\pm$ 0.59
HSD	20.2 $\pm$ 7.9	22.6 $\pm$ 8.6	23.6 $\pm$ 15.1	37.6 $\pm$ 31.8	25.5 $\pm$ 18.6	25.9 $\pm$ 19.2

3 Results

3.1 Evaluations of lung lobe segmentation

We measured the accuracy of each lobe, since the lung lobes have different anatomical variations. Table 1 depicts the mean and standard deviation of lung lobe segmentation accuracy using DSC, JSC, MSD and HSD. In addition, we have dramatically reduced processing time. Conventional image processing method such as Hessian analysis [8], [9] with user intervention takes nearby 570 second, semi-automatic algorithm with manual correction, nearby 283 second, and this method nearby 51 second without any user intervention.

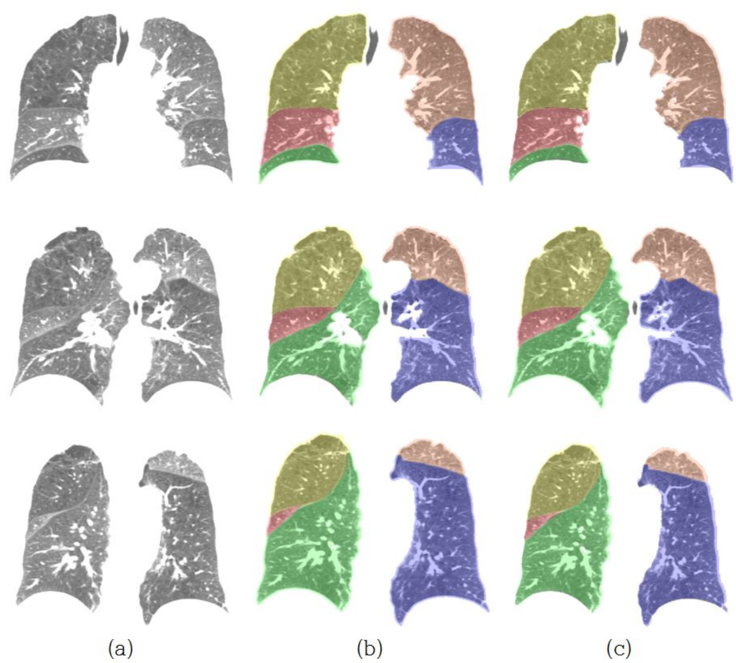

Figure 2: Lobe segmentation results using 3D U-Net. (a) CT image (b) Gold standard (c) 3D U-Net

4 Conclusion and discussion

In this study, we proposed full-automatic pulmonary lobe segmentation using 3D U-Net. Our method has shown good results in the both normal and COPD patients. Because we trained only pulmonary lobes information, our model is regarded as robust to fissure variations including the incomplete fissure or fake fissure. In addition, since our method is fully automated method, it can be performed about large amounts of data in background task. In the further study, we need to research on pulmonary lobe segmentation in multi-center trial and severe diseased patients. If the lung has a severe disease, the lung structure has changed accordingly, which causes difficulties in segmentation.

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