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Lung CT Image Segmentation Using Deep Neural Networks

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Abstract

Lung CT image segmentation is a necessary initial step for lung image analysis, it is a prerequisite step to provide an accurate lung CT image analysis such as lung cancer detection.
In this work, we propose a lung CT image segmentation using the U-net architecture, one of the most used architectures in deep learning for image segmentation. The architecture consists of a contracting path to extract high-level information and a symmetric expanding path that recovers the information needed. This network can be trained end-to-end from very few images and outperforms many methods.
Experimental results show an accurate segmentation with 0.9502 Dice-Coefficient index.

Keywords: Lung CT; Image Segmentation; Deep Learning; U-net;

1. Introduction

Lung cancer is a lethal lung disease that causes more than one million of deaths yearly [1]. It is one of the most common medical conditions in the world. By definition, lung cancer is a malignant lung tumor that is characterized by uncontrollable growth in the lung tissue. Early detection of lung cancer could reduce the mortality rate and increase the patient's survival rate when the treatment is more likely curative. Computed tomography (CT) imaging is an efficient medical screening test used for lung cancer diagnosis and detection. The physician uses the obtained CT images to analyze and diagnose the lung tissues. However, in many frequent cases, it is difficult for the physician to obtain an accurate diagnosis without the help of additional tool known as Computed Aided Diagnosis (CAD) System.

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Computer Aided Diagnosis (CAD) system is an efficient medical diagnosis tool and a prerequisite for today's medical imaging practicality. The physician uses the CAD system to provide an additional second opinion in order to obtain an accurate diagnosis. It is widely useful to improve the effectiveness of the treatment.

For Many CAD systems, an accurate segmentation process of the target organ is always needed. It is a prerequisite initial step for an efficient quantitative lung CT image analysis.

However, designing an effective lung segmentation method is a challenging problem, especially for abnormal lung parenchyma tissue, where the nodules and blood vessels need to be segmented with the lung parenchyma. Moreover, the lung parenchyma needs to be separated from the bronchus regions that are often confused with the lung tissue.

A large number of medical image analysis techniques have been proposed for automatically separate the lung parenchyma region in CT images. Most of the methods are signal thresholding techniques [2], [3] and they are based on the contrast information as mentioned in the review presented by Sluimer et al.[4]. The fact that the lung regions have lower densities compared with the other body regions makes the lung region appears dark surrounded by a denser region (i.e. the aorta and the body cavity). The based scheme of these methods is simple and effective for normal lung segmentation, but they greatly fail when we extend the term "lung" to represent not only the normal lung tissues but also abnormal tissues and blood vessels [2].

Hu et al. [3] proposed a stepwise segmentation method. First, an iterative thresholding is used to obtain an initial segmented region. Second, the obtained region is refined by an opening-closing morphological operator. Another segmentation method [5] is to use wavelet transform and an optimal thresholding to obtain the first segmentation. Then refine the obtained segmented region using mathematical morphology operations.

Deep learning is a particular kind of machine learning that is composed of multiple processing layers to achieve high levels of abstraction when it comes to learning representations of data. In different domains such as speech recognition and visual object recognition. Convolutional Neural Network (CNN), which is commonly known as a branch of machine learning approach and a class of deep learning, nowadays supersedes many image segmentation approaches (see [6] for up to date review of Deep Learning techniques applied to semantic segmentation). It is based on multiple layer processing to model high level and complex abstractions in data.

Nowadays, the application of deep learning techniques for medical image segmentation received a great interest due to their ability to learn and process large amounts of data in a fast and accurate manners. In [7], M. Havaei et al. presented an automatic brain tumor segmentation based on deep learning networks that improves over the currently published state-of-the-art. In [8], Z. Akkus et al. published a review of deep learning approaches that aims to present an overview of deep learning-based segmentation methods for brain MRI.

SegNet is an efficient novel approach of a Deep fully CNN architecture for semantic pixel-wise segmentation proposed by Vijay Badrinarayanan et al.[9]**.** This core trainable segmentation engine consists of an encoder network, a corresponding decoder network followed by a pixel-wise classification layer. We can see the use of this architecture in [10] for X-Ray lung (coronal view) segmentation.

In this paper we provide a lung segmentation using one of the common architectures used for image segmentation with deep learning called U-net [11]. Thus, this step is necessary to erase unnecessary information provided in lung CT images. Our network achieves an accurate segmentation (with a 0.9502 Dice-Coefficient index) based on a small image set that contains a few hundreds of manually segmented lung images.

This paper is organized as follows: in section 2, the U-net architecture is summarized. In section 3 we present the resultant segmentation accuracy using the LIDC image dataset. In section 4, concluding remarks are stated.

2. Methods

Deep learning has dramatically improved the state of the art. Over the past several years, since 2006 when Hinton proposed his new algorithm[12], this approach, deep learning in general and convolutional neural networks in particular, has risen up to be the approved for a variety of pattern recognition problems. The proof is that since then they have won many international competitions in pattern recognition[13].

As with image classification, CNN has had huge success on image segmentation problems. In 2015, Fully Convolutional Network (FCN) [14] was introduced by Long et al. and made CNN architecture popular for dense prediction without any fully connected layers, this novel approach allowed to generate segmentation maps for any image and was much faster compared to classical approaches of image segmentation.

Fully connected layers were not the only challenge, but also the pooling layers that reduce the object details, thus, the up-sampling layers were adopted to tackle this issue. Hence, this approach was used in the encoder-decoder architecture, where the encoder reduces the spatial dimension of objects with pooling layers and the decoder recovers the object details with up-sampling layers. The U-net, the architecture adopted in this work, is one of the popular architectures in the class of encoder-decoders.

In [11], Ronneberger et al. proposed an architecture, U-net (see ***Fig. 1)***, based on the FCN architecture, the basic elements of the U-net can be viewed as an association of convolution layers in the contracting path and deconvolution layers in the expansive path.

The contracting path is like a classic architecture of a convolutional neural network that consists of Convolution layers with Rectified Linear Units *(1)* (ReLU see ***Fig. 2***) and Max-pooling layers. On the other side, i.e. the expansive path, it consists of an upsampling of the feature map followed by up-convolution and convolution layers with ReLU. Due to the loss of border pixels at every convolution, it is necessary to crop a corresponding feature map from the extracting path and concatenate it with corresponding layers in the expansive path.

$$f(x)=\max(0, x) \tag{1}$$

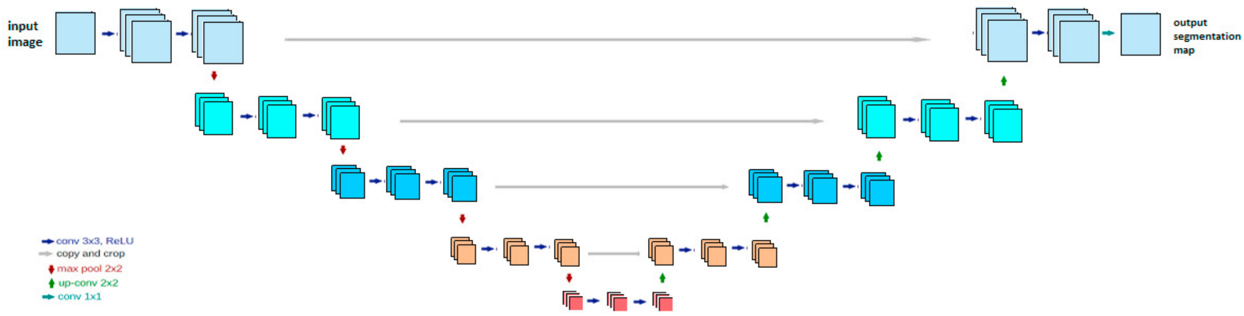

Fig. 1: The u-net architecture used in [11]. Consists of two paths: the left path that consists of two convolutions with the same padding followed by ReLU and a 2*2 max-pooling with stride 2, this operation is repeated four times on this path, and the right path that consists of an up-convolution of the feature map from the left side and two 3*3 convolutions followed by ReLU, this operation is repeated four times in this path. Between the two paths, it is necessary to crop and concatenate corresponding feature maps from the left side with their corresponding in the other path due to the loss of border pixels in convolution layers.

In the training phase, the input images and their corresponding masks are used to train the U-net, and in the test phase, we give an image as input to generate the corresponding mask as output as shown in ***Fig. 3***. And then, we apply the mask to the corresponding image to segment the area of interest, i.e. the lung parenchyma in our case.

The dataset used in this experimentation is the Lung Image Database Consortium image collection (LIDC-IDRI) [15] that consists of diagnostic and lung cancer screening thoracic computed tomography (CT) scans with marked-up annotated lesions. It is a web-accessible resource for the development of CAD methods for lung cancer segmentation and diagnosis.

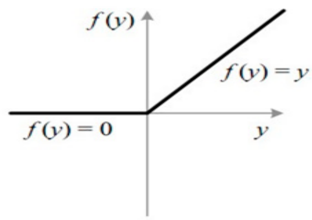

Fig. 2: Rectified Linear Units (ReLU), presented in (1).

The ground truth of the lung parenchyma was provided by a manual segmentation, and before performing our experimentation in the dataset, we did a pre-processing step that consists of cropping the images to simply remove any information that doesn't belong to the area of study.

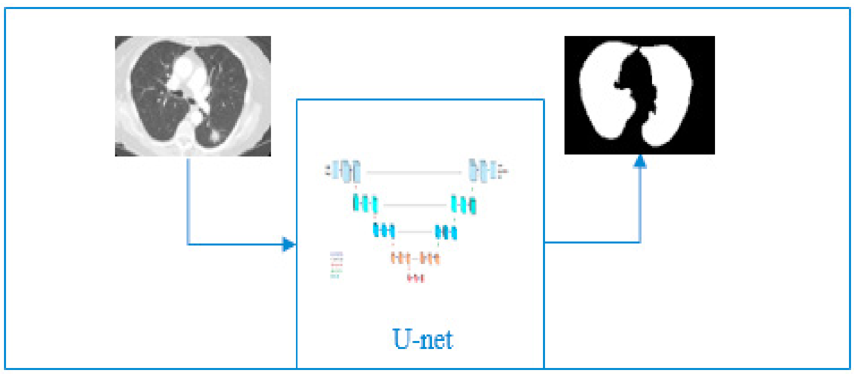

Fig. 3: the way that U-net architecture works is that it takes the input image and generate the corresponding map for segmentation.

3. Results

Our experimentation was based on Keras, which is a high-level neural networks API, written in python, able to run on top of either Tensoflow or Theano, and runs seamlessly on CPU and GPU. Thus, our network was trained on a graphics processor NVIDIA GTX 1050 equipped with 640 CUDA Cores and 4Gb of memory in order to exploit its computational speed. Hence, we run our code on a GPU in order to greatly accelerate the execution, with Tensorflow backend. The network parameters were set to:

- Batch size: 32.
- Number of epochs: 50.

In order to evaluate the performance of our network, we use the dice coefficient index as a similarity metrics considering that it is currently the most popular similarity measurement which is calculated with this formula:

$$DSC = 2 * \frac{||S \cap T||}{||S \oplus T||} \quad (2)$$

Where S is the lung parenchyma area obtained with the dynamic segmentation based on our network, and T is the ground truth resulted from manual segmentation.

With our network, the average dice coefficient index reached is 0.9502. The Fig. 4 shows the experimentation results in which we show resultant segmentation using our network and the manual segmentation using the ground truth map. The figure contains five columns. From the left to the right, each one represents the original image, the Ground Truth of the Lung parenchyma, the segmentation map generated by our network, the result segmentation using the manual ground truth and the result segmentation using the generated map respectively.

The 5th column shows that the lung segmentation performed by the U-net network does not contain parts of the trachea and the bronchus regions and does not eliminate lesions such as nodules and parts of the blood vessels, which means that this approach is accurate.

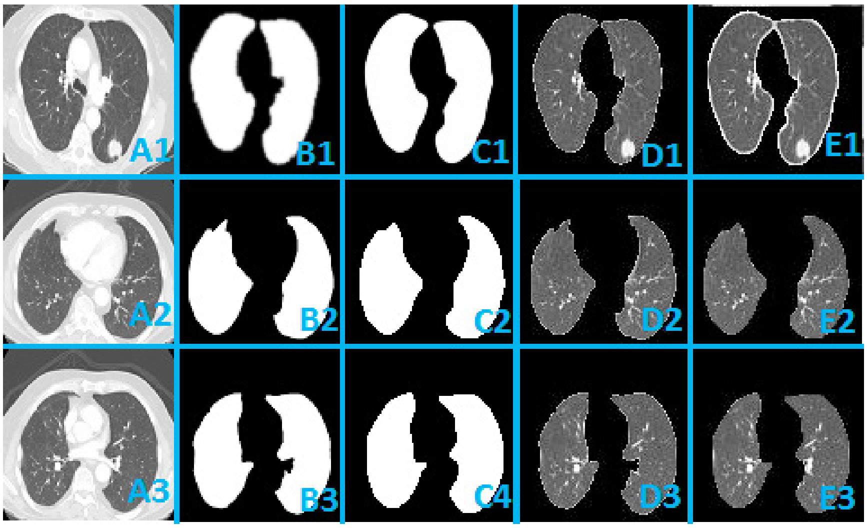

Fig. 4: block (A) represents a sample from the image set, (B) is the manual ground truth of the image set, (C) is the generated maps segmentation using our network, (D) is the segmentation of lung using the ground truth maps and (E) represents the segmentation of lung using the generated maps using U-net respectively.

4. Conclusion

In this work we presented a lung parenchyma segmentation using the U-net architecture and we obtained an accurate segmentation with 0.9502 Dice-coefficient index. The advantage of the method presented in this work is the fact that it is uniform and can be applied to a wide area of different medical image segmentation tasks. Our objective in the next stage is to perform a lung nodule segmentation based on the results of this work.

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