**Pulmonary lobar segmentation from computed tomography scans based on statistical shape model**

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**Abstract**

Automatic identification of pulmonary lobes from imaging is important in lung disease assessment and treatment planning. However, the pulmonary lobar fissure can be difficult to detect automatically, as it is thin, can often run close to the imaging plane, and can be obscured by or confused with features of disease. In this study, we aim to overcome difficulties in identifying pulmonary fissures by using a statistical shape model to guide lobar segmentation. By deforming an average lobar model onto an individual’s lung shape, we predict fissure locations approximately, to refine our search region for lobar structures. Then, we use an eigenvalue of Hessian matrix analysis and a connected component eigenvector based analysis to determine a set of fissure-like candidate points. A smooth multi-level B-spline curve is fitted to the most fissure-like points (those with high fissure probability) and the fitted fissure plane is extrapolated to the lung boundaries. The method was tested on 20 inspiratory and expiratory CT scans in healthy young subjects and older subjects with idiopathic pulmonary fibrosis. A quantitative evaluation showed that the mean difference of left oblique, right horizontal and right oblique fissure to the reference was 2.06mm, 4.06mm and 2.85mm for healthy cases and 3.41mm, 5.79mm and 5.01mm for pathological cases.

**1 Introduction**

Human lungs are divided into five lobes which form distinct anatomical regions separated by a fissure. Identification of these lobes in imaging is of great importance for assessment of lung disease severity and treatment planning [ref]. For clinical applications, the distribution and location of pulmonary disease are beneficial for doctors to recognize pathogenesis, guide therapy and have further value in surgical planning. The lobes are difficult to segment automatically as they can appear as faint or fuzzy lines in imaging, fissures can be incomplete (even in healthy patients), and there is anatomical variation in lobe shape and size between individuals [more refs(Gülsün et al 2006).]. This anatomical variation is usually associated with age, sex and body type [refs].

In a broad sense, existing algorithms that aim to automatically segment pulmonary lobes consist of two steps: lung segmentation and fissure detection. Lung segmentation lung segmentation methods are well-established and results are typically reliable [refs]. In contrast, automated fissure detection is challenging [refs]. Some proposed fissure detection methods make use of either local or global knowledge of lung anatomy, such as airway and vessel trees, to identify fissures [refs]. For example, there are not typically any large vessels in the vicinity of lobar fissures, so fissures should be located in the gaps between airway and vessel trees. These methods can be time consuming as airways and blood vessels must be identified as an intermediate step. A second class of fissure detection algorithm makes use of gray-level information and shape information to detect the fissures [ref]. Generally, lobar fissures can be regarded as bright planes crossing the pulmonary volume because of the higher density value of fissures comparing to the surrounding tissues [ref]. Based on this information, several published methods use local filtering algorithm to detect the voxels which lie on these planes, so that these detected voxel points can construct a continuous fissure surface (van Rikxoot et al 2008, Ukil and Reinhardt 2009, Lassen et al 2013, Ross et al 2010, Doel et al 2012). These algorithms often face problems when lobe fissures are blurry or incomplete.

In this paper, we propose a statistical shape model (SSM) guided method to segment pulmonary lobes from CT images. Our new procedure does not depend on prior segmentation of anatomical structures (airway lobar classification) and has promising potential as a clinically useful automatic lobe segmentation procedure. A user-interactive interface is also developed for user to control and visualize the whole segmentation process and, if necessary, do some manual correction on the segmentation results.

1. **s**

We follow a three-step approach for lobe segmentation (Fig 1): in the first step, a threshold-based lung segmentation method defines the lung boundary. In the second step, a statistical shape model is deformed provide a ‘search region’ for fissure locations. In the third step, fissures are located using a Hessian matrix protocol combined with connected component filters and surface fitting algorithm.

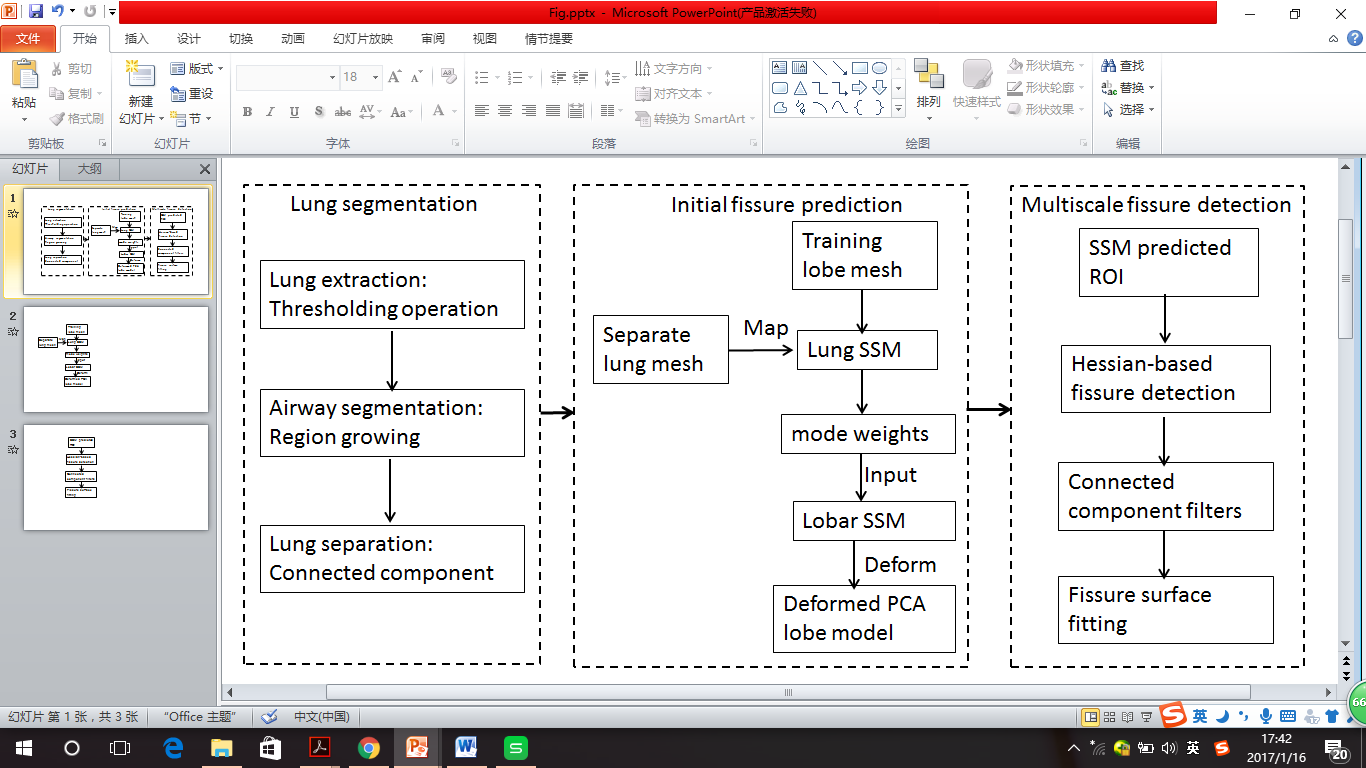


Fig. 1. Flow diagram of the lobar segmentation process.

* 1. Lung segmentation

Here we use commonly used thresholding method to segment lungs [ref]. The method uses a thresholding operation (-775 Hounsfield Units) and connected component identification to find an initial approximation to the lung regions and trachea location. Using the most apical point of trachea as a start point, a region growing technique is applied to detect the airway trees. Then, left and right lungs are separated as the two largest connected components remaining after removing the trachea and main left and right bronchi.

2.2 Active shape model of lung shape

A Statistical Finite element analysis of Lobe (SFeaL) which is based on an active shape model (ASM) of the lung is constructed and deformed onto the individual’s images to predict an initial fissure to guide fissure detection. The SFeaL model was constructed using a training set consisting of imaging of the lung … The open-source visualization software CMGUI (<https://www.cmiss.org/cmgui>) was employed to manually digitize all three fissure points between adjacent lobes by an expert user to provide a gold-standard fissure location for each subject in the training set.

A finite element volume mesh is used to describe the shape of the lung and its fissures both in terms of the ASM and also to define initial fissure location in the segmentation algorithm. A high order (bi-cubic Hermite) finite element mesh template was fitted to lung surface data obtained from the lung segmentation (Section 2.1). The template mesh for the left lung mesh has 35 nodes and 44 elements, while the right lung mesh has 50 nodes and 62 elements. Each node has 12 degrees of freedom (DoF) which store the global coordinates and first and second nodal derivatives. A least squares fit of the mesh to the lung surface data was conducted using CMISS (<https://www.cmiss.org>), a finite element modeling environment. The average root mean square (RMS) error of this fitting method was 0.52mm for the 30 training subjects (Fig 3(a)).

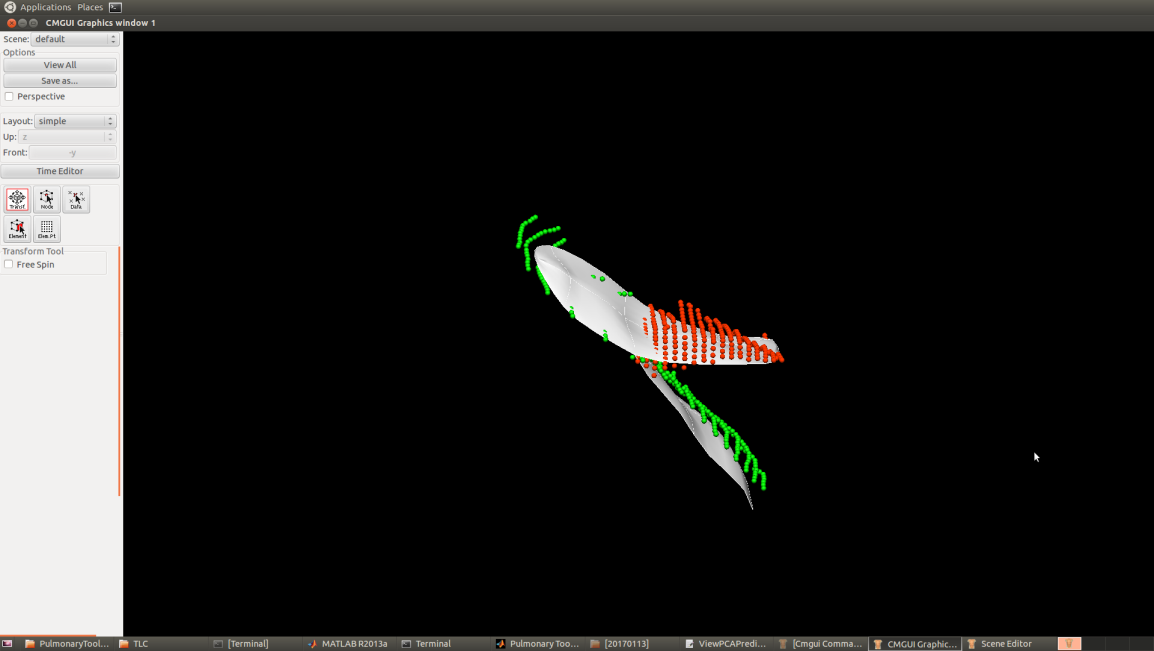
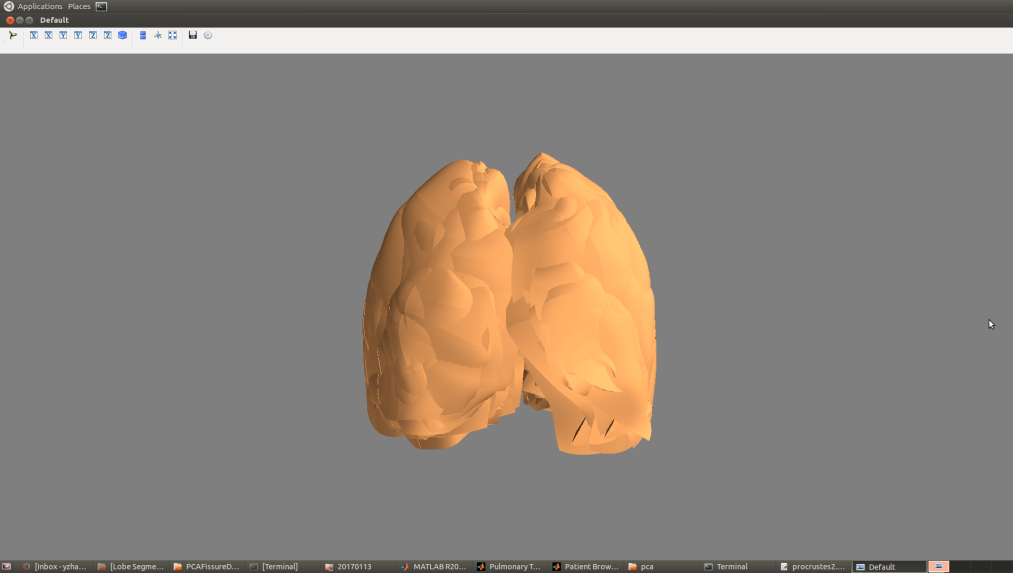
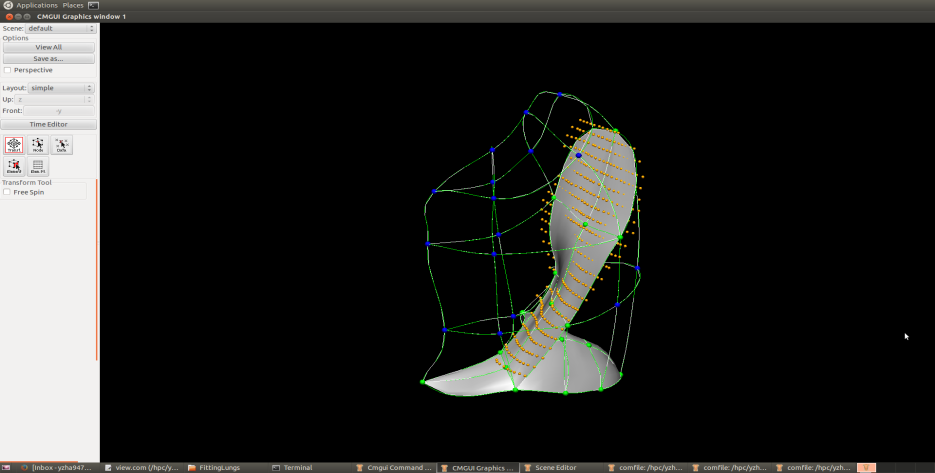
To construct the ASM, each node in the finite element mesh was used as a pseudo-landmark and a principal component analysis (PCA) conducted on the training set. To remove the orientation and scaling differences between shapes, a general procrustes alignment (GPA) method was used to minimize the distance between subjects through calculating the optimal rotation matrix and translation (Fig 3(b)) [ref]. The volumes of all the subjects were normalized to 1L during the processing. The procrusted aligned meshes is represented by

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where p is the total node number of all the subjects (2550 nodes for our study, 30 subjects in total), and the over-line represents GPA to the mean. The matrix B was then decomposed into modes of variation by a PCA [ref]. Each mode symbolizes one type of lobe shape variation. PCA is a statistical procedure using an orthogonal transformation to help us find the principle components, which here are the modes with the most lobar shape variation through analyzing the eigenvectors and eigenvalues of the covariance matrix of the data matrix B. The results of principle components of variation showed that the first seven principal components account for over 90% of the total variation. The PCA provides a definition of a statistically averaged lobar shape.

2.2 Initial prediction of lobar location in an individual

To predict the fissure locations in volumetric CT imaging from a subject not part of the training cohort a finite element mesh of the lung surface (without fissure information) is generated for this subject. This lung surface mesh is projected on to the PCA-trained average lung statistical mesh (no fissure surfaces). The principal component weight values were calculated from the projection and these weights were then used on the deformation of PCA-trained average lobar statistical mesh (with fissure surfaces) to derive an initial estimation of fissure locations (Fig 3(c) (d)). This initial ASM based prediction of lobar fissures provides a reduced search area for subsequent image analysis and ensures definition of complete lobar structures even if a fissure is incomplete or difficult to detect in a small region of the image.



1. (b) (c) (d)

Fig. 3. SSM based initial fissure prediction results. (a) Lung surface fitting and fissure digitizing manually. (b) Procrustes aligned meshes of 30 subjects. (c) (d) Fissure prediction compared to manual tracing points. White mesh is the predicted fissure surfaces.

2.3 Multiscale Hessian-based fissure detection

The location of ASM predicted fissure planes (Fig 3d) are used to guide a Hessian based fissure detection in an individual. Gaussian filters with a range of kernel sizes from 0.5mm to 2.5mm was applied to the image set. The responses at each are combined to get a maximum response for each voxel of the image. This multiscale operation guarantees fissures of variable size can be captured by Hessian operations. At each image voxel, the Hessian matrix was constructed as a symmetric matrix. For a fissure structure, which presents as a light plane on a dark background two large positive second derivatives across the plane and a small second derivative (of either sign) along the plane are expected. This is reflected in the Hessian matrix as two small eigenvalues corresponding to the eigenvectors along the fissure planes and one large eigenvalue perpendicular to the plane. Thus with the relationship of eigenvalues , , is defined as . is expected to much larger than and at the fissure. From these characteristics, we can get a fissure probability of each voxel derived as follows:

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The parameter surpresses, and is defined as

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Splane detects plane or :

Swall suppresses signals of noise and ‘blob’-like structures:

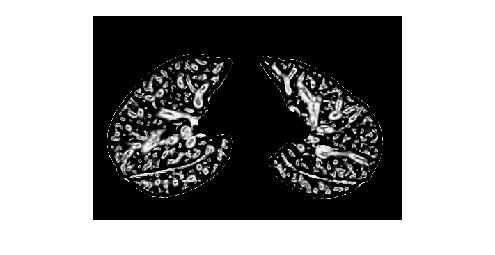
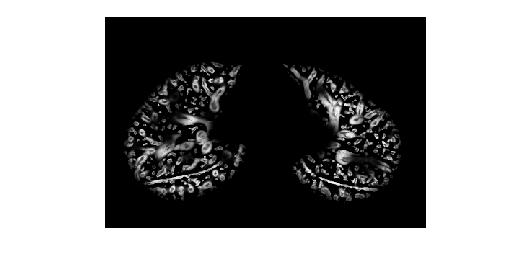
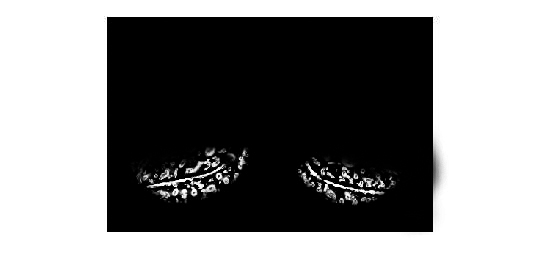
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S then gives a high response to local sheet-like structures such as fissures and suppresses other pulmonary structures. An example of a fissure enhancement filter applied in an individual is shown in Fig 4(a).

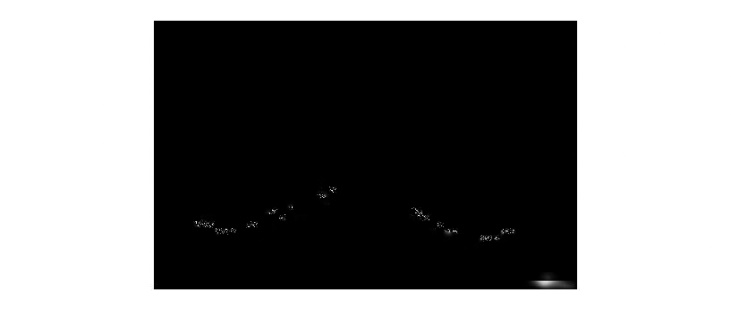
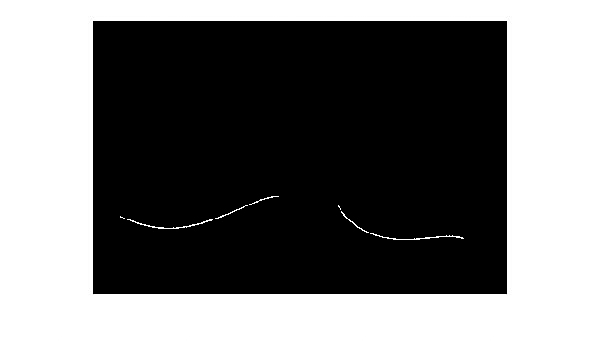
Blood vessels, which appear as similar structures locally to fissures are removed from the fissure enhanced result using prevousy described methods (Frangi et al 1998), which removes tube-like structures with , , (Fig 4(b)).

The fissure location predicted by the ASM allows definition of a search region for the fissure (Fig. 4(c)). Candidate points are selected within a certain distance of the initial fissure approximation. A 2D, 4-neighborhood connected component filter and a 3D 6-neighborhood vector-based connected component filter are employed successively to eliminate noise arising from small plane-like structures in this search region (Fig 4(d)). The vector-based connected component filter uses the inner product of the normalised largest eigenvector of the Hessian matrix in adjacent voxels. These largest eigenvectors are perpendicular to the fissure plane, and their inner product provides a criterion for component connection. As fissure curvature of a fissure is locally low, adjacent fissure voxels should have similar largest eigenvectors and thus large inner product values.

The detected points are then divided into a set of small subsections corresponding to different . For each subsection, the point of the highest fissure probability (the highest S value) is selected as the finial candidate fissure point (Fig 4(e)). Then a continuous smooth fissure surface is generated using a B-spline method with a thin-plane spline and extrapolated to the lung boundaries, see Fig 4(f).

1. (b) (c)

(d) (e) (f)

Fig.4. Hessian-based multiscale fissure detection results. (a) Hessian-based fissure enhancement. (b) Remove vessel voxels. (c) ROI of fissure locations based on SSM projection. (d) 2D and 3D eigenvector based connected component filter. (e) Fissure candidate points. (f) B-spline curve fissure surface fitting.

2.4 Interactive user control interface

For a successful lobar segmentation a series of parameter values need to be defined. However, one fixed value of parameter is usually not suitable for all the subjects due to a wide variation of lung tissue and fissure appearances across the population. Therefore, a fast and convenient interactive way to control the segmentation procedure may be necessary on a case by case basis. Based on an open source Pulmonary Toolkit (PTK, <https://github.com/tomdoel/pulmonarytoolkit>), we developed an improved user-friendly interactive interface to control the segmentation parameters as input. By making use of some built-in objects and visualization system of PTK, we add our lobar segmentation algorithm into the algorithm package and make parameter control buttons available on the interface (Fig 5).

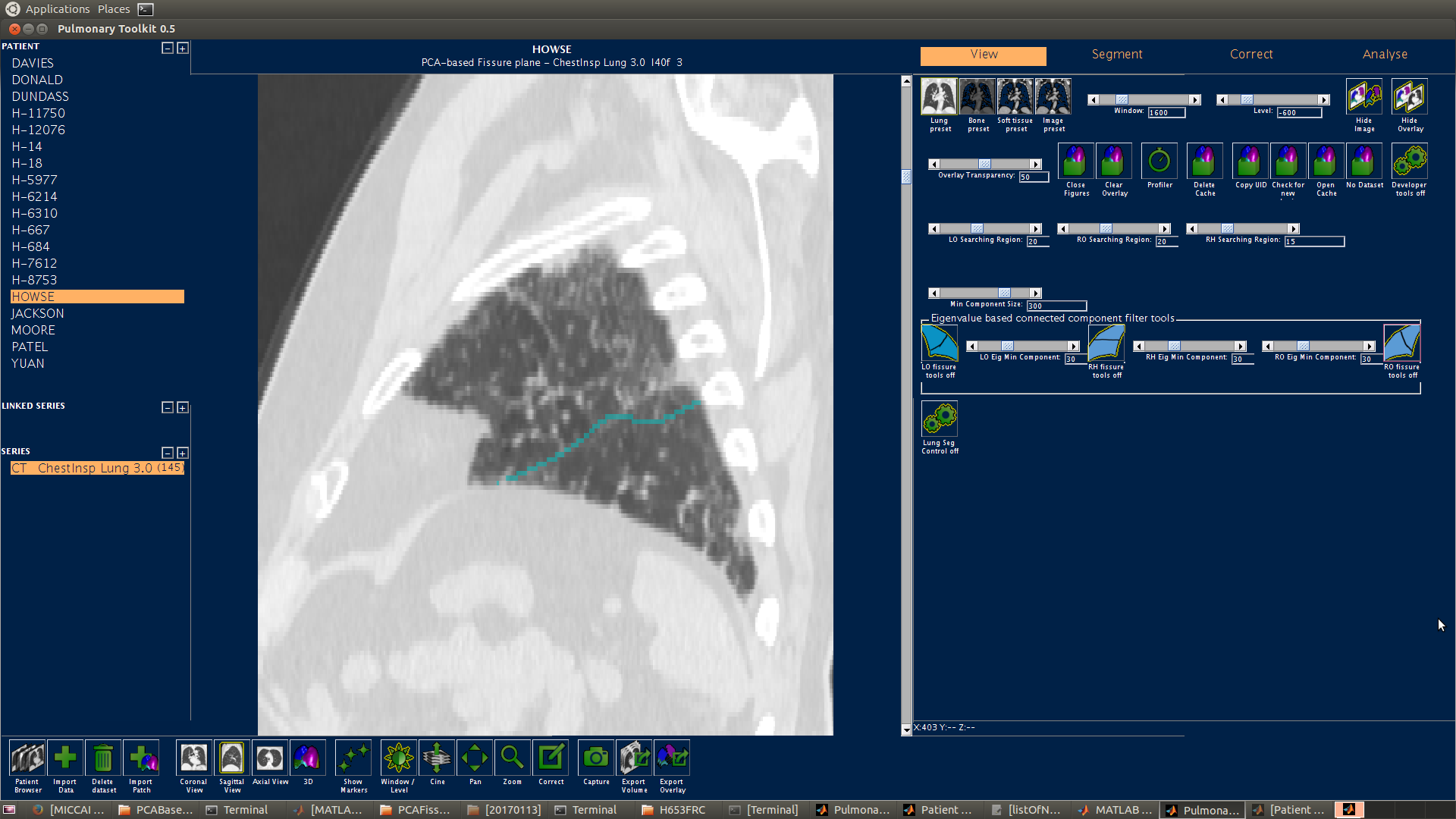


Fig. 5. User interactive interface. The yellow frame shows the slides for changing search region size of fissure detection, the red frame shows the slides for changing connected component sizes for each filter.

1. **Experiment**

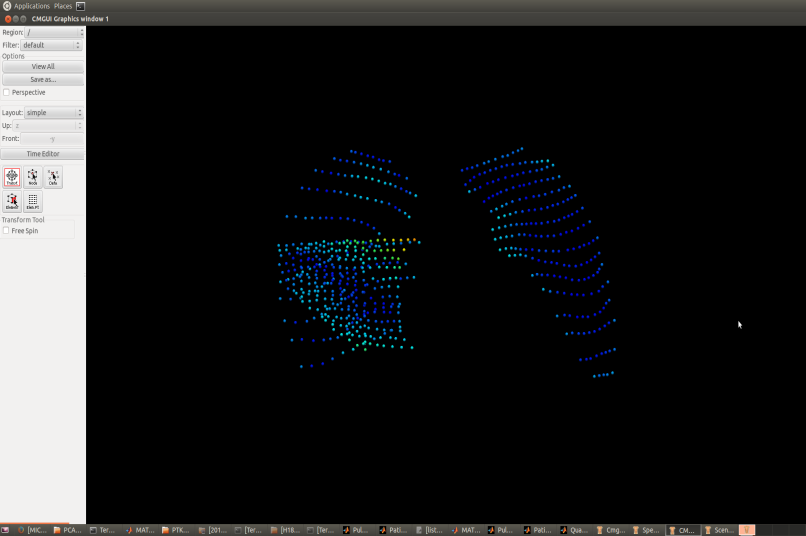
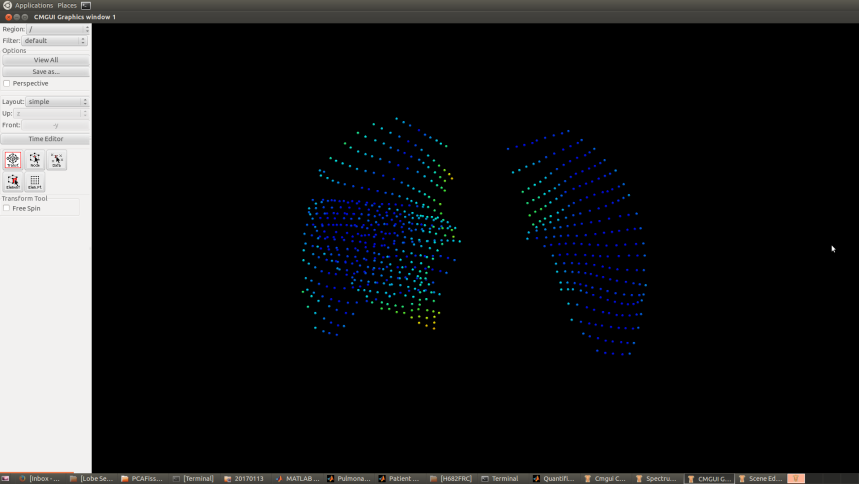
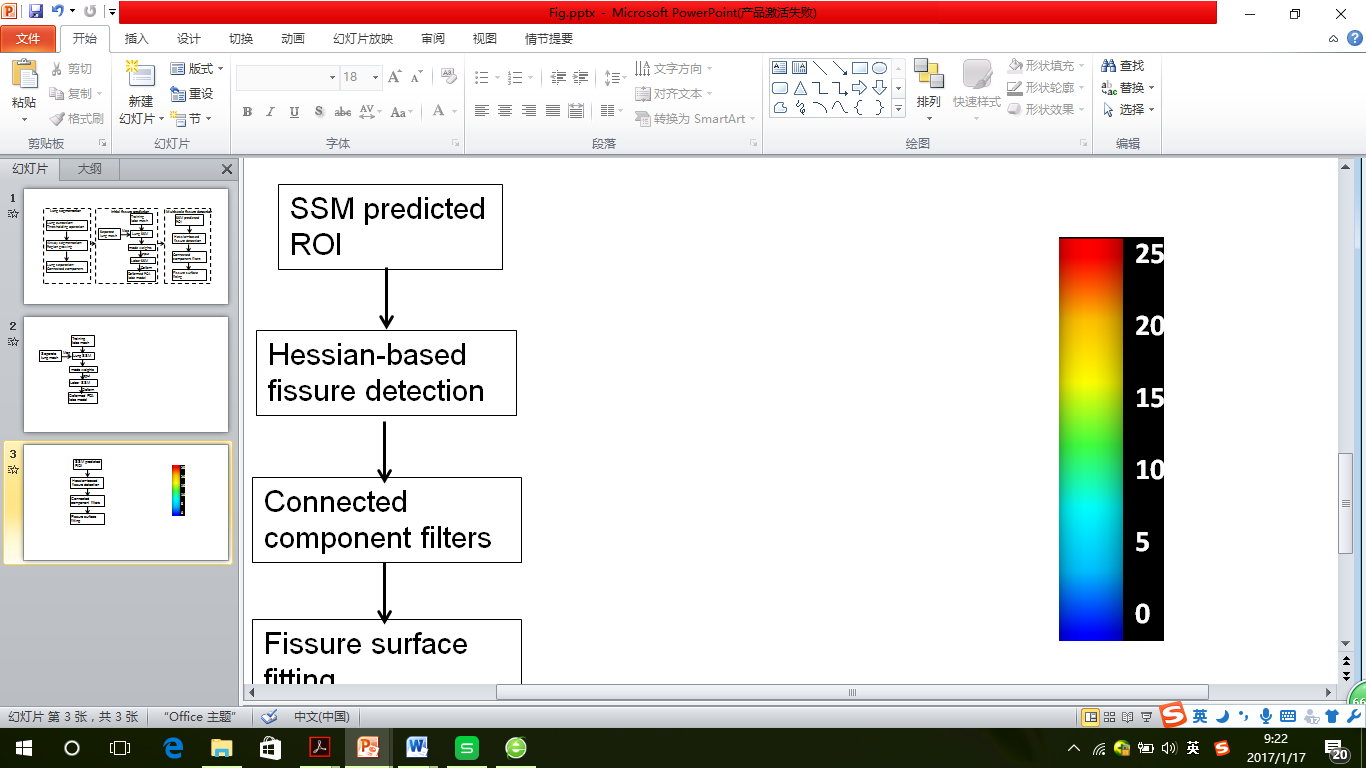
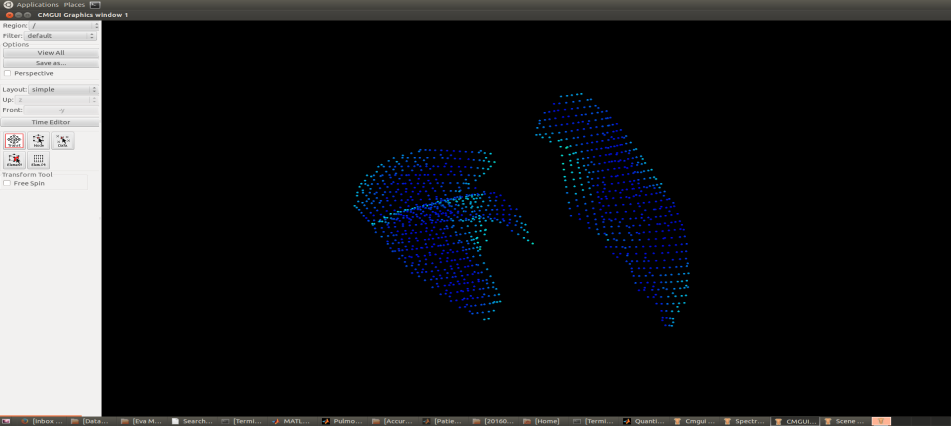
3.1 Data

We tested our automatic lobar segmentation method on two datasets : 1) CT images of young normal volunteers taken at different lung volumes and with different thickness . Normal subjects are selected from Human Lung Atlas (HLA) dataset which is approved by the University of Iowa Institutional Review Board and Radiation Safety Committees. The selected subjects are consists of 5 functional residual capacity (FRC) cases and 5 total lung capacity (TLC) cases. Slice thickness was 0.5-0.7mm. These diseased subjects are acquired from Auckland District Health Board (ADHB) under the supervision of Dr. Wilsher, following ethics committee approval for this study. Slice thickness was 1.25-3mm.

* 1. Result

To assess the accuracy of the automatic lobar segmentation method in the normal and disease subjects, we compared the automatic segmentation results to gold-standard manual segmentations. Segmentation accuracy was quantitatively evaluated by computing the mean difference and percentage of fissure points <3mm between gold-standard and automatic segmentations. The 3mm criterion approximates the thickness of clinical CT images that surgeons and radiologists read in clinical settings [ref].

The average mean difference assessed on normal subjects and IPF subjects are 2.06mm, 4.06mm, 2.85mm and 3.41mm, 5.79mm, 5.01mm for left oblique, right horizontal and right oblique fissure respectively. The average percentile accuracy on normal subjects and IPF subjects are 78.39%, 61.62%, 72% and 65.86%, 55.94%, 60.06% for left oblique, right horizontal and right oblique fissure respectively. List same info on IPF.

1. (b) (c)

Fig.7. Accuracy distribution results of some example subjects.

Replace this using info on how parameters that can be controlled need to be altered for successful segmentation

1. **Conclusions and Discussions**

In this paper, we present an automatic pulmonary lobar segmentation method combined with some manual interaction. The result shows that our segmentation method can perform well on CT images of normal subjects and get a relative accurate result for most of the IPF abnormal subjects. In the future work, a statistical shape model dataset could be developed. The dataset could contain different kinds of statistical model for different ages, sexes, lung volume or diseases, since it can help us prediction a more accurate ROI for the future fissure detection. Meanwhile, the method need to be assessed on more diseased subjects and be improved combined with the disease characteristic of these images. A user-friendly interaction and more time-saving programming is also a key point in the future study.

Due to the lower resolution and pathologic abnormalities, IPF subjects got a worse accuracy. In addition, the segmentation method performs well on left oblique fissure than right oblique fissure and right horizontal fissure, because left lung has simpler anatomic structure with only one fissure, in contrast, misdetection happens more often in the area of right lung where the two fissures are closed. See Fig 7, which shows the accuracy distribution of the three fissures with different colors. It can be seen that the method causes higher error in the lung boundary area, since the fissures here are commonly incomplete, thus few fissure candidate points can be detected accurately.

Reference