Lung Nodule Proposals Generation based on 3D Convolutional Neural Network

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Abstract

Detecting nodules from patients with lung disease is important, which help prevent lung cancer deteriorating and improve the cure rate. To detect lung nodules automatically, we construct a 3D lung nodule extraction model based on an existing state-of-the-art lung cancer prediction method https://github.com/lfz/DSB2017. The method combines Fast R-CNN and U-net together, and convert these traditional 2D networks to 3D ones. Based on the lung nodule detection network, we discuss some key problems involved in 3D CNN model, and we will release our full paper later on.

1 Introduction

Lung cancer is nearly the most deadly cancer and receives much attention these years [1]. Some malignant masses existing in the lung cavity is the manifestation of early stage lung cancer. These masses are usually treated as nodules, which can be identified from CT scans. Identifying these malignant nodules is very important, which can assist in preventing lung cancer deteriorating and improving the cure rate.

Since the nodule proposals generation task is so important that many researchers have paid attention to it. Depending on the dimension of the input data, the existing DNNs based nodule proposals generation methods can be classified into two categories, the 2D algorithms [2-3] and the 3D ones [4-6]. The 2D methods [2-3] treat each slice of the CT scans as an individual image, and perform trained neural networks on each slice separately to extract series of 2D nodule proposals which will be further merged to output nodule locations finally. However, in the real world, nodules are continuous solid 3D objects existing in the lung cavities. When project them into the CT scans, they usually appear in several successive CT slices instead of an individual one. Therefore, treating each slice as an individual image for nodule detection will ignore highly correlative spatial context information, resulting in unsatisfactory nodule extraction results. To extract nodules directly in 3D forms end-to-end and capture spatial context information between CT slices, some methods extend the traditional 2D neural networks into the 3D forms [4-6]. In the 3D network, the computing units such as convolutional kernels are in 3D form. Besides, the input data are 3D stereo cubes instead of the original 2D plane images, and the outputs are coordinates information related to 3D positions. Using the 3D network, nodule proposals generation performance is highly improved, due to more information and features being taken into account.

2 Lung nodule proposal generation approach

Usually, different CT scans are in different voxel length. Taking CT scans in Luna'16 dataset [7] for example, spacing on z-axis of the CT scans in this dataset ranges from 0.625mm to 2.5mm, which are the same for the x and y axes. Thus, for the raw CT scans, we firstly set a fixed sampling frequency (e.g. 1mm×1mm×1mm) to convert these different CT scans to the same voxel spacing. Different sampling frequency results in different resolutions of 3D lung data, the influence of which will be discussed in detail in the experiments.

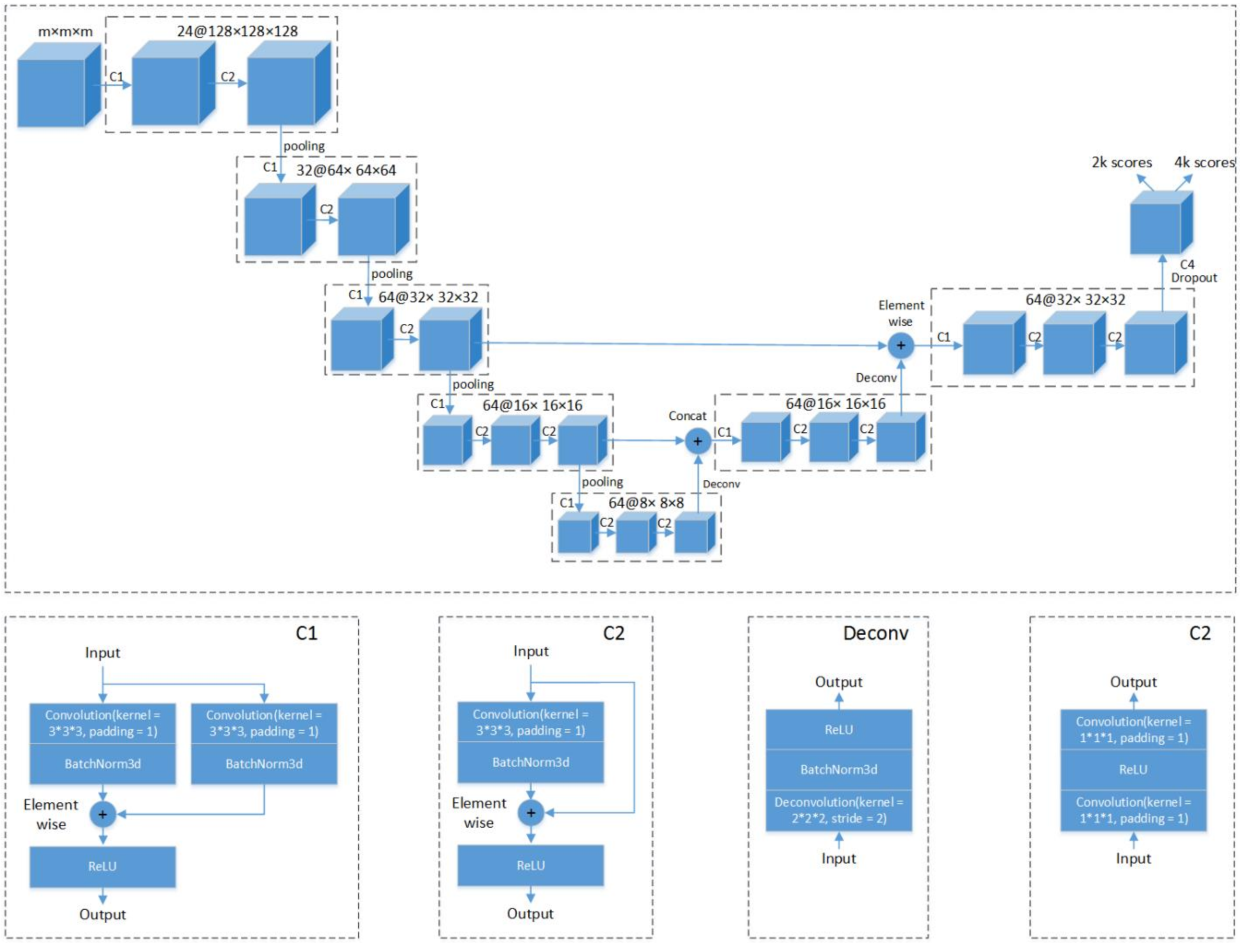

Fig. 1. Nodule proposal generation network architecture.

Based on the resampling data, we firstly convert it into Hounsfield units and apply Gaussian filter as well as binarization approach to generate series of connected components, among which the satisfied components are used to generate preliminary lung mask. Then, morphological operations are applied on the preliminary lung mask and we obtain relatively integrated lung regions. Finally, data is transformed from Hounsfield to integers and we combine the integer data image with the obtained integrated lung mask to generate the final preprocessing result.

To extract lung nodules from the preprocessing result, a 3D neural network combing Fast-RCNN [8] with U-net [9] is constructed. The main structure of the network is shown in Fig.1, which consists of down sampling and up sampling parts. The down sampling network composes of five groups of 3D residual blocks interleaved with four pooling layers. Each group contains several blocks composing of convolution, batch-norm and ReLU computation unites together with residual structures. The detailed descriptions of these basic computation unites are also shown at the bottom of Fig.1. We add some de-convolutional computation unites to up sample the feature maps obtained from the down-sampling layers. During the up sampling process, we combine the output feature maps with those produced by the down-sampling layers with the same sizes, and obtain the final feature maps which contains both local and global information of the original input data.

The network has two sibling output layers. The first outputs a two class labels, which indicates the corresponding proposal being a nodule or not. The second sibling layer outputs bounding-box regression offsets. Each ground truth nodule targets to two labels: a ground-truth class and a ground-truth bounding-box regression.

Based on the obtained loss, stochastic gradient descent (SGD) and step-wise learning rate strategies are adopted to train the network, which will be used for lung nodule proposal generation.

3 Results and discussion

3.1 datasets

We use Luna'16 dataset [21] for model training and testing, which is based on the publicly available Lung Image Database Consortium (LIDC) [10] and the CT data form is DICOM. The dataset contain 888 CT scans and 1186 nodules in total. Four experienced radiologists identify that each mark lesion is nodule smaller than 3mm or not, respectively. The Luna dataset treat the nodule candidate who is identified as nodule larger than 3mm as the real nodule. The other candidates who are treated as nodules by only one or two radiologists or with size smaller than 3mm as the irrelevant findings. Some examples of lung nodules in Luna'16 dataset are shown in Fig.5. Besides, the total Luna'16 dataset are divided into ten subsets, which are used for both training and testing CNN models. To allow easier reproducibility, the aforementioned lung nodule detection method is trained on the given subsets for 10-folds cross-validation.

3.2 evaluation measure

The evaluation is performed by measuring the detection sensitivity of the algorithm and the corresponding false positive rate per scan. Analysis is performed using free receiver operating characteristic (FROC) analysis. To obtain a point on the FROC curve, only those findings of a CAD system whose degree of suspicion is above a pre-set threshold tare selected, and the sensitivity and average number of false positives per scan is determined. All thresholds that define a unique point on the FROC curve are evaluated. The final score is defined as the average sensitivity at 7 predefined false positive rates: 1/8, 1/4, 1/2, 1, 2, 4, and 8 FPs per scan.

3.3 Experiment setup

In this paper, we implement the aforementioned 3D CNN model on CPU platform (Skylake8180, 28 cores) with Linux operation system and use Caffe framework [11]. Since the Caffe framework in official version does not contain all the needed 3D computational functionalities, we extend the official Caffe framework into a 3D supported version and name it as Intel extended-Caffe, which has been opened source at https://github.com/extendedcaffe/extended-caffe.

4 Reference

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