Automatic Lung Segmentation in CT Images Using Dilated Convolution Based Weighted Fully Convolutional Network

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Abstract. Lung cancer is one of the primary lung malignant tumour with the fastest increasing morbidity and mortality and the greatest threat to people's health and life. Early detection of lung cancer can significantly increase patients’ chance of survival. Lung parenchymal segmentation is an essential pre-processing step for analysing thoracic computed tomography(CT) images. Conventional methods for lung segmentation rely on user generated features, and do not segment lung parenchymal with juxta-pleural nodules accurately. Deep learning has outperformed other methods in image classification and target recognition tasks. In this study, a new dilated convolutional based weighted fully convolutional network (FCN) has been proposed for the segmentation of lung parenchyma to minimize the juxta-pleural nodule issue. The effectiveness of this method was verified by experiments on 173,694 diagnosis CT images of lungs and their corresponding segmentation maps. The Dice similarity coefficient and pixel accuracy achieved are 0.9702 and 0.9833 respectively. The experiment results show that the proposed method can provide more accurate and robust results than traditional FCN.

1. Introduction
As the most common and fatal types of cancer, lung cancer causes the death of approximately daily 422 people around the world [1]. Because the small size of the lesion, early recognition of lung cancer is difficult, and 80% of patients were diagnosed when tumour size is increased and tumour becomes malignant. At this moment, the best treatment opportunity is missing. Therefore, control the disease at the initial level is of great significance for improving human survival rate [2]. Computed Tomography (CT) imaging of the chest has been proven to be effective in the early diagnosis of various lung disease. However, it is intensive and tedious for radiologists to distinguish the suspected lesion areas in a large number of CT slices. With the development of image processing technology, computer aided diagnosis system (CAD) provides reliable diagnostic information for early detection, and helps the determination of therapy options [3]. Where, lung segmentation is a necessary prerequisite step for quantitative analysis of lung image, which affects the stability and performance of lung cancer CAD systems. However, designing and implementing a reliable lung segmentation method is still a challenging task due to anatomical variations, intensity inhomogeneity, juxta-pleural nodules, as well as scanners from different manufacturers [4].

Researchers have put forward various medical image analysis techniques [5-9] on automatic lung segmentation. The approaches used in these days can be classified into two general categories: traditional methods, including signal thresholding techniques, region growing, watershed transform superpixels and so on, and machine learning based methods. However, an important limitation that most methods share is that they can’t accurately differentiate juxta-pleural nodules from the surrounding tissue, who have noticeable attachment to the pleural surface. Those nodules often
disconnect plural border due to their manifestation similar to that of the intrapulmonary trachea, non-pulmonary tissue or even noises. Under-segmentation problems caused by juxta-pleural nodules are commonly observed, and creating an algorithm to solve this problem is quite challenging. Several researchers found in CAD systems that about 17 percent of nodules were excluded from the pulmonary segmentation [10,11]. The juxta-pleural nodule outside the lung profile eventually leads to missed nodules and errors of quantitative analysis.

Deep learning, emerged almost 10 years ago, is an important machine learning technology based on artificial neural networks [12]. It is composed of several interconnected layers that transform inputs into high level and complex abstractions as it learns representations of complex data [13]. By fine-tuning the parameters in the network, a training algorithm involves automatically learning of the mapping from inputs to outputs with a sufficient large dataset. Convolutional Neural Network (CNN), which is generally referred to a class of deep learning, is designed to handle data with regular spatial dependency using three basic architectural ideas: local receptive fields, weight replication, and subsampling [14]. CNN comprises of several type of layers. (1) convolutional layer: abstract local features at different locations among the image with learnable filters. (2) pooling layer: reduce the size of input layer. (3) fully connected layer: feature representation for further processing. Recently, semantic end-to-end pixel-wise segmentation networks based on CNN have superseded many image segmentation approaches [15], and has also been applied to lung CT image segmentation [16,17]. Although CNN based semantic segmentation network can achieve excellent performance, the juxta-pleural nodules under-segmentation issues still exist.

In the work reported in this paper, we applied a lung segmentation method using dilated convolution and weighted FCN. The rest of the paper is organized as follows: The detailed description about the Lung Image Database Consortium and Image Database Resource Initiative (LIDC/IDRI) dataset is introduced in section 2. Section 3 detail the proposed approach in terms of weighted FCN architecture and dilated convolution. Experimental results and analysis are demonstrated in section 4. Finally, conclusions and directions for future work. are presented in section 5.

2. LIDC/IDRI Dataset

The LIDC/IDRI [18] is a publicly available database, which provides big data support for spurring lung CAD development, validation, and dissemination. At present, the LIDC/IDRI database includes 244,527 spiral CT images of the chest from 1,018 sets of 1,010 different patients. Each of which includes the DICOM images that accompanies XML with annotation records from four experienced thoracic radiologists. The database contains 7,371 lesions marked nodules by at least one radiologist, of which 2669 were marked as nodule ≥3 mm. Images have a matrix size of 512×512 pixels, 0.5-0.9 mm pixel sizes, and slice thickness ranges between 0.5-5 mm. A pre-processing software [19] was used in this study to pre-process of lung CT images and visualize annotation.

3. Weighted FCN with Dilated Convolution

Traditional lung segmentation methods are usually based on a feature extractor designed by experts. While recent CNN based segmenting approaches can automatically extract features. Fully Convolutional Network (FCN) [20] by Long et al. is modified from CNN. It takes advantage of existing CNNs to learn hierarchies of features, and replaces fully connected layer of CNN architecture with convolution layers to enable heatmap output. FCN takes CT images as inputs and labels the outputs at the pixel level.

FCN architecture has several variants, which mainly differ in the spatial precision of the outputs. In this study, we used FCN-2 variant. The proposed net architecture is showed in Figure 1. The backbone network is transformed from the VGG16 which contains nine convolutional layers, four pooling layers and three fully convolution layers. Dilated convolution can expand the receptive field of convolutional kernel with the same model parameters, and preserve more detail information, so the first fully connected layer (FC7) was replaced with dilated convolution in $3 \times 3$, and dilated rate was set at 3. The network is designed with contractive path and an expansive path. Combining layers with different precision helps to retrieve precise spatial information and precise semantic information.
In segmentation domain, juxta-pleural nodules are more challenging to segment. We designed a weighted FCN for this issue by assigning extra more weights for the class of the lung wall. Weighted by using SGD algorithm, FCN model can be trained end-to-end by minimizing the cross-entropy loss $L(x_i)$.

$$L(x_i) = -\sum_{k=1}^{K-1} y_{k-1} \log f_{k-1}(x_i) - \lambda y_k \log f_k(x_i)$$  \hspace{1cm} (1)

Cross entropy is a distinction measurement between the predicted probability $f_k(x_i)$ and ground truth label $y_k$. $\lambda$ is the weight for the class of the lung wall, the value is fixed at 10 in this study. The images was divided into 5 region labels, including background, left lung, right lung, lung wall and lung trachea.

![Dilated convolutional based weighted FCN architecture (FCN-2)](image)

**Figure 1.** Dilated convolutional based weighted FCN architecture (FCN-2)

### 4. Result

We evaluated our proposed method on the LIDC/IDRI database hosted by the lung nodule analysis (LUNA) challenge. In total, 888 CT scans were included. 590 of them have one or more nodules, and the rest 298 have none. 38 CT scans were removed due to quality issue such as slice dislocation in the DICOM header. From the LUNA, we can get the binary mask image as the golden standard for algorithm performance evaluation. We split the rest 850 CT scans 20%-80% between testing and training. CT sequence data were converted into 2D slices. In training set, we have 173,694 CT images and label images, while in testing set we have 40,417 CT images and label images. To reduce the computational cost, all images were resized to 256×256. After 100,000 iterations of training, the segmentation model had good result. The experiments was conducted on a workstation equipped with a NVIDIA GeForce RTX 2070 graphics card, and 2.60GHz Intel Xeon processors with 16GB RAM memory.

The proposed algorithm relies on Dice similarity coefficient index and pixel accuracy for performance evaluation. They were 0.9702 and 0.9833 for our proposed method. Table 1 shows the performance comparison of the method for FCN and our proposed. The lung segmentation results with juxta-pleural nodules for FCN and our proposed method are demonstrated in Figure 2. Our proposed approach achieved more accurate lung segmentation with juxta-pleural nodules.
Table 1. The Dice similarity coefficient and pixel accuracy score of the method for FCN and our proposed.

| Method                          | Pixel accuracy | Dice similarity coefficient |
|---------------------------------|----------------|-----------------------------|
| FCN                             | 97.97%         | 96.11%                      |
| Dilated Convolution Based Weighted-FCN | 98.33%         | 97.02%                      |

Figure 2. Lung extraction by FCN and our proposed algorithm.

The left and right columns are the processing of two CT slices. The original CT image with juxta-pleural nodules is in the top of the image, the middle ones are the mask images and the bottom ones are the segmented results.

5. Discussion and Conclusion
The automatic lung extraction is a challenging task due to the existence of juxta-pleural nodule. In this work, we design a new network which combines the advantage of dilated convolution with FCN2 and weighted loss function. Dilated convolution implemented in FC6 improves the performance in VGG16 and speeds up convergence. The receptive field is effectively increased with fewer learning parameters. Experiments demonstrated the capability of the proposed model, obtaining a Dice score of 0.9702, outperforming FCN. The weighted FCNs that we used in this study are based on 2D kernels, 3D kernels can be more convenient to extract feature for small tissues like juxta-pleural nodule. Thus, utilization of 3D kernels may enable the extraction of further contextual information. Also, replacing VGG16 with other backbone networks like DenseNet, combined with enhancements in the skip architecture, may also lead to improvements.

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