Pulmonary fissure segmentation in CT images based on ODoS filter and shape features

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Abstract

Pulmonary fissure segmentation in computed tomography (CT) images can be treated as important ancillary information in the diagnosis and treatment of pulmonary diseases, yet it poses a nontrivial uncertainty for the segmentation task due to complex structures such as indistinguishable pulmonary vessels, blurring pulmonary fissures and unpredictable pathological deformation. To address these challenges, a useful approach based on an oriented derivative of stick (ODoS) filter and shape features is presented for pulmonary fissure segmentation. Here, we adopt an ODoS filter by fusing its orientation and magnitude information to highlight structural features for fissure enhancement, which can effectively distinguish between pulmonary fissures and undesirable clutter. Motivated by the fact that pulmonary fissures appear as linear structures in 2D space and planar structures in 3D space in the orientation field, an orientation curvature criterion and an orientation partition scheme are fused to separate fissure patches and other structures in different orientation partitions, which is expected to achieve more complete fissure detection and suppress other structures. Considering the shape difference between pulmonary fissures and tubular structures in the magnitude field, a shape measurement approach and a 3D skeletonization model are combined to remove clutter for pulmonary fissure segmentation. When applying our scheme to 55 chest CT scans acquired from publicly available LOLA11 datasets, the median F1-score, false discovery rate (FDR), and false negative rate (FNR) were 0.90, 0.11, and 0.10, respectively, which indicates that our scheme has satisfactory pulmonary fissure segmentation performance.

Keywords CT images · Shape features · 3D skeletonization model · Pulmonary fissure segmentation

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1 Introduction

The human lungs are naturally separated into five independent functional compartments called lobes. The physical boundaries between the lung lobes are known as lobar fissures [32]. On the basis of anatomy, the left lung is separated into two lobes by an oblique fissure, whereas the right lung is separated into three lobes by a horizontal fissure and an oblique fissure [42]. For clinical diagnosis, pulmonary fissure completeness is useful in lung disease assessment and treatment [9, 13, 22, 31]. However, pulmonary fissure segmentation is a formidable mission due to various factors, such as indistinguishable pulmonary vessels, blurring pulmonary fissures and unpredictable pathological deformation [10, 33].

Numerous studies have been presented for pulmonary fissure segmentation, which can be described by three different categories. The first category mainly employed methods implementing the shape and structure information from the fissure itself, such as the line-enhancing operator [20], multiple section model [46], DoS filter [45], ODoS filter [30], Hessian-based filter [44], and directional derivative of a plate filter [52]. These fissure-based methods have great difficulties handling deformed and disrupted fissures, which are caused by complex lung diseases, noise and pathological deformation. The second strategy generally exploited lung anatomical knowledge to identify pulmonary fissures under different frameworks [25], such as alpha expansion [14], the watershed transform [4, 23], atlas-based approaches [39], multilevel B-splines [11] and active contour models [2]. Unfortunately, these lung anatomy-based methods require considerable time for pulmonary trachea and vessel segmentation. Although the third category typically used deep learning models to highlight pulmonary fissure representation, all of these computational methods have the drawback of being time-consuming in the training stage. However, there are no universal methods to remove other structures for pulmonary fissure segmentation [10, 18, 51].

Based on the observation that pulmonary fissures appear as curved-line structures in 2D CT slices and sheet-like structures in 3D CT images, Xiao et al. presented a DoS filter to suppress undesirable interferences and designed a unique postprocessing pipeline to isolate fissure patches [45]. Although plausible results were acquired, many adhering clutters still cannot be removed. To overcome this shortcoming, Peng et al. proposed an ODoS filter by taking advantage of orientation and magnitude information to distinguish between pulmonary fissures and adhering clutters [30]. Similarly, Zhao et al. used a directional derivative of a plate filter to probe fissure objects [52]. However, these fissure-based methods have great difficulties handling deformed and disrupted fissures. Motivated by the fact that lung anatomy is a complementary whole, Bragman et al. used a Gaussian mixture model to highlight fissure representation, and then the pulmonary vessel density and airway tree distance transform were employed to remove irrelevant pulmonary structures [4]. Similarly, Giuliani et al. proposed a sheet-like filter to enhance pulmonary fissures and suppress tubular structures; then, a lung vessel distance map was constructed to acquire purified fissures [14]. Using a different strategy, Peng et al. [32] presented a unique framework by combining the location distribution of different pulmonary anatomical structures and an alpha model to accurately isolate fissure regions and remove adhering sheet-like clutter. Although these lung anatomy-based methods were effective in pulmonary fissure segmentation, they took a great deal of time for pulmonary trachea and vessel segmentation. In addition, a number of studies exploited deep learning models to detect pulmonary fissures. Based on this strategy, Gerard et al. presented a cascade FissureNet approach to segment pulmonary fissures [12], but the computational method has the drawback of being time-consuming in the training stage. To overcome this problem, Roy et al. designed a multiview
deep learning network [28] to highlight fissure representations and save time [34]. However, these deep learning models inherited the shortcomings of machine-learning methods, and a great deal of time was wasted in the training stage. A summarized review of pulmonary fissure segmentation techniques is presented in Table 1.

In this paper, a reliable and valuable scheme is presented for pulmonary fissure segmentation. Inspired by previous works [30, 45], the ODoS filter is used to distinguish between pulmonary fissures and undesirable clutters for pulmonary fissure enhancement in CT images. Subsequently, the shape difference between pulmonary fissures and tubular structures in magnitude and orientation field is exploited to isolate sheet-like structures for pulmonary fissure segmentation. The main contributions of this paper are as follows:

- An ODoS filter is applied to extract orientation and magnitude information for pulmonary fissure enhancement.
- A preprocessing pipeline based on the orientation curvature criterion in 2D space and an orientation partition scheme in 3D space is presented to achieve more complete fissure detection and suppress other structures by using the shape difference in the orientation field.
- A postprocessing pipeline based on the shape measure approach and 3D skeletonization model is introduced to separate pulmonary fissures from clutter by exploiting the shape difference in the magnitude field.
- The merits of 2D line detection and 3D surface models in orientation and magnitude fields are tightly integrated to generate an efficient pulmonary fissure detection scheme.

This paper is organized as follows. The datasets, the manual references and the algorithms are described in detail in Section 2. Section 3 presents the visual inspections and quantitative evaluations of experimental results with different methods. In Section 4, the

| Authors          | Datasets     | Models                                      |
|------------------|--------------|---------------------------------------------|
| Peng et al. [32] | 15 CT images | Alpha Model                                 |
|                  |              | Medial Model                                 |
| Xiao et al. [46] | 55 CT images | ODoS filter                                  |
|                  |              | Multiple section model                       |
| Xiao et al. [45] | 78 CT images | DoS filter                                   |
|                  |              | Branch-point removal algorithm               |
| Peng el al. [30] | 55 CT images | ODoS filter                                  |
|                  |              | Orientation partition scheme                 |
| Zhao et al. [52] | 105 CT images| Directional derivative of a plate filter      |
| Giuliani et al. [14] | 80 CT images | Sheet-like filter                            |
|                  |              | Geodesic distance map                        |
| Bragman et al. [4] | 165 CT images| Multiscale fissure enhancement filter        |
|                  |              | Gaussian mixture model                       |
| Gerard et al. [12] | 3736 CT images| FissureNet                                   |
| Roy et al. [34] | 55 CT images | Multiview deep learning-driven iterative watershed algorithm |
advantages and disadvantages of our scheme are introduced. And in Section 5, a conclusion is drawn by analysing the simulation results.

2 Materials and methods

Pulmonary fissure segmentation in CT images is useful in the diagnosis and treatment of pulmonary diseases. To achieve this purpose, a useful approach based on the ODoS filter and shape features is presented for pulmonary fissure segmentation. First, an ODoS filter is exploited to enhance pulmonary fissures and suppress adjacent interference tissues. Then, a preprocessing pipeline is presented to preserve the completeness of pulmonary fissures and remove parts of clutters. Finally, a postprocessing pipeline is introduced to remove adhering clutter and achieve efficient pulmonary fissure segmentation. Compared with many state-of-the-art methods, the experimental results showed that the proposed scheme has the best performance in pulmonary fissure segmentation.

2.1 Data and reference

In this study, 55 CT scans were selected from the Lobe and Lung Analysis 2011 (LOLA11) dataset [24, 26, 40, 50], which were acquired from different scanners and protocols. To evaluate the performance of our scheme, we regarded the fissure references that were verified by two medical experts [30, 45] as the ground truth to evaluate the proposed scheme.

2.2 Overview of the proposed scheme

In this paper, we present a reliable and valuable method for fissure segmentation. To reduce the impact of nonlung tissues, lung masks [7, 38] are used to extract lung regions in advance. The flow chart of our scheme is shown in Fig. 1.

2.3 ODoS filter

Due to the poor detection of weak and abnormal fissures, Peng et al. [30] presented an ODoS filter to highlight fissure representation. The main idea is to take advantage of the intensity and orientation difference between fissures and their surrounding tissues. As shown in

![Fig. 1 The framework of the computational scheme](image-url)
Fig. 2, the ODoS filtering kernel [30, 45] is composed of the left (Ls), middle (Ms) and right (Rs) sticks with different colors, where $\theta$ and $S$ represent the filtering orientation and the interstick spacing, respectively. To better express the ODoS filter, the mean intensities along the left, middle and right sticks are denoted as $u_L$, $u_M$ and $u_R$, respectively. The nonlinear differentials perpendicular to the filtering kernel were defined as [45]

$$
\lambda_{S,\theta}^{\perp,\max}(x) = \max(u_M - u_L, u_M - u_R) \\
\lambda_{S,\theta}^{\perp,\min}(x) = \min(u_M - u_L, u_M - u_R)
$$

(1)

(2)

where $x$ denotes the spatial location in CT images.

To suppress tubular structures, a tubular structure suppression operator was defined [45]

$$
\lambda_{S,\theta}^{\parallel}(x) = \sqrt{E(I_j^2) - (E(I_j))^2}
$$

(3)

Therefore, the fissure line strength measures can be described as

$$
l_{S,\theta}^{\max}(x) = \lambda_{S,\theta}^{\perp,\max}(x) - \kappa \cdot \lambda_{S,\theta}^{\parallel}(x)
$$

(4)

$$
l_{S,\theta}^{\min}(x) = \lambda_{S,\theta}^{\perp,\min}(x) - \kappa \cdot \lambda_{S,\theta}^{\parallel}(x)
$$

(5)

Here, $\kappa$ is equal to 0.7 [45].

Considering that the intensity of fissures is greater than that of surrounding tissues, the 2D line strength measure functions were defined by Xiao et al. [45]

$$
F_{\max}(x) = \max\left(\max_{1 \leq i \leq 2(L-1)} (l_{S,\theta}^{\max}), 0\right)
$$

(6)

$$
F_{\min}(x) = \max\left(\max_{1 \leq i \leq 2(L-1)} (l_{S,\theta}^{\min}), 0\right)
$$

(7)

Fig. 2 ODoS filtering kernel. (a) The ODoS filtering kernel in the right lung. (b) The ODoS filtering kernel in the left lung.
where \( L = 11 \) and \( \theta \) represent the stick length and orientation, respectively. Subsequently, a cascaded scheme was established to enhance pulmonary fissures and suppress pathological abnormalities. Mathematically

\[
F_o(x) = F_{\text{max}}(x) \circ F_{\text{min}}(x)
\]

(8)

Here, \( \circ \) indicates the cascading operator [45]. The response \( F_o \) from the sagittal, axial and coronal cross-sections is denoted as \( F_S \), \( F_A \) and \( F_C \), respectively.

Motivated by the reality that \( F_{\text{max}} \) plays the major role in \( F_o \) for pulmonary fissure enhancement, the orientation response was described as follows [30]:

\[
\theta_{\text{max}} = \arg \max_{1 \leq i \leq 2(L-1)} (L - 1) (l_{S,i}^{\theta_{\text{max}}})
\]

(9)

A vector representation

\[
\vec{V}_{\text{max}}(\theta_{\text{max}}) = (\cos \theta_{\text{max}}, \sin \theta_{\text{max}})
\]

(10)

Therefore, the vectors \( \vec{V}_{\text{max}} \) from sagittal, axial and coronal cross-sections are denoted as \( \vec{V}_S^{\text{max}}, \vec{V}_A^{\text{max}} \) and \( \vec{V}_C^{\text{max}} \), respectively.

Inspired by the geometric representation of the vesselness filter [16, 35, 37, 48], a shape-tuned response was defined as

\[
F^{3D} = (F_A^o + F_S^o + F_C^o) \ast \frac{\text{median}(F_A^o, F_S^o, F_C^o)}{\text{max}(F_A^o, F_S^o, F_C^o)}
\]

(11)

As a result, the intensity and orientation response of the ODoS filter can be fused into a vector form

\[
\vec{F}(\theta_{\text{max}}) = F^{3D} \ast \vec{V}_{\text{max}}(\theta_{\text{max}})
\]

(12)

To illustrate the validation of the ODoS filter, a sagittal slice and its corresponding vector field are given in Fig. 3(a) and (b). Figure 3(c) denotes the magnified rectangular region of Fig. 3(b). As observed, the vector field was regularized by the ODoS filter. Subsequently,
Fig. 4 Orientation curvature criterion. (a) Subregion $R_i$. (b) The filtering results after using the orientation curvature criterion

a minimal threshold $T = 1$ [30] was selected to avoid some fissures being eliminated as clutter. Mathematically

$$\vec{F}_v(\theta_{\text{max}}) = \begin{cases} \frac{\vec{F}(\theta_{\text{max}})}{F^{3D}}, & F^{3D} > T \\ 0, & \text{others} \end{cases}$$ (13)

Different from traditional methods, we adopt an ODoS filter by merging the magnitude and orientation information to highlight pulmonary fissure representation, which can effectively distinguish between pulmonary fissures and clutters.

### 2.4 Preprocessing pipeline

Although the above operations have a perfect performance in pulmonary fissure enhancement, some undesired structures, such as vessels and airways, still cannot be eliminated. To eliminate undesired structures, an orientation curvature criterion and an orientation partition scheme are fused to separate candidate fissure profiles from clutters in the orientation field.

To suppress clutters, the normalized vector $\vec{F}_v(\theta_{\text{max}})$ is divided into $n = 8$ [30] overlapped subregions and denoted as $R_1, R_2, ..., R_{n-1}$ and $R_n$. Mathematically,

$$\vec{F}_{vi} = \begin{cases} \vec{F}_v(\theta_{\text{max}}), & \theta_{\text{max}} \in R_i \text{ and } |\vec{F}_v(\theta_{\text{max}})| > 0 \\ 0, & \text{others} \end{cases}$$ (14)

In each subregion $R_i$, pulmonary fissures appear as linear structures in 2D space. Therefore, pulmonary fissures have similar orientations in 2D space. As shown in Fig. 4(a), all objects in the subregion are denoted as $S_1, S_2, S_3,..., S_{m-1}$ and $S_m$, and the corresponding orientations are labeled with $\theta_1, \theta_2, \theta_3,..., \theta_{m-1}$ and $\theta_m$. We consider the object $S_i$ with the orientation $\theta_i$ belonging to $[\theta_x, \theta_y]$ as fissures and others as clutters in 2D space. Here,
\[ \theta_i(S) \subset [\theta_x, \theta_y] \] (15)

After using the orientation curvature criterion, clutters were removed. As shown in Fig. 4(b), the approach has good performance in clutter suppression.

In the same way, in each subregion \( R_i \), pulmonary fissures appear as planar structures in 3D space, and an orientation partition scheme is adopted to remove clutters. As shown in Fig. 5, in each subregion, pulmonary fissures appear as planar structures, and clutters appear as small structures due to their shape features. Based on this theory, a connected component analysis \([15, 41]\) is used to select candidate fissures and eliminate small structures. Finally, all of the candidate fissures are integrated to form a complete fissure patch.

Unfortunately, Peng et al. [30] used only sagittal information alone to detect pulmonary fissures, and the approach may cause parts of fissures to be undetected. To address this problem, we integrate the sagittal, axial and coronal information to compensate for the drawback.

The fissure patches detected using the sagittal, axial and coronal information to enhance pulmonary fissures are shown in Fig. 6(a), (b) and (c), respectively. Figure 6(d) shows the corresponding integrated results. It can be seen that the simple strategy can effectively detect complete fissures. Using only sagittal information may cause parts of fissures (marked with red arrows) to be undetected.

### 2.5 Postprocessing pipeline

After using the preprocessing pipeline, some undesired structures, such as vessels and airways, still cannot be eliminated. To solve this problem, a shape measurement approach and
a 3D skeletonization model are combined to segment pulmonary fissures for clutter removal in the magnitude field.

Pulmonary fissures appear as curvilinear profiles in sagittal slices, and clutters such as airways and vessels appear as tubular structures in 2D space. A MATLAB function 'region-props' was used to acquire the selected object property for tuber structure removal. In this section, $K_1, K_2, K_3, \ldots, K_{n-1}$ and $K_n$ were used to represent the selected object, $H$ was the major axis length of $K_i$, and $W$ was the minor axis length of $K_i$. To remove tuber structures, a shape measure approach [1, 36, 46] was used:

$$W(K_i)/H(K_i) \geq T_s$$

where $T_s$ is a threshold value. The purpose is to remove tubular structures.

As shown in Fig. 7, parts of clutters are labeled with red circles in Fig. 7(b). After using the shape measure approach, the clutter is removed from the filtering image, and the final results are labeled with $Q$. 

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**Fig. 6** Integrating the sagittal, axial and coronal information. (a) Sagittal information. (b) Axial information. (c) Coronal information. (d) Integration
As shown in Fig. 8, the threshold $T_s$ is too large, which may result in much clutter being unremoved. In contrast, if the threshold $T_s$ is too low, it may cause parts of fissures to appear as clutter and be removed. To address this problem, a clutter removal method based on a 3D skeletonization model [19, 29, 49] is presented to achieve complete fissure segmentation. The main idea is to select fissure profiles from clutters by breaking their connectivity with the 3D skeletonization model. As shown in Fig. 9, the detailed algorithms mainly consist of five steps: 3D skeletonization, branch-point removal, connected component analysis, hole-filling and fissure repair.

Step 1. The 3D skeletonization model is adopted to thin the filtering image $Q$ by computing the complex medial axis of the objects. The purpose is to ensure the invariance of the
 objects’ topological structures and geometric features. Therefore, the 3D Euler criterion $X(Q)$ is employed by the global formula

$$X(Q) = O(Q) - H(Q) + C(Q)$$

where $Q$ is the filtering image and $O(Q)$, $H(Q)$ and $C(Q)$ are the numbers of connected objects, holes and cavities of $Q$, respectively. The filtering image $Q$ can be treated as a finite collection of points. Therefore, a local formula $G(Q)$ can be exploited to reduce
the computational complexity of the global formula \( X(Q) \). The local formula \( G(Q) \) from algebraic topology can be translated as

\[
G(Q) = v - e + f - t
\]  

(18)

where \( v, e, f \) and \( t \) represent the number of vertices, edges, faces and octants in \( Q \), respectively.

To ensure the invariance of the objects’ topological structures and geometric features for thinning operations, the change of the Euler characteristic \( \delta \) is useful in the sense of the Euler criterion in a 3*3*3 cube

\[
\delta G(Q) = \frac{1}{8} - \frac{\delta e}{4} + \frac{\delta f}{2} - \delta t = 0
\]  

(19)

where \( \delta t, \delta f \) and \( \delta e \) represent the changes in the number of octants, faces and edges in the 3*3*3 cube, respectively. In this section, an Euler table for six connected objects is adopted to extract the medial axes of the filtered CT images \( Q \), and the skeletonized image is denoted as \( Q_k \). As shown in Fig. 9, airways and vessels are thinned into single-pixel structures. Generally, the branching regions among fissures, airways and vessels are thinned into branch points. In other words, the branch points are removed from the filtered binarized image, and pulmonary fissures, airways and vessels are naturally separated from each other.

**Step 2.** A practical and useful approach is used for branch-point removal in the skeletonized image \( Q_k \). In 3D CT images, pulmonary fissures resemble planar structures, whereas airways and vessels appear similar to tubular structures. Based on this reality, a simple but effective approach is defined

\[
|((N_{26}(p)) \cup Q_k)| \geq 4
\]  

(20)

where \( p \) and \( N_{26} \) denote the pixel in the skeletonized objects \( Q_k \) and its 26 neighborhood regions, respectively. As shown in Fig. 10, Figure 10(a) and (c) represent the tubular structures, Figure 10(b) and (d) represent the bifurcated structures, and the green dots and yellow dots denote \( p \) and its 26 neighborhood regions, respectively. If there are four or more points within a 3*3*3 cube (\( p \) and its neighborhood of 26), we regard the pixel \( p \) as the branch point. After removing all branch points, the complex branching structures, such as airways and vessels, are naturally divided into a series of small fragments.

**Step 3.** The connected component analysis is used to select the candidate fissures. After removing the branch points, the pulmonary fissures still retained good connectivity, whereas the airways and vessels were divided into small fragments. Based on this strategy, connected component analysis is adopted to remove clutter. Generally, the branching regions among fissures, airways and vessels are thinned into branch points. In other words, the branch points are removed from the filtered image, and pulmonary fissures, airways and vessels are naturally separated from each other.

**Step 4.** A hole-filling algorithm is used to achieve complete segmentation. There is a large number of holes in the candidate fissure surfaces. To circumvent the problem, we put the previously eliminated branch points back to fill the holes. Finally, a volume sorting scheme [30, 45] is employed to isolate fissure profiles for pulmonary fissure segmentation. The segmented fissure is denoted as \( Q_S \).

\[
Q_L = Q - Q_S
\]  

(21)
As a result, clutters are treated as larger objects in the remaining objects $Q_L$, the larger objects $B_1 = \max(Q_L)$, $B_2 = \max(Q_L - B_1)$, ..., $B_n$. Therefore, small objects in the remaining image $Q_L$ are preserved

$$Q'_L = Q_L - \sum_{i=1}^{n} B_i$$  \hspace{1cm} \text{(22)}

Subsequently, the small objects $Q'_L$ and the segmented fissure $Q_S$ are mathematically integrated into many objects:

$$Q''_L = Q'_L + Q_S$$  \hspace{1cm} \text{(23)}
Finally, a connected component analysis approach is used to select larger objects from $Q''_L$ as the final segmented pulmonary fissures. As shown in Fig. 9, the missed fissure (labeled with red arrows) can be repaired.

3 Experimental results

In this section, our scheme is validated on the LOLA11 dataset. The corresponding code is implemented with a hybrid program by combining MATLAB and C++, and pleasant 3D visualization results are achieved by MeVisLab software [5, 6]. All experiments are carried out on a Windows 10 system running on a computer with 20 GB of RAM and a 3.00 GHz CPU. As a comparison, seven typical methods designed by Klinder et al. [20], Xiao et al. [46], Xiao et al. [45], Peng et al. [30], Wiemker et al. [44], Doel et al. [11], and Roy et al. [34] were implemented and applied to the same dataset. The runtimes with seven different state-of-the-art methods for a typical 400*512*512 size image are listed in Table 2. As depicted in Table 2, these Hessian-based methods [11, 20, 44] require less time for pulmonary fissure segmentation. While these deep learning methods [12] have the drawback of being time-consuming in the training stage. Although the proposed method takes more time than the methods of Klinder et al. [20], Peng et al. [30], Wiemker et al. [44], and Doel et al. [11], it has the best performance in pulmonary fissure segmentation in CT images.

3.1 Evaluation criteria

In this study, a 3 mm width around the segmented fissure is labeled as $S_1$, whereas a 3 mm width around the corresponding ground truth is denoted as $R_1$. The overlapped areas between the segmented fissure and $R_1$ are treated as $TP_1$, and the rest are $FP$. In a similar way, the overlapped areas between the ground truth and $S_1$ are treated as $TP_2$, and the rest are $FN$. Accordingly, the false discovery rate ($FDR$), false negative rate ($FNR$) and F1-score ($F_1$) are defined as

$$FDR = FP / (TP_1 + FP)$$

$$FNR = FN / (TP_2 + FN)$$

$$F_1 = \frac{2(1 - FDR)(1 - FNR)}{2 - FDR - FNR}$$

| Methods                  | Runtime(400*512*512 size image) |
|--------------------------|---------------------------------|
| The proposed method      | 1460s                           |
| Klinder et al. [20]      | 320s                            |
| Xiao et al. [46]         | 1410s                           |
| Xiao et al. [45]         | 1470s                           |
| Peng et al. [30]         | 1390s                           |
| Wiemker et al. [44]      | 130s                            |
| Doel et al. [11]         | 600s                            |
| Roy et al. [34]          | 3600s                           |
3.2 Visual inspection

To select an optimal threshold $T_s$ in the shape measure approach, one representative segmentation is chosen with a different threshold. As shown in Fig. 11, the threshold is too low, which may cause parts of fissures (marked with red ellipses) to be undetected. In contrast, if the threshold is too large, it may cause parts of clutter (marked with red arrows) to be unremoved.

To demonstrate the segmentation performance, we compared the computerized scheme against three typical methods [11, 30, 45]. Figure 12(a), (b), (c) and (d) show the computerized scheme, ODoS [30], DoS [45] and fissureness filter [11] filtering segmentation, respectively. The segmentation results, the ground truth and their overlapped areas are rendered in green, yellow and purple. The benefits of the computerized scheme can be discovered in the areas marked with red ellipses. Weak and abnormal fissures can be found by
Fig. 12  Pulmonary fissure segmentation with different methods. (a) The proposed method. (b) ODoS filter [30]. (c) DoS filter [45]. (d) Fissureness filter [11]

our scheme and lead to a lower FNR value. Experimental results show that the computerized scheme performs well in weak and abnormal fissure segmentation.

3.3 Quantitative evaluation

The box plots of indices corresponding to the computational scheme with different thresholds $T_s = 0.4$, $T_s = 0.5$, $T_s = 0.6$ and $T_s = 0.7$ are shown in Fig. 13. The corresponding median values are reported in Table 3. Both visual inspection and quantitative evaluation illustrated that $T_s = 0.5$ is the most appropriate choice in our computational scheme.

In Fig. 14, the box plots of indices corresponding to the computational scheme (s), ODoS (o), DoS (d), and Fissureness (f) filtering scheme are drawn next to each other. The median values are reported in Table 4. Both visual inspection and quantitative evaluation illustrated that the computational method can outperform the compared methods [11, 30, 45].
Fig. 13  Quantitative evaluation of the computational scheme with different thresholds $T_s$

Table 3  The indices of different thresholds in the public LOLA11 dataset

| Threshold $T_s$ | $F_1$ | $FDR$ | $FNR$ |
|----------------|------|------|------|
| 0.4            | 0.89 | 0.10 | 0.11 |
| 0.5            | 0.90 | 0.11 | 0.10 |
| 0.6            | 0.90 | 0.11 | 0.09 |
| 0.7            | 0.89 | 0.12 | 0.09 |

Fig. 14  Segmentation validation on the LOLA11 dataset with different methods

Table 4  The indices of four different methods in publicly LOLA11 dataset

| Methods               | $F_1$ | $FDR$ | $FNR$ |
|-----------------------|------|------|------|
| The computational scheme | 0.90 | 0.11 | 0.10 |
| ODoS                  | 0.88 | 0.07 | 0.15 |
| DoS                   | 0.83 | 0.10 | 0.24 |
| Fissureness           | 0.82 | 0.10 | 0.26 |
In Table 5, compared with many different methods, the proposed method has the largest median F1 values, which indicates that the presented method can efficiently segment fissures in 3D CT images. The proposed method has the lowest median FNR value, which means that the presented method has good performance in the detection of weak and abnormal fissures.

4 Discussion

In this study, a computerized scheme based on an ODoS filter and shape features is introduced for pulmonary fissure segmentation in CT images. In terms of methodology, our scheme has many unique merits and characteristics. First, an ODoS filter based on a vector field instead of the intensity field is developed to enhance pulmonary fissures, which can accurately discriminate between fissure profiles and other tissues. Second, an orientation curvature criterion and an orientation partition scheme are combined to highlight fissure representation and suppress clutter. The original orientation partition scheme may cause parts of weak and abnormal fissures to be undetected. Third, the postprocessing pipeline is performed on pulmonary fissure segmentation under a 3D branch-point removal framework. Unlike traditional methods [20, 45] that work in 2D space, this operation reasonably expels clutter. In addition, with the help of the improved ODoS filter, orientation curvature criterion, orientation partition scheme and 3D skeletonization model, our scheme is expected to preserve the integrity of weak and abnormal fissure segmentation.

The computerized scheme outperformed these typical state-of-the-art methods [11, 12, 20, 30, 44–46]. The experimental results show that our scheme performs well in weak and abnormal fissure segmentation. Compared with the ground truth, the proposed method obtained a higher F1-score of 0.90 than the compared methods. The reason is that the computerized scheme used sagittal, diagonal and coronal information to detect weak and abnormal fissures, and then a 3D branch-point removal framework was designed to segment fissures. Peng et al. [30] employed only sagittal information, which may cause some fissures to be undetected. In contrast, Xiao et al. applied only the intensity information to segment fissures, and parts of fissures were regarded as clutters and removed [45]. Using a different method, Doel et al. utilized a 3D vessel distance transform to suppress clutter [11]. Unfortunately, parts of vessels cross fissures, which may cause some fissures to be simultaneously suppressed.

| Methods             | $F_1$ | $FDR$ | $FNR$ |
|---------------------|-------|-------|-------|
| The proposed method | 0.90  | 0.11  | 0.10  |
| Klinder et al. [20] | 0.58  | 0.09  | 0.57  |
| Xiao et al. [46]    | 0.89  | 0.09  | 0.12  |
| Xiao et al. [45]    | 0.83  | 0.10  | 0.24  |
| Peng et al. [30]    | 0.88  | 0.07  | 0.15  |
| Wiemker et al. [44] | 0.69  | 0.09  | 0.45  |
| Doel et al. [11]    | 0.82  | 0.10  | 0.26  |
| Roy et al. [34]     | 0.89  | No    | No    |
However, the computerized scheme has many shortcomings and disadvantages. The fatal limitation of our scheme is the longer computation time. Although the proposed method takes more time than the approaches of Klinder et al. [20], Peng et al. [30], Wiemker et al. [44], and Doel et al. [11], it has the best performance in pulmonary fissure segmentation in CT images. In addition, parts of pathological clutters appear as planar structures, which cannot be eliminated by the computerized scheme. As shown in Fig. 15, the adhering planar clutters are marked with red arrows and cannot be removed by the proposed method. Although our scheme has many drawbacks, the integrity of the fissure segmentation has been greatly improved under the fissure segmentation framework.

5 Conclusion

In this paper, a reliable and valuable computerized scheme is presented for fissure segmentation. Considering the reality that pulmonary fissures resemble line-curved structures in 2D space and planar structures in 3D space, an ODoS filter and an orientation partition scheme are developed to highlight pulmonary fissures and suppress clutters, which are expected to achieve more complete fissure detection. Another contribution of our scheme focuses on the processing pipeline. Using an ingeniously designed shape difference strategy between pulmonary fissures and tubular structures in the magnitude and orientation fields to isolate weak and abnormal fissure patches in CT images finally leads to more complete and purified fissure segmentation. Compared with seven typical state-of-the-art methods, our scheme has a satisfactory pulmonary fissure segmentation performance. In the future, many methods, such as deep learning frameworks [3, 21], prior knowledge-based segmentation [17, 43] and feature extraction [8, 27, 47], may be adopted to improve the presented framework. In particular, pathological clutter removal will be the focus of our attention.

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**Data Availability** The LOLA11 dataset can be downloaded in the website [https://lola11.grand-challenge.org/](https://lola11.grand-challenge.org/).

**Declarations**

**Ethics approval and consent to participate** Not applicable

**Consent for Publication** Not applicable

**Conflict of Interests** The authors declare no conflicts of interest.

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