Lung nodule segmentation with convolutional neural network trained by simple diameter information

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Abstract

Lung nodule segmentation can help radiologists' analysis of nodule risk. Recent deep learning based approaches have shown promising results in the segmentation task. However, a 3D segmentation map necessary for training the algorithms requires an expensive effort from expert radiologists. We propose a new method to train the deep neural network, only utilizing diameter information for each nodule. We validate our model with the LUNA16 dataset, showing competitive results compared to the previous state-of-the-art methods in various evaluation metrics. Our experiments also provide plausible qualitative results comparable to the ground truth segmentation.

1 Introduction

Accurate lung nodule segmentation from computed tomography (CT) images plays an important role for radiologists in pulmonary nodule analysis. The deep convolutional neural networks (DCNN) have recently shown outstanding achievements in the nodule segmentation task. A central focused pooling based CNN model [1] has yielded powerful results by combining 2D and 3D feature maps. Training the deep neural network in this study, however, requires elaborate pixel-wise segmentation label maps (i.e., foreground or background), generated from burdensome annotation of expensive human resources. Meanwhile, a weakly supervised approach has been employed in [6]. This method trains the CNN model using a label that indicates a cropped input image contains a nodule or not (like a classification task,) then it applies a threshold to the activation map resulting from the training. Although showing the possibility of the simple annotation, this method hardly presents comparable outputs, probably due to the lack of detailed label information segmenting the nodules.

In this work, we propose a new method to train the deep neural network with labels generated from diameter information for each nodule. Our algorithm produces competitive results compared to other state-of-the-art methods in terms of various metric scores. Obtaining a diameter of a nodule is not only an easier task than a whole segmentation work for the nodule, but it is the actual way of measuring the nodule size in a radiologist's reading process. We believe that exploiting a diameter is more efficient and more natural way to gather training data for the nodule segmentation task.

2 Proposed method

2.1 Defining foreground using nodule diameter

For a training input, we use a cropped 3D image around the center of a nodule. Since the background occupies a much larger proportion than the foreground (i.e., nodule area) in the cropped image, we employ a sampling approach to address the imbalance problem as well as the algorithm complexity,

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which may occur in calculating a loss. Instead of computing losses for the entire pixels, N pixels can be randomly sampled in the foreground and the background regions respectively. In this regard, we may simply limit the sampling space for the foreground using the diameter; that is, assuming that nodules are spherical, the pixels within a radius of (diameter / 2) $\times$ K from the center of the nodule can be regarded as a foreground while the pixels outside the radius can be regarded as a background (Figure 1). The constant K is adopted to reduce outliers in the foreground labels by controling the size of the virtually spherical nodule. In our work, we set $K = 0.75$.

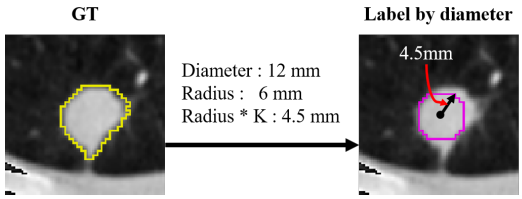

Figure 1: An example of defining foreground for the sampling space in loss calculation using nodule diameter. The region within 4.5 mm from the nodule center is considered as the foreground, while outside the region is considered as the background.

2.2 Overall algorithm detail

Overall deep neural network structure in our work is motivated from the U-Net [2], famous for state-of-the-art performance in many object segmentation tasks. Since the original U-Net works on two-dimensional input images, we modified the network to deal with three-dimensional nodule images in CT scans. Our model includes 24 convolutional layers, 2 pooling layers, 2 decovolutional layers, and one fully connected layer. The convolutional kernel size in the 3D-CNN is $3 \times 3 \times 3$, and the deconvolutional kernel size is $2 \times 2 \times 2$. After the last convolutional layer, a fully connected layer is applied to determine the class that each pixel corresponds to. The cropped 3D input images have the size of $24 \times 40 \times 40$. The algorithm samples $N = 30$ pixels in the foreground and the background regions respectively, when the input images are fed into the network. The final segmentation result may contain some non-nodule regions, thus we apply thresholding-based post-processing according to the research on [5], improving the performance.

3 Experimental results

All the experiments were performed on a Linux operating system (Ubuntu 16.04) using an NVIDIA TITAN Xp GPU and the Tensorflow library (version 1.3). Publicly available LUNA16 [3] dataset is employed to train the proposed model. The dataset, collected in the U.S., contains 888 CT scans from LIDC/IDRI [4] database including more than 2,000 nodule candidates accompanying segmentation maps marked by four radiologists. These maps are only employed in our testing phase, in a way that an area marked by more than two radiologists (i.e., over 50% consensus) is adopted as a ground-truth foreground label. At training phases, in contrast, we utilize the segmentation labels generated by the proposed method which only uses diameter information for each nodule.

We randomly split the LUNA16 dataset into 1,000 nodules for training set, 113 nodules for test set. To demonstrate the segmentation accuracy, we evaluate our model with following three metrics: dice similarity coefficient (DSC), sensitivity (SEN), and positive predictive value (PPV).

As shown in Table 1, the proposed model yields competitive results compared to several previous methods. All the results from the previous methods are referred from [1]. The first two methods utilizing classic computer vision approaches present inferior results rather than the new approaches using the DCNN including ours.

Since we use our own random split which is probably different from that of [1], we cannot directly compare the accuracy in great detail. However, the readers can be convinced that our model presents noninferior results reminding the fact that our method only utilizes simple diameter information to train the DCNN rather than the elaborated segmentation map from expert radiologists. Figure 2 also illustrates qualitative results showing that our approach performs reasonably well.

Table 1: Nodule segmentation accruracy comparison using various evaluation metrics; dice similarity coefficient (DSC), sensitivity (SEN), and positive predictive value (PPV), shown in mean ± standard deviation format. All the other results are referred from [1].

	DSC (%)	SEN (%)	PPV (%)
Level Set	60.63 ± 17.39	64.38 ± 22.75	71.03 ± 24.35
Graph Cut	68.90 ± 16.03	80.81 ± 15.25	65.09 ± 22.42
U-Net	79.50 ± 13.95	86.81 ± 18.43	87.18 ± 16.13
CF-CNN	82.15 ± 10.76	92.75 ± 12.83	75.84 ± 13.14
Ours	**78.78 ± 18.68**	**91.70 ± 14.96**	**74.17 ± 23.68**

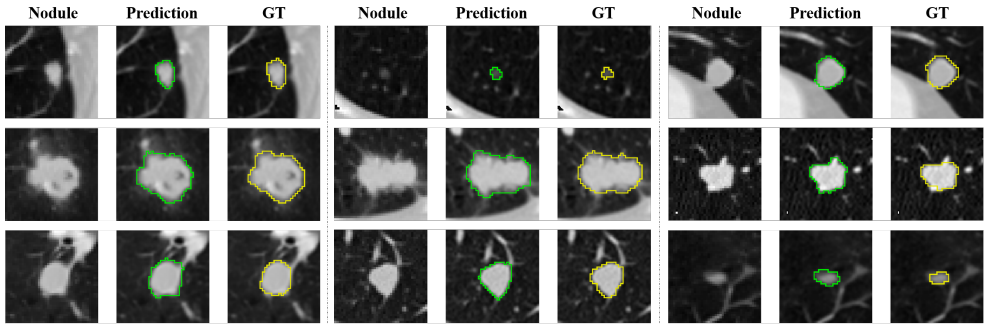

Figure 2: Qualitative comparison with ground-truth labels. (Nodule: input images, Prediction: predicted results from our model, GT: ground truths from the LIDC/IDRI dataset)

4 Conclusion

Lung nodule segmentation is important for radiologists to analyze the risk of the nodules. The DCNN based methods recenlty produce plausible automatic segmentation results, however, obtaining detailed 3D segmentation maps to train those DCNN requires too much efforts. We proposed a novel method that requires only diameter information for each nodule, still yielding competitive results shown in quantitative as well as qualitative manner. In future work, we plan to validate the segmentation result can actually predict clinical nodule analysis metric, e.g., the Lung-RADS score.

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