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Airway segmentation for low-contrast CT images from combined PET/CT scanners based on airway modelling and seed prediction

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ABSTRACT

Combined positron emission tomography (PET) and computed tomography (CT) scanning provides superior access to both functional information and the anatomical structures of the airway tree. However, due to the complex anatomical structures, limited image resolutions and partial volume effect (PVE), segmentation of airway trees from low-dose and low-contrast CT images from PET/CT scanning is a challenging task. Conventional airway segmentation algorithms usually produce less than satisfactory results. In this paper, we propose a novel region growing approach for automated airway tree segmentation in CT images from combined PET/CT scanners. In our approach, we employ prior anatomical knowledge of the airway to predict, extract, and validate the seeds of bronchi regions, and use those seeds to identify the airway branches that are not detectable by conventional 3D region growing. Through analyzing the size of the bronchi in two successive slices, this approach allows airway seeds to grow sufficiently while avoiding leakages. Our method was compared to the traditional 3D region growing algorithm on 14 clinical thoracic PET/CT images. The experimental results demonstrate that the proposed technique is capable of retrieving considerably larger number of branches and providing more accurate airway segmentation.

1. Introduction

The airways have a tree structure with branches that become narrower, shorter, and more numerous as they penetrate deeper into the lungs [1]. Many diseases, such as bronchitis, lung cancer, emphysema and tuberculosis, are related to the airways and their surrounding organs. Therefore, assessing the changes in regional airway structure and function plays a pivotal role in the early diagnosis of these diseases.

The remarkably increasing availability of CT scanners has contributed to thoracic CT imaging becoming a routine diagnostic tool in clinical practice at many medical centres. Reliable airways segmentation is an essential step in thoracic CT image analysis. It not only serves as the pre-process for airway construction but also provides the basis for quantitative evaluation of the physiological and pathological abnormalities of the airways, such as stenosis and tumors [1]. Automated airways segmentation in CT images has been widely investigated in recent years. As a result, a variety of segmentation techniques have been proposed in the literature [2], which can be roughly categorized into: (1) knowledge based [3–5]; (2) region growing [6–15]; (3) central-axis [14,16,17]; (4) mathematical morphology [1,18,19]; and (5) fuzzy connectivity [20] algorithms.

Sonka et al. [3] proposed a typical knowledge based airway segmentation technique where the locations of bronchi were identified based on the relationship between airways and their surrounding vascular trees. This method was further improved by Park at al. [5] using the fuzzy-logic connectivity to validate the membership and thresholding the members to determine the airway tree. More detailed anatomical prior knowledge, including the expected size, shape, relative position to other structures, and X-ray attenuation of organs, was used by Brown et al. [4] to guide the segmentation process. To cope with the variability in human anatomy, each of the priors was described by a fuzzy set that indicated the range of normal subjects. Confidence scores were used to assess how well an image study satisfied these anatomical constraints. Since this approach was originally designed to distinguish other parts of thoracic structures, it can barely detect the accurate positions of smaller bronchi.

Region growing is a procedure that spans pixels or sub-regions into larger regions based on predefined criteria [21]. Mori et al. [6] described the 3D painting region growing algorithm, which extracts the airways by gradually increasing the growing threshold until the resultant volume explodes into the lungs. To overcome the draw-

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back of the global threshold, Kitasaka et al. [11] introduced local adaptive thresholds to identify each bronchus. However, these traditional region growing methods are critically dependent on the detection of bifurcation points and identification of true bronchi, the failure of which might result in serious leakage of the detected airways into the lungs. To address this problem, Zhou et al. [12] developed a leakage detection technique that was based on matching labelled airways with the structure of a normal anatomical bronchi tree. Singh et al. [8] used an entropy-based measure called information gain as a heuristic prior to identify the voxels that were most likely to represent the airway regions. Although they avoid the tiresome manual selection of thresholds, these methods still suffer from under-segmentation caused mainly by the similarity in voxel values between the airways and their surrounding tissues.

In central-axis airway segmentation algorithms, a series of airway axes are generated to create a discrete model, which is a sparsely spaced set of airway axes. Airway segmentation can then be achieved by performing the generalized-cylinder model construction [16]. The simultaneous airways segmentation and reconstruction method proposed by Thorsten [17] performed the skeleton algorithm during the segmentation phase, which in turn helped to prevent leakage of the fast marching growth process into the lung parenchyma.

Mathematical morphology methods employ a range of morphological structuring elements (SE) for the segmentation process. Francoise et al. [19] combined morphological filtering, connection cost-based marking and the conditional watershed algorithm for segmentation of the bronchi. Aykac et al. [1] first performed 2D gray-scale airway reconstruction using the morphological close operation with an increasing kernel size, then applied iterative close and dilation operations to obtain all the potential airways, and finally adopted 3D morphological reconstructions consisting of forward and backward passes to suppress noise and extract the airway tree.

Another group of airway segmentation algorithms are based on the theory of fuzzy connectivity [22–29]. Tschirren et al. [20] assigned each voxel a fuzzy membership based on the intensity similarity between the input image and two landmarks, the trachea and airway wall. This algorithm allowed two regions to compete against each other, and thus decided the class labels of all voxels. Fuzzy connectivity was also used for pulmonary vessel segmentation [27,30].

Despite the successes of these algorithms, airways segmentation in CT images remains a challenging problem. The difficulties arise from the complex anatomic structure of airways, and the similar voxel values of the bronchi and their surrounding tissues, mainly caused by the limited spatial resolution, narrow contrast, and the partial volume effect (PVE) [20]. In addition, due to the relatively large space between transverse slices, small bronchi will become difficult to detect if their axes are parallel to the slices [6]. Therefore, these algorithms sometimes result in either under- or over-segmentation [31].

Recently, combined PET/CT scanners with the unique capability of acquiring aligned functional and anatomical images in the same imaging session have been widely used for diagnosis, disease staging, and therapy monitoring [32]. The fusion of molecular/metabolic and anatomical/morphological information has been shown to improve diagnostic accuracy in the identification and characterization of tumors in the lung region [33]. In PET/CT scanning, the CT component uses a low-dose protocol, and hence results in low spatial resolution and low-contrast CT images [34]. The aforementioned airway segmentation algorithms are not specifically designed for low-contrast CT images and might fail by stopping early or leaking into the lung regions. Consequently, few of them have conclusively proved adequate for the CT images acquired from PET/CT scanning.

In this paper, a novel region growing based airway segmentation approach is developed specifically for low-contrast CT images from combined PET/CT scanners. In this approach, the traditional 3D region growing is adopted to detect the primary volume of airway. More seeds of airway branches are extracted by using a prediction and validation scheme that is heuristically guided by the prior knowledge of airway anatomy. With these seeds, our approach can detect many more branches of the airway tree. The leakage problem that plagues conventional region growing algorithms is successfully overcome by creating a set of validation rules. To demonstrate its improved performance, the proposed airway segmentation technique was compared with the 3D region growing approach proposed by Mori et al. [6] on 14 clinical thoracic PET/CT images.

2. Method

2.1. Overview

The proposed airway tree segmentation method consists of two main stages: automated 3D region growing and iterative 2D operations. In the first stage, automated 3D region growing is performed to acquire an initial airway segmentation result. In the second stage, iterative 2D airway segmentation is initiated slice-by-slice to identify potential airway locations in the 2D cross-sectional images. This stage is primarily divided into three steps. Firstly, seeds are extracted from the previously segmented regions according to the topological modelling of bronchus regions; secondly, potential seeds on the subsequent slice are predicted based on the seeds selected. Thirdly, a 2D region growing process is applied on each slice to extract the detailed airway branches. These 2D operations will be iterated until there are no new regions identified. The workflow of this approach is shown in Fig. 1.

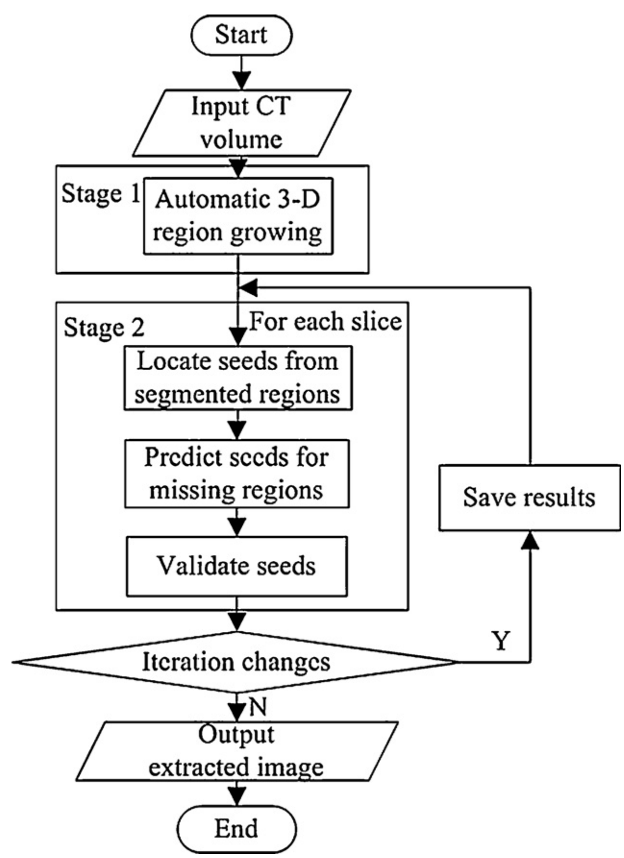

Fig. 1. Workflow of the proposed airway tree segmentation algorithm.