



Developing Advanced Algorithms for Medical Image Analysis

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Abstract

Lung cancer represents the leading cause of death for malignancy in the world. Pulmonary nodules are caused by the uncontrollable irregular growth of cells in the lung parenchyma. Detecting these nodules in the lung tissue in an early phase increases the chances of survival for the patient and improves the efficiency of the treatment. Computed Tomography (CT) is one of the most sensitive methods for detecting pulmonary nodules. A thin-section CT scan of the whole thorax generates a large data set and requires radiologists to spend a considerable amount of time interpreting the images. As a means to reduce radiologists' workload, Computer-Aided Detection (CAD) systems may be used. CAD systems help scan digital and highlight conspicuous sections, such as possible diseases, and provide a second opinion to the radiologists.

This thesis proposes a CAD algorithm for detecting lung nodules in CT scans through five main steps: image acquisition, preprocessing, lung segmentation, nodule detection, and false-positive reduction. Preprocessing is implemented using contrast stretching and enhancing. Lung segmentation and nodule detection stages are performed using a combination of region growing, thresholding and morphological operations. Each 3D structure is then subjected to tabular structure elimination to provide nodule candidates. In the false positive reduction stage, some of the basic nodule features are extracted from the training data to set thresholds for a simple rule-based classifier. The final classification is done using a multi-view 2D Convolutional Neural Networks (CNNs) as a powerful tool in the deep learning field. The CNN is built specifically to handle the provided inputs and is customized to provide the best possible outputs without the extra computational complexity that is required when compared to a 3D network. Extensive experiments are done on a wide labeled dataset downloaded from the Lung Image Database Consortium (LIDC). The CAD achieved a sensitivity of 85.25%, a specificity of 90.66% and accuracy 89.89 % with an average of 1.57 fps/scan. The results show that the proposed multi-view 2D network is a simple, yet effective algorithm for the false positive reduction problem.

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