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An oriented derivative of stick filter and post-processing segmentation algorithms for pulmonary fissure detection in CT images

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ABSTRACT

Knowledge of pulmonary fissure anatomy is valuable in localization of lesions and evaluation of lung disease. Under CT imaging, pulmonary fissure detection is an intricate task due to factors such as pathological deformation, partial volume effect and intensity variability. To solve the problem, an oriented derivative of stick (ODoS) filter and a post-processing segmentation algorithm are introduced for pulmonary fissure detection. Here, the ODoS filter is proposed as an improvement to an existing derivative of stick (DoS) filter by merging the stick orientation information for pulmonary fissure enhancement, which will increase its clutter discriminating ability especially on those linking to the fissure object. Based on an observation that the pulmonary fissures often appear as coplanar structures and have similar directions across the sagittal plane, we present an orientation partition scheme for fissure patches and noise separation in different orientation partition. After removing the small-sized noise, the purified patches from different partitions are iteratively integrated by a fissure patches integration scheme for pulmonary fissure segmentation. With the additional direction constraint, the ODoS filtering response can be more completely detected and the noise residual could be kept at the lowest level. The performance of our algorithms is validated in experiments with a publicly available challenge dataset, i.e. the LObe and Lung Analysis 2011 (LOLA11) data, including 55 CT scans. Compared with manual references, the proposed method acquired a high median F_1-score of 0.877. The effectiveness of our scheme was verified by visual inspection and quantitative evaluation.

1. Introduction

Human lungs are composed of five lung lobes, separated by pulmonary fissures. Anatomically, the right lung is subdivided into upper, middle and lower lobes by the right oblique fissure and horizontal fissure, and the left lung is subdivided into upper and lower lobes by the left oblique fissure [1]. Under CT imaging, pulmonary fissures typically appear as bright thin curved lines or narrow ribbons across the transverse planes [2]. Clinically, knowledge of the pulmonary fissure anatomy is valuable in localization of lesions and evaluation of lung disease [3]. In particular, quantification of fissure completeness is becoming increasingly important in clinical diagnosis, which is related to pulmonary function in patients [4] and can be used to assess lung disease distribution [5]. However, pulmonary fissure segmentation is a challenging task due to complicated factors such as pathological deformation, partial volume effect and intensity variability.

Many reliable and valuable methods have been ingeniously designed for pulmonary fissure detection, either directly through the appearance and shape of fissures in CT images, or indirectly through information about lung anatomy and atlas methods. One of the indirect strategies is to use the anatomical knowledge about the vessels, bronchi and fissures to locate the fissure regions under different frameworks [6], such as the watershed transform [7–10], minimal path [11], adaptive sweeping [12], Voronoi division [13], neural network algorithm [14,15], sagittal adaptive fissure scanning [16] and alpha expansion [17]. Another indirect strategy is the atlas-based approach [18,19] by constructing a pulmonary atlas to guide fissure detection. These indirect approaches could be considered as auxiliary means to find the fissure regions and limit the search area, but the most useful and valuable information still originates from the fissure itself [19–21]. Therefore, a number of studies pay more attention to the appearance and shape of fissures in either 2D or 3D CT images for localization and refinement [8–10,20–25].

Taking the fact that pulmonary fissures appear as bright thin curved lines in 2D CT images into account, a direct strategy is to

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detect the curved-line structures in 2D CT images. Following this strategy, a template matching method has been presented by Kubo et al. using the VanderBrug operator to highlight the fissure representation [26]. In a similar way, Zhang et al. applied a ridgeness measure method to enhance the fissure profiles, then a fuzzy reasoning system was used to integrate the direction and intensity to segment the fissure patches [18]. Wang et al. [2] utilized a ridge map approach to enhance the major fissures, then a curve-growing algorithm was modeled by a bayesian network for fissure segmentation. However, their algorithms [2,18] need manual interaction for initialization. To automatically identify pulmonary fissures and overcome the shortcomings [2,18], Wei et al. presented an approach based on adaptive fissure sweeping and wavelet transform to segment the fissure patches [12]. Recently, Kinder et al. designed a line-enhancing filter using multiple hypotheses testing to enhance pulmonary fissures [27], but the method used only the magnitude information of fissures, ignoring orientation information.

Motivated by the fact that pulmonary fissures appear as plate-like structures in 3D CT images, the second direct strategy is to detect the plate-like structures in 3D CT images. Based on this, Wiemker et al. proposed an unsupervised method using the structure tensor and Hessian matrix to describe the plate-like structure characteristics of fissures [28]. To further discriminate between fissures and other structures, Doel et al. [23], Shamonin et al. [29] and Lassen et al. [10] presented three different Hessian eigenvalue-based filters to highlight fissure representation and simultaneously suppress other structures. For the same purpose, Ross et al. utilized a particle system to find the fissure regions, then the maximum a posteriori (MAP) estimation was employed to select the fissure patches from noise [30]. However, this method spent a lot of time for the MAP estimation. Using a different strategy, Saita et al. presented a sheet-emphasis filter and applied a region-growing method based on the normal vector of the emphasized sheet shadow to segment the fissure patches [31]. Similarly, Pu et al. [32] proposed a computational geometry method based on random normal vector to extract the pulmonary fissures in 3D space. Its improved version [33] proposed an anisotropic morphological processing approach to smooth the extracted fissure surface, then a fissure decomposition algorithm was designed for individual fissure identification. Later, the method was improved by Gu et al. [22], where they utilized a piecewise plane fitting algorithm to directly extract the plate-like structure in original lung CT images, but this approach may cause parts of the fissures to be undetected. Recently, Bragman et al. proposed a multi-scale fissure enhancement filter to enhance pulmonary fissures, then a gaussian mixture model was used for subsequent segmentation [9], but the method is computationally expensive.

In addition, a number of studies employed the hybrid 2D/3D approach to detect pulmonary fissures. Van Rikxoort et al. [34] presented a supervised enhancement filter to select a set of features for fissure detection, but the method inherited the drawback of machine-learning techniques and a lot of time was spent in the training stage. To reduce the time consumption, Qi et al. utilized a line enhancement filter followed by a uniform cost search to isolate the complete fissure [16]. Ukil and Reinhardt [8] employed the method of MLSEC-ST (multilocal level set extrinsic curvature and its enhancement by structure tensors) [35] to enhance pulmonary fissures in the 2D CT images, then used the biharmonic spline interpolation technique to complete the incomplete fissures, but the method may cause a few fissure patches to be undetected. Similarly, Wei et al. [25] presented a hybrid 2D/3D approach to segment diseased lobar fissures, then used the surface-fitting model to fill in the incomplete fissures. Recently, Xiao et al. [21] proposed a derivative of stick (DoS) filter for pulmonary fissures detection. Because only the magnitude response was adopted, a complex post-processing pipeline combining the multi-threshold binarization with a specific branch-point removal operation was needed to achieve the final segmentation. Although plausible results were obtained, the adhering interferences such as small vessels and fibrosis still remain a problem for accurate and automatic segmentation of lobar fissures.

Based on an investigation that the original DoS method often suffers from a difficulty to tradeoff between weak object detection and interference suppression, we propose to merge the orientation information of the stick kernel to remedy the drawback and thus form a new oriented derivative of stick (ODoS) filter. Since the interferences usually take a direction obviously different from the fissure lines in the section planes, an orientation partition scheme and a fissure integration scheme can be further adopted to isolate the fissure patches from noise in the 3D space. With this basic idea, we present a novel framework to merge the direction and magnitude of stick derivatives as well as the 3D coplanar assumption to achieve efficient pulmonary fissure segmentation in CT images. The remainder of the paper is organized as follows. The datasets, the manual references and the algorithms are introduced in Section 2. Section 3 presents the evaluations and comparisons of experimental results. In Section 4, we present the advantages and disadvantages of the proposed method. And in Section 5, the conclusion and future work are presented.

2. Material and methods

2.1. Data and references

We adopted a dataset from the LObe and Lung Analysis 2011 (LOLA11) challenge [36] for validation. The dataset includes 55 CT scans, obtained from varieties of scanners and protocols. The inplane resolution ranges from 0.53 mm to 0.78 mm whereas the slice thickness ranges from 0.3 mm to 1.5 mm.

A manual segmentation of the lung lobes has been provided by the organizers of LOLA11 on nine coronal slices for each case by two observers. Both observers were instructed not to draw a lobar border when they felt it was not possible [10]. Furthermore, pulmonary fissure segmentation and lung lobe segmentation are two different topics [32], accurate fissure references are urgently needed for evaluation [21]. As a result, the LOLA11 references were verified by two specialists [21], parts with invisible fissure references on CT scans were removed and visible parts that were missed in the LOLA11 reference were added [21]. In this work, the fissure references [21] were considered as a ground truth for experimental evaluation.

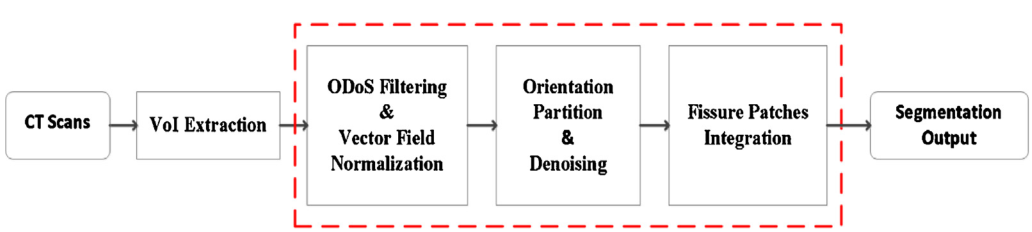

Fig. 1. A pipeline for pulmonary fissure segmentation.