Lobe Segmentation (Automatic segmentation method)

1. Subjects and ethics

The data sets used in this research consist of …Human Lung Atlas (HLA) subjects and ….idiopathic pulmonary fibrosis (IPF) subjects. The HLA is an imaging-based resource comprising imaging and lung function data acquired at the University of Iowa Comprehensive Lung Imaging Centre (I-Clic). Ethics approval for data acquisition and use of data was approved by the University of Iowa Institutional Review Board and Radiation Safety Committees. Subjects had no history of cigarette smoking, no history of lung disease, and had normal spirometry (FRV1≥80% predicted and FEV1/FVC≥0.7). Images were obtained in the supine posture using a Siemens Sensation 64 MDCT scanner ( scan parameters: 120kV, 100mA, a pitch of 1.2, slice width 0.6mm, and slice interval 0.6 mm). Lung volumes were controlled to 80% vital capacity (end-inspiratory) and 55% vital capacity (end-expiratory).

1. Overview

A flow diagram of the overall process of our method is shown in Fig. 2. It begins with the segmentation of lungs. The lungs are segmented using a common thresholding based method, reported in [].The method firstly uses a thresholding operation and connected component identification to find the trachea location. Use the highest 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 connected components remaining after removing the trachea and main left and right bronchi. Then, a PCA average model is deformed to predict the initial location of fissures, which is used to narrow the search region of accurate fissure location detection. A multi-scale eigenvalue analysis of Hessian matrix is used to enhance the fissure structures and remove the vessel structures. Next, some non-fissure points are removed using a 2D connected component filter and 3D eigenvector based connected component filter. The finial fissure is generated using B-spline curve surface fitting algorithm.

PCA deformation

In the last two decades, model-based segmentation approaches have been established as one of the most successful methods for image segmentation. By matching a model which contains information about the expected shape and appearance of the structure of interest to new image, this approach is more stable against local image artifacts and perturbations than conventional low-level algorithms. While a single template shape is an adequate model for industrial applications where mass-produced, rigid objects need to be detected, this method is prone to fail in case of biological objects due to their considerable natural variability. Information about common variations thus has to be included in the mode. A straight-forward approach to gather this information is to examine a number of training shapes by statistical means, leading to statistical shape model (SSM).

We introduce SFeaL, a Statistical Finite element analysis of Lung, which is based on the Active Shape Model (ASM) concept. It provides an efficient parameterization of shape variability of lung models which leads to a compact representation of shape and allows shape constraints to be applied effectively during image analysis. SFeaL ensures that an estimate for fissure location can always be made, and provides an important step towards improving the accuracy of fissure segmentation algorithms.

Statistical shape modeling (SSM) is the use of statistical methods to model variation in shape. SSM can be used to model and quantify shape difference and correlate shape to other measurements. SSM can also provide the description of the mean shape of a data set and analysis of its variation.

In this study, we use a statistical shape model (a principal component model) to guide lobar segmentation. As with any other SSM, the first stage here was training a lung statistical shape model using our fifteen FE lung meshes. This shape model is crucial for driving the (later) estimation of pulmonary fissure location. Lung shape was described using a high-order FE mesh accurately fitted to the digitized surface data points acquired from CT images.

The open-source visualization software CMGUI (<https://www.cmiss.org/cmgui>) was employed to render volumetric masks from segmented lungs. Densely packed points (approximately 25,000 points) were generated to represent a 3D lung shape by a set of discrete data points in computer space. To define lobe shape, we manually digitized all three fissures using CMGUI. This process yields a fissure data cloud (similar to a lung surface data cloud) and creates the boundary between each lobe.

A high-order (bi-cubic Hermite) finite element mesh template was constructed for fitting the lung and lobe data. By geometry-fitting the surface data to the mesh we are able to mathematically describe a three-dimensional subject-specific lung shape.

Using CMISS (<https://www.cmiss.org>), a mathematical modeling environment that allows the application of finite element (FE) analysis, the sum of the distances between each data point and its projection on to the nearest element is minimized during the fitting process. This distance is a function of the element location and shape parameters. In this process, the nodal parameters are interpolated to find the projected points. A least squares fitting optimization is solved in CMISS to correctly fit the mesh to the data cloud.

Results of shape model training on the fifteen training set lungs, in terms of resulting principal components of variation showed that the first seven principal components account for over 90% of the total variation.

A separate subject volumetric CT image was chosen from the same HLA database, to use as a test sample. The lung was segmented using the previous introduced method. Then the lung boundary data cloud was then projected on to the PCA-trained model and its principal components’ weight scores were calculated. By using the projection weights (quantification) from these modes of variation, we then back-projected the weights on to the PCA-training set and derived an initial estimate of fissure location and shape.

For SSM, the node distribution of the mesh must be consistent across the training set, particularly at well-conserved anatomical landmarks. The lung has very few anatomical landmarks, therefore we used the entire interpolated nodal parameters (i.e. surface node coordinates and derivatives) as pseudo landmarks across our subjects. In this way the whole lung and fissure surfaces act as landmarks which guarantee a certain level of anatomical and mathematical correspondence across the training set.

A prerequisite in all SSM is object alignment to remove the orientation and scaling differences between shapes. Since we have pseudo landmarks in our training set, a General Procrustes Alignment (GPA) problem is a suitable registration method. The GPA algorithm finds the optimal rotation matrix and translation vector which minimizes the overall distance between two sets of points with respect to the Euclidean norm.

In our case, a reference lung model sample from the training set is chosen which constitutes the first average lung anatomy. Then all other samples are aligned to the reference sample. The Euclidean mean is computed across all subjects for all shape parameters.

Hessian matrix

The general approach of multiscale methods is to choose a range of scales and to compute a response for each scale from the initial image. All the responses are then combined to get a single multiscale response which contains the sought features. The general foundations of the scale-space theory can be found in [T. Lindeberg. Scale-Space Theory in Computer Vision. Kluwer Academic Publishers, Dordrecht, Netherlands, 1994]. More formally, for a fixed scale s, we calculate a response image at that scale where I is the initial image. Then we calculate the multi-scale response for the iamgewhich is for each point the maximum of the response over scale.

We expect a significant second derivative across a plane structure, since the grey-value increases rapidly from the plane-structure border to the center and decrease again to the opposite border. Longitudinally to a plane-like structure only insignificant second derivatives should occur.

The multiscale second order local structure of an image (Hessian matrix) is examined with the purpose of developing a fissure enhancement filter. Hessian matrix is a square matrix of second-order partial derivatives of a scalar-value function. It describes the local curvature of a function of many variables. Hessian matrix is a way of organizing all the second partial derivative information of a multivariable function. At each image point the Hessian matrix was constructed. The first step of the fissure segmentation process is an enhancement of the fissures based on the eigenvalues of the Hessian matrix that gives a fissure probability for each voxel.

An analysis of the Hessian matrix can be used to detect plane structures, like the fissures. In the 3D case, a light plane structure on a dark background is characterized by two large positive second derivatives across the plane and a small second derivative of either sign along the plane. This is reflected by a Hessian matrix having two large positive eigenvalue and a small eigenvalue of negative sign. Fissures can locally be modeled as a sheet where the eigenvalue orthogonal to the fissure plane is large, and the other two eigenvalues are small. Thus, on the bright fissures, the ideal relationship is defined as and .

At each image point the Hessian matrix is constructed. Its eigenvalues , , are computed and ordered such that . At each point we define the fissureness as follows:

The first factor suppresses points whose largest eigenvalue is positive, since fissures are locally bright :

The second factor detects plane or curve-like structures by searching for locations where the two largest eigenvalues are significantly different:

, ,

With p (set to 0.5 in our case) acting as a soft threshold on . The third factor suppresses signals from vessel walls, which, in contrast to plane-like fissures, have relatively large second, and possibly also third, eigenvalues. A soft threshold parameter w is used, in this case set to 3:

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The final term decreases the fissureness value at points in the vicinity of blood vessels:

Here DT{vessels} is the distance transform to segmented blood vessels, found by thresholding the vesselness filter described above. The idea is to suppress points in the vessel walls that are not detected by the wall term because they locally appear plane-like. They are detected because they are close to high-vesselness pixels in the vessel interior. is a characteristic distance over which fissureness should be suppressed close to vessels. We set v to 5mm.

We represent each fissure as a function where and are define on a fissure estimation plane described below, and is the coordinate of the fissure surface on an axis perpendicular to the plane at point . The function corresponding to the fissure is the one that maximizes the values F of fissureness over a set of candidate points {p} for at each value of :

The candidate points are selected as points within a certain distance (20mm) of the initial lobar boundary approximation generated using the vesselness density watershed method above. The coordinateds of each candidate are transformed to the basis and grouped into ‘bins’ corresponding to each value . Within each bin the candidate voxel with the highest fissureness F is selected. In this way we keep our image in its original coordinate system, avoiding resampling and interpolation errors.

The estimation plane is initially computed as a best fit plane from the watershed fissure estimation, found by applying principal component analysis to the points on the initial approximation surface. Once the maxima have been found, outliers are moved by examining the connectedness of the plane after a morphological dilation using voxel cube structural element. Connected components comprising fewer than 200 voxels are removed. The estimation of fissure plane and removal of outliers is carried out in an iterative way. Finally, the resulting surface points are used to compute a smooth fissure surface using a multilevel B-spline method with a thin-plane spline used to extrapolate the values to the lung boundaries.

The resulting mask C contains spurious responses on small plate-like structures. To obtain the final fissure segmentation we use a vector-based connected component analysis. The largest eigenvalue of a sheet is perpendicular to the plane. Thus, the corresponding eigenvector of the largest eigenvalue show the orientation of structure. The curvature of a fissure is locally low, so adjacent fissure voxels have similar largest eigenvectors. Taking advantage of this property, a 3D vector-base connected component analysis with a 6-neighborhood is applied on the candidate voxels in C. The similarity is calculated by the inner product of the normalized eigenvectors, so that the inner product is 1 for identical vectors. Since pulmonary fissures are usually slightly bent, the inner product for fissure voxels can be slightly smaller than 1. Empirical analysis showed good fissure segmentation results for joining adjacent voxels inside mask C with an inner product0.98 to a connected component. All 3D components with a volume of at least 0.1 ml are kept to obtain all significant fissure parts and remove most of the noise. Afterwards, a morphological closing with a cubic kernel of voxels is applied to close minor gaps.