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, and deep learning based approaches have shown promising results in this task. However, generating 3D segmentation label which is necessary to train deep learning algorithms requires too much effort to researchers. Therefore, we propose a new way of training deep learning model by generating 3D segmentation label using only diameter information of each nodule. Our model is validated with LUNA16 dataset, and the results show comparable with other models in evaluation metrics, DSC, PPV and sensitivity.

1 Introduction

Accurate lung nodule segmentation from computed tomography (CT) plays an important role for radiologists in pulmonary nodule analysis. Deep Convolutional Neural Networks (DCNNs) have recently shown outstanding achievements in the nodule segmentation task. A central focused pooling based CNN model [1] combining 2D and 3D feature maps has yielded powerful results using the segmentation label from expert radiologists. Training this deep neural network, however, requires elaborate pixel-wise labels (i.e., foreground or background), which are the outcome from burdensome annotation using expensive human resources. Meanwhile, a weakly supervised approach has been employed in [7]. This method trains the CNN model using labels that indicate 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 a simple annotation, this method hardly presents comparable results, probably due to the lack of detailed label information segmenting nodules.

In this work, we propose a new method to train the deep neural network with labels from only a diameter information for each nodule, showing competitive results with other stat-of-the-art methods in terms of DSC, SEN, and PPV scores. Obtaining a diameter of a nodule is not only the easier task than a whole segmentation of 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 natural way to gather training data for the nodule segmentation task.

2 Proposed method

2.1 Dataset

Publicly available LUNA16 [4] dataset is employed to train our segmentation model. The dataset, collected in the U.S., contains 888 CT scans from LIDC/IDRI [5] database including more than 2,000 nodule candidates accompanying segmentation maps marked by four radiologists. These maps are

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only employed in the testing phase, in a way that an area marked by more than two radiologists (i.e., 50% consensus) is adopted as a ground-truth foreground label, which is also the case for other works in comparison []. At the training phase, we utilize the labels generated by our method which only uses a diameter information of each nodule.

2.2 3D U-Net model

Overall deep neural network structure in our work is motivated from the U-Net [3], 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 3x3x3, and the deconvolutional kernel size is 2x2x2. The ReLU function is used as the activation function. After the last convolutional layer, a fully connected layer is applied to classify which class each pixel corresponds to. All of our models exploit cross-entropy loss function to train the network.

At training phase, we provide cropped 3D images with size of 24x40x40 at the center of nodule as inputs to the network.

Since the generated label includes some non-nodule areas and the inaccuracy of the segmentation algorithm itself, the final nodule segmentation result is likely to include non-nodule regions. Therefore, at testing phase, in order to remove non-nodule areas of the segmentation result and improve the performance, we perform thresholding based post-processing according to the research on [6].

2.3 Generating segmentation label using diameter information

We generate segmentation label assuming that nodules are spherical, and we assume that pixels within a radius (diameter / 2) * K from the center of the nodule correspond to a nodule and pixels outside the distance from the center are a background (Figure 1). The constant value, K, is used to reduce noise in the nodule of the generated label by measuring the size of the nodule to be less than the actual size. In our work, we set the K to 0.75.

Since the background occupies a much larger proportion than the nodule in cropped images, the imbalance problem occurs when calculating a loss, thus, we use the sampling to solve it. For example, when computing the loss of the network, instead of calculating the loss for the entire pixels, N pixels were sampled in the nodule and background regions, respectively, and the loss is calculated from the total 2*N sampled pixels. We set the sampling ratio of nodule and background to 1: 1 in a mini-batch by random sampling at each time step when the cropped images are fed into the network.

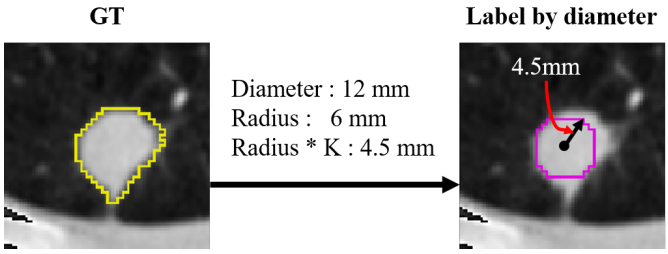

Figure 1: An example of generating segmentation label by using diameter information. In this example, a region with a distance of 4.5 mm or less from the center is nodule, and the other region is labeled with a background.

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). We randomly split the LUNA16 dataset into 1,000 nodules for training set, 113 nodules for test set. To demonstrate the nodule segmentation

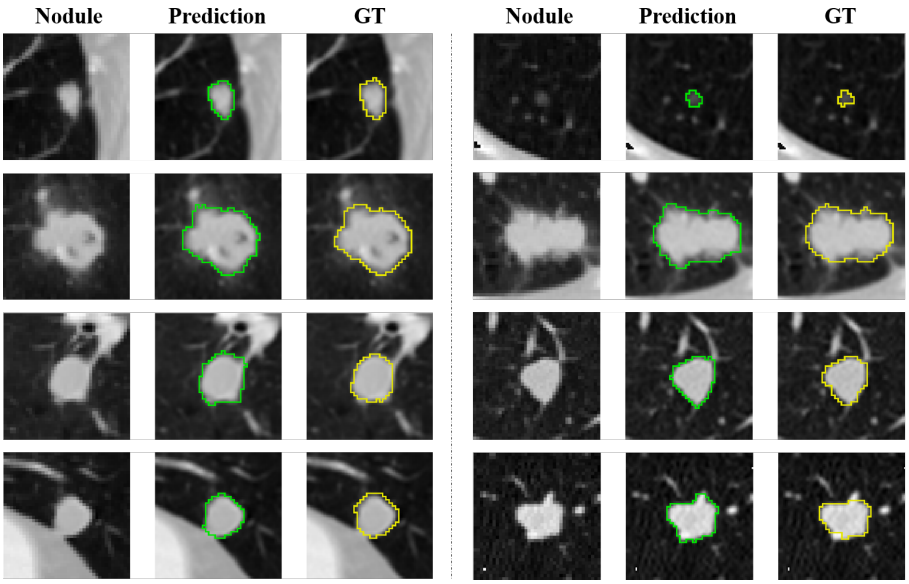

Figure 2: Qualitative comparison with ground-truth labels. (Nodule: input images, Prediction: predicted results from our model, GT: ground truth from LIDC/IDRI dataset)

accuracy, we evaluate our model on the test set 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 other 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 our result.

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 a 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 $\pm$ 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	$\mathbf{78.78 \pm 18.68}$	$\mathbf{91.70 \pm 14.96}$	$\mathbf{74.17 \pm 23.68}$

4 Conclusion

Lung nodule segmentation is important for radiologists to analyze the risk of the nodules. The DCNN based methods produce plausible automatice segmentation results, however, obtaining detailed 3D segmentation maps for training requires too much efforts. We proposed a novel method that requires only a 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 LungRADs score.

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