Computerized assessment of pulmonary fissure integrity using high resolution CT

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Purpose: Knowledge of pulmonary interlobar fissure integrity is of interest in a number of clinical and investigational applications. The authors developed and tested a high resolution CT based automated computerized scheme for this purpose.

Methods: The fissure integrity assessment scheme consists of the following steps: (1) Fissure detection, (2) individual fissure identification, (3) fissure type determination, (4) “complete” inter-lobe surface estimation, and (5) fissure integrity estimation. For evaluation purposes, 50 anonymized chest CT examinations were ascertained and the complete and “incomplete” regions of the fissures of interest were manually marked by two experienced radiologists. After applying the scheme to the same examinations, differences among fissure percent completeness estimates based on the radiologists’ manual markings and the automated computerized scheme were computed and compared.

Results: Average differences in estimated fissure percent completeness (integrity) between the results of the computerized scheme and that based on each of the two radiologists’ markings were $6.88\% \pm 5.86\%$, $9.57\% \pm 7.77\%$, and $4.19\% \pm 5.64\%$ for the right major fissures, the right minor fissures, and the left major fissures, respectively. The differences between results based on radiologists’ markings for the same fissures were $4.27\% \pm 3.32\%$, $7.02\% \pm 5.54\%$, and $4.23\% \pm 4.93\%$, respectively. The difference among the three matched measurement sets for each fissure were statistically significant (Friedman’s test, $p \leq 0.005$) but paired comparisons showed that much of the observed difference was related to inter-reader differences rather than reader-computerized scheme differences. Computerized estimates were correlated with each of the radiologist’s estimates (Spearman, $p < 0.0001$).

Conclusions: While variability between readers-based estimates of fissure integrity was smaller than differences between the computerized scheme and each of the readers, the result reported here are quite encouraging in that the magnitude of these differences were in the same magnitude, demonstrating the feasibility of using a computerized scheme for this purpose. © 2010 American Association of Physicists in Medicine. [DOI: [10.1118/1.3475937](https://doi.org/10.1118/1.3475937)]

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I. INTRODUCTION

As pulmonary fissures (i.e., major and minor) subdivide the human lungs into lobes that function as relatively independent units, they often serve as landmarks for precise localization of abnormalities with respect to the presence (or absence) of diseases within specific pulmonary lobes.^{1–3} A large number of studies demonstrated that interlobar fissures were highly variable among individuals in shape and configuration and are frequently incomplete.^{4–9} The existence of incomplete fissures may reduce barriers that prevent the spread of diseases, such as pneumonia, and could also affect the distribution pattern of pleural effusion. Air leaks after lobectomies represent but one type of complication in lung cancer patients with incomplete fissures.⁴ Knowledge of the presence of a complete interlobar fissure could be used to alert surgeons of specific situations, such as lung torsion.^{10,11} In addition, the types (i.e., major, minor, and/or accessory) of pulmonary fissures and their specific appearance may have

an important role in the assessment of different lung diseases.^{12–16} However, pulmonary fissures appear often as complicated three-dimensional surfaces and therefore it is difficult for a clinician to visualize the complete fissure construct and specifically to subjectively quantify accurately their integrity through visual assessments. Although manual meticulous marking of complete and incomplete sections of fissures could lead to a relatively accurate assessment of fissure integrity, this is a time consuming task because of the large number of CT images included in high resolution examinations (typically ~400–600 slices per examination). Therefore, developing a computerized tool that can automatically, efficiently, and accurately provide objective quantitative assessments of fissure integrity may prove to be useful to both clinicians and investigators attempting to characterize lung diseases.

Despite extensive efforts in computerized pulmonary lobe/fissure segmentation,^{17–23} to the best of our knowledge,

FIG. 1. Schematic diagram of the fissure integrity assessment approach. The shaded steps indicate the work developed and presented as a part of this investigation.

there are no automated methods developed to date that compute/estimate the integrity of pulmonary fissures. The primary challenges to doing so arise from: (1) The requirements of a “thorough” detection followed by acceptable smoothing of the pulmonary fissure surfaces depicted on CT images and an accurate estimation of their “complete” versions that can serve as a reference for the integrity computation, and (2) the difficulty in identifying individual fissures due to the involvement of a complicated shape analyses, as pulmonary fissures are often fused with each other in space. Although we previously developed fissure/lobe segmentation schemes,^{24,25} the use of these schemes for integrity assessment purposes encountered the problems mentioned above as well. First, the fissure segmentation scheme typically results in irregular (“rugged”) fissure surfaces that are also frequently associated with small “holes” due to the fuzzy depiction of the fissures on CT images. Second, the lobe segmentation scheme does not guarantee smooth interlobe surfaces that can be regarded as complete versions of the detected fissures. The use of these schemes in fissure integrity assessments often results in significant underestimation or overestimation of fissure integrity. Last, our previously developed schemes do not provide for a robust approach to identify each individual fissure by type (i.e., major, minor, or accessory), making it essentially impossible to estimate the integrity of each individual fissure. Thus, specific developments are needed to resolve these issues for this very purpose. In this study, we present an automated computerized approach to quantitatively assess fissure integrity or completeness levels. A detailed description of the scheme and the results of a preliminary test on 50 high resolution chest CT examinations are described.

II. METHODS AND MATERIALS

II.A. Scheme overview

The proposed approach consists of four stages (Fig. 1): (1) Detection of pulmonary fissures depicted on CT images, (2) geometric analysis of the detected fissures, (3) estimation of complete fissure, and (4) fissure integrity quantification. The first stage is designed to obtain smooth and continuous fissures depicted on CT images. Previously, we developed a fissure segmentation scheme;²⁴ however, the fissures obtained were typically irregular and frequently contained a

large number of small holes (Fig. 2). In addition, the detected fissures (major, minor, and accessory) were fused with each other in space. These issues would lead to incorrect integrity assessment of individual fissures. To address these issues, we developed a set of geometric operations that were applied in the second stage. These included (1) an anisotropic morphological filter for fissure surface smoothing and hole repairing, (2) a progressive shape decomposition algorithm for individual fissure identification, and (3) an anatomy knowledge based fissure type classification. The third stage estimates the complete fissures by fully separating neighboring lobes using implicit surface fitting of the identified and classified fissure surfaces. As we previously discussed,²⁵ the adaptive sampling strategy specifically designed for the reduction of memory usage could result in irregular interlobe surfaces. This could lead to a significant overestimation of the surface areas of completed individual fissures. In this study, we developed and adopted a uniform sampling strategy that leads to “smooth” interlobe surfaces. The fourth stage in the scheme quantifies the integrity of individual fissures by computing the differences between actually detected (“smoothed and filled in”) fissures and their complete versions. In Fig. 1, we highlight the contributions in this work as a part of the complete process (shaded as dark background). A detailed description of the methodology for fissure and lobe segmentation is provided elsewhere.^{24,25}

II.B. Anisotropic morphological processing

Since pulmonary fissures appear as curves within a single CT image (slice), we developed a simple linear morphological filter to “fill in” the small holes as shown in Fig. 2. This filter approximates the two-dimensional curved fissures in each slice using a set of short straight line segments. Given the location (x, y) of a voxel located on detected fissures, the linear filter computes the orientation of the local line segment centered at this voxel by performing an intensity transform

$$I'(x, y) = \max_{0 \leq \theta < 2\pi} \left\{ \frac{1}{2r} \int_{-r}^r I(x + \rho \cos \theta, y + \rho \sin \theta) d\rho \right\}, \quad (1)$$

where 2γ is the length of a straight line segment.

FIG. 2. An example of our pulmonary fissure detection result. (a)–(c) are the original CT images viewed along the axial, coronal, and sagittal directions, (e)–(g) show the automated fissure detection results as an overlay, (d) shows the three-dimensional fissure surfaces, and (h) shows the smoothed version of (d) after applying the Laplacian smoothing algorithm. The arrows labeled as “1” indicate the incomplete fissure not depicted on the CT images and the arrows labeled as “2” indicate detected accessory fissures.

The implementation of this transform consists of the following steps: (1) Rotating a line segment around each voxel on the detected fissures within the two-dimensional slice space by an angle θ ; (2) computing the average intensity I of the voxels on the line segment; (3) setting the specific orientation $\theta_{\max}$, along which the maximum average intensity is reached, as the orientation of the line segment at the given voxel; and (4) connecting the two ends of the computed line segment, where the fissure voxels are located, using a straight line. All voxels on this line segment are regarded as parts of the pulmonary fissures. In this study, we empirically set the length (i.e., 2γ) of a line segment at 15 mm and the incremental rotation angle at 10° . Hence, for each voxel, a line segment is rotated 36 times. This linear filter can be easily extended to a three-dimensional space using a local plane approximation, where a plane is rotated along the azimuth (longitude) and zenith (latitude) angle in a spherical coordinate system. However, the computational cost involved is high, since rotations at 10° increments would require a plane patch to be rotated 648 times. Therefore, we chose a linear morphological operation in two-dimensional space for this purpose. When applied to the example in Fig.

2, this procedure resulted in a relatively smooth fissure surface with the small holes filled in as shown in Fig. 3.

This linear filter is in principle similar to a morphological operation (or an intensity transform). However, unlike the traditional isotropic “open”/“close” morphological operation that expands fissure surfaces uniformly in all directions, this anisotropic approach extends the fissure surface linearly along the directions of the fissure curves in each slice (i.e., along the directions tangent to the fissure surface). Due to its smoothing effect, this linear procedure is also useful for a relatively accurate estimation of surface curvatures.

II.C. Individual fissure identification

The human lungs are subdivided into lobes by different pulmonary fissures. In most individuals, the right lung contains a major/oblique fissure and a minor/horizontal fissure and the left lung contains only a major fissure. In some individuals, there may be additional “accessory” fissures that represent normal anatomic variants,¹⁴ and quite seldom these could separate lung volumes into additional lobes (i.e., accessory lobes). Typically, accessory fissures are not consid-

FIG. 3. The estimated fissure surfaces after linear morphological filtering. (a)–(c) show the results after applying the developed morphological filter to the detected fissures in Figs. 2(e)–2(g), respectively, and (d) shows the smoothed three-dimensional fissures modeled using the MCA (Ref. 26).

FIG. 4. Illustration of the progressive fissure decomposition scheme. (a) The originally detected fissures; (b) a set of separated surface patches after the removal of regions of pulmonary fissures with high curvature; (c) the final marked fissure regions with their unique identifications after applying a progressive decomposition strategy (Fig. 5); and (d) individually segmented fissures after a merging operation.

ered important in clinical practices; however, their presence may affect accurate identification and analysis of the major or the minor fissures in the lungs.^{2,14,15} Awareness of each individual fissure is often useful when interpreting radiological images and could be important in some clinical practices (e.g., lobectomy). Hence, identification of accessory fissures in addition to the major and the minor fissure is desirable, but we do not assess the integrity of any identified accessory fissure since we cannot estimate their complete versions. As the detected fissures are usually connected to each other in space [Fig. 2(d)], to correctly identify each fissure, we first need to divide the detected construct of pulmonary fissure surfaces into individual patches and then identify the type of fissure these belong to (i.e., major, minor, or accessory).

We previously proposed to decompose fissures by taking advantage of the relative occlusions among the different fissure types along the z -axis (i.e., the direction from the base of the lungs to the apices) and then classify these using an area-based size criterion.²⁵ However, this occlusion-based decomposition approach is orientation-dependent and could result in an incorrect identification/classification of different fissures. For example, the accessory fissure in a C-like shape attached to the minor fissure in Fig. 4(a) may be decomposed incorrectly when using this occlusion-based approach because the front side or back side of the accessory fissure is broken into two parts (i.e., regions in blue and red) along the z -axis. A size alone criterion may lead to incorrect fissure type identification as well, and we presented such a case previously.²⁵ To improve robustness of the individual fissure identification procedure, we developed an orientation-invariant approach to progressively decompose pulmonary fissures by combining curvature analysis with fundamental anatomical knowledge of pulmonary fissures (Figs. 4 and 5).

To simplify the description, we abstracted the three-dimensional surface structures of the detected pulmonary fissures [e.g., Fig. 3(d)] as a two-dimensional form shown in Fig. 4. Pulmonary fissures are represented as hollow (or double layered) regions because they appear as a platelike shape with specific thicknesses. This enables the modeling of fissure surfaces with a front-side surface and a back-side surface. In this study, we used “double layering” information to identify individual fissures. The abstracted model in Fig. 4 can be regarded as a generalization of the fissure structures in

both right and left lungs with accessory fissures taken into account as well. After the linear morphological operation, we used a progressive fissure decomposition algorithm to identify individual fissures. This procedure consisted of the following steps (Fig. 5):

- (1) Representing fissures as a surface model using the marching cubes algorithm²⁶ (MCA) and smoothing surfaces using a Laplacian smoothing algorithm. This step enables a relatively accurate estimation of the curvature tensor at a given point on the fissure surface.
- (2) Computing the curvature tensor at each point on the fissure surface and decomposing the surface into a set of patches by removing regions with high curvature as “junction regions” (or concave ridges) between individual fissures since these junction regions typically have a high curvature. In our implementation, the threshold for curvature was set empirically at 0.2 (unit: 1/mm), corresponding to a circle with a radius of 5 mm.
- (3) Finding the surface patch with the smallest area and marking the associated fissure by painting along the opposite direction of the normal vector at each vertex on this patch. The marked fissure is then assigned with a unique ID. Isolated surface patches can be obtained by simply clustering connected triangles.
- (4) Repeating steps 1–3 above until all fissures are marked. As a result, detected fissures are decomposed into different regions with unique IDs [e.g., regions marked with different colors in Fig. 5(c)]. Figure 6 shows an example demonstrating the performance of the fissure decomposition procedure when applied to a chest CT examination.

Due to the discrete representation of a triangle mesh surface, we estimated the curvature at a vertex v_i on the mesh surface by approximating the neighboring vertices of v_i using a quadratic polynomial surface, namely,

$$z = ax^2 + bxy + cy^2 + dx + ey. \quad (2)$$

A simple way for selecting the neighboring points of v_i is to identify its one-ring vertices, defined as the vertices sharing edges with v_i . The number of neighboring vertices must be larger than the number of unknown coefficients (i.e., a , b , c ,

d , and e). If this condition cannot be met, we use the two-ring vertices of v_i , defined as the vertices sharing edges with the one-ring vertices and with v_i . Assuming there are n neighboring points $\{x_i, y_i, z_i\}$, where $0 \leq i < n$, the overly determined system as defined by Eq. (2) can be solved using a standard least square fit, aimed at minimizing

$$F(a, b, c, d, e) = \sum_{i=1}^n (ax_i^2 + bx_iy_i + cy_i^2 + dx_i + ey_i - z_i). \quad (3)$$

Once the unknown coefficients are determined, the Gaussian curvature K and the mean curvature H can be calculated as

$$\begin{cases} K = k_1 k_2 = \frac{4ab - b^2}{(1 + d^2 + e^2)^2} \\ H = \frac{k_1 + k_2}{2} = \frac{a + c + ae^2 + cd^2 - bde}{(1 + d^2 + e^2)^{3/2}} \end{cases}, \quad (4)$$

where k_1 is the maximum normal curvature and k_2 is the minimum normal curvature at a vertex v_i . The example in Fig. 7 visualizes the results after applying the curvature estimation method to the fissure surface in Fig. 4(d). The removal of high curvature regions (in red and green), which is typically located at the highly convex and concave ridges of the mesh surface, results in a set of separated surface patches [Fig. 7(d)] corresponding to the abstracted pattern shown in Fig. 4(b).

II.D. Fissure type determination

The decomposition procedure described above resulted in the separation of individual fissures. For fissure integrity quantification, we need to identify what type of fissure each of the surface patches represents. As a simple area-based size criterion (e.g., major fissure has a larger surface area than minor fissure) is not sufficient for a robust classification, we explored additional anatomic information to determine the type of fissure that the patches in question represent. The definition of major/minor fissures (i.e., oblique/major fissures separate the middle from the lower lobes and minor/horizontal fissures separate the superior and middle lobes²⁷) implies that minor fissures in the right lungs are typically located above oblique fissures. Additional anatomical information that can be exploited for this purpose includes: (1) Minor fissures are typically connected directly with major fissures and (2) major fissures in the lungs generally have the largest surface areas because they “cut through” the whole lung with an “oblique” direction (orientation). The first criterion typically excludes the possibility of misclassifying the lower accessory fissure (in purple in Fig. 4) as a minor fissure. The second criterion typically excludes the possibility of misclassifying upper accessory fissures (shown in Fig. 4) as a minor fissure even if these have larger surface areas than the minor fissure. At the same time, the second criterion typically eliminates the ambiguity related to the major fissure in the left lung. As there is only one oblique fissure, the patch with the largest area can be quite safely regarded as the major (oblique) fissure. In cases where these conditions are not

FIG. 5. A flowchart of the fissure decomposition algorithm.

met, the scheme automatically selects the individual fissure with the second largest area as the minor fissure as the right lung typically contains both major and minors fissures. Applying this simple fissure type determination strategy to the decomposed fissures resulted in the classification shown in Fig. 6(d), in which different fissures were identified by different colors.

II.E. Complete fissure estimation

To quantitatively estimate fissure integrity (percent completeness), one needs to define a complete version of the fissure construct. A simple solution is to use the boundary surface between neighboring lobes as the complete version. Unfortunately, the lobe segmentation scheme we previously developed²⁵ often leads to rugged interlobe surfaces because interlobe surfaces only pass through the sampled points without consideration of the associated normal vectors. As the example in Fig. 8 shows, for a given set of points, the fitted

FIG. 6. An example of individual fissure identification when applying the fissure classification procedure to the CT examination in Fig. 2. (a)–(c) show the identification of different types of fissures in image space and (d) shows a three-dimensional representation of the identified fissures in geometric space.

curve (or surface) may vary even when the locations of the points are the same in space but their normal vectors n_i ($1 \leq i \leq 8$) are different. The variations in normal vectors at the end points (i.e., points “1” and “8” in Fig. 8) could lead to extensions of the fitted surfaces along different directions (i.e., extrapolated regions located outside points 1 and 8 in Fig. 8). Hence, the selection of constraint points with stable normal vectors for the implicit fissure surface fitting procedure is extremely important for accurate estimation of the complete fissure construct. In this study, we improved the “incomplete” fissure extension algorithm by replacing the previously described greedy sampling strategy with a uniform sampling strategy guided by curvature analysis [Fig. 8(d)]. The basic idea is to use “averaged” normal vectors over small regions rather than individual vertices as the constraint points for the implicit surface fitting to alleviate random perturbations associated with neighboring constraint points in terms of their normal vectors.

The uniform sampling strategy we implemented consisted of the following steps [Fig. 8(b)]: (1) Computing the average normal vector n of the major/minor fissure patch; (2) projecting the mesh vertices of the fissure patch onto a plane that is perpendicular to the average normal vector n and computing the bounding box of the projected fissure patch, followed by division into a set of grids where the size of these grids controls the sampling rates; and (3) finding the vertices in-

cluded in each grid of the projected plane having minimum curvature at the constraint points for implicit surface fitting and replacing their normal vectors with the averaged normal vector for all vertices within the same grid. The number of constraint points for implicit surface fitting is predetermined by the size of each grid. The surfaces between neighboring lobes represent an estimation of the complete major/minor fissures in the right and left lungs (Fig. 9). As shown in Fig. 9, after applying this strategy, the resulting boundaries between lobes are quite smooth in appearance, in both image and geometric spaces.

II.F. Estimation of fissure integrity (completeness)

Given the representation of complete fissures as geometric surfaces extending to the boundaries of the lungs, a simple way to quantify the fissure integrity C_f (or completeness) in terms of surface area is

$$C_f = \frac{A'}{A_0}, \quad (5)$$

where A_0 is the area of a complete fissure [e.g., the curve or surface in blue in Fig. 9(a)] and A' is the corresponding area of the actually “detected” fissure [e.g., the curve or surface in green in Fig. 9(b)]. When computing A' , it is unavoidable to overestimate the surface area of a specific fissure due to the

FIG. 7. Visualization of the curvature of different fissure surfaces in Fig. 3(d). The visualized curvature in (a)–(c) represent the larger of $|k_1|$ and $|k_2|$. The arrows in (a) and (b) point to the regions connecting the major and minor fissures and the arrow in (c) point to the region connecting the accessory and minor fissures. The result of removing regions with high curvature is shown in (d).

FIG. 8. Possible impact of the sampling strategy on implicit surface fitting. (a)–(c) show the fitted curves/surfaces for given sets of constraints points with the same space positions but different normal vectors. The extrapolated regions of these points are located outside the end points (i.e., points 1 and 8); (d) illustrates a uniform sampling strategy where surface regions are divided into a set of uniform grids and the constraints points are selected as the averaged (including positions and normal vectors) of the vertices with small curvatures within each grid.

existence of “uneven” regions. Moreover, one needs to account for possible involvement of false positive detections when computing A' . In this study, given a complete version of an individual fissure, we projected its detected neighboring fissures onto its surface (Fig. 10) to “align” the detected fissures with their estimated complete versions. We simply checked all neighbors to the centroid of each triangle in the polygonized fissure surface along its positive/negative normal vector. If a voxel belonged to a nearby fissure (within 3 mm), the triangle was considered a “detected fissure region.” Finally, the areas of all marked regions [curves or surfaces in green in Fig. 9(b)] were regarded as “belonging” to a particular detected fissure. Using this approach false positive detections near the complete fissure (within 3 mm) are in-

cluded in the estimation but we avoid inclusion of all other false positive detections that are farther away from the complete fissure.

II.G. Testing CT data set and performance assessment

Fifty fully anonymized chest CT examinations acquired from a chronic obstructive pulmonary disease (COPD) screening cohort at the University of Pittsburgh Medical Center were selected by an experienced board certified thoracic radiologist. For the purpose of fissure integrity assessment, the radiologist was asked specifically to ensure that the majority of the selected examinations exhibited some fissure

FIG. 9. Complete fissure estimation based on the uniform sampling strategy. (a)–(c) show the interlobe boundaries in image space and (d)–(f) show the interlobe boundaries in geometric space viewed from different perspectives.

FIG. 10. An illustration of the projection based fissure integrity quantification. The irregular region represents a set of actually detected fissure regions, the smooth curve (or surface) in (a) represents the estimated complete fissure (or interlobe boundary), the arrows denote the positive/negative of the normal vectors at points on the complete fissure, the smooth curve (or surface) in (b) represents the overlapping regions after projecting neighboring detected fissure region onto the complete fissure surface.

incompleteness. All participants in the COPD screen cohort had a relatively low level of airflow obstruction measured or were identified as visually depicting emphysema on their CT examinations. These CT examinations were performed under an Institutional Review Board (IRB) approved protocol using a LightSpeed VCT 64-detector scanner (GE Healthcare, Waukesha, WI) with subjects holding their breath at end inspiration. CT data were acquired using a helical technique at a pitch of 0.969, 120 kVp, 0.4 s gantry rotation, and 250 mA (or 100 mA s). The detector configuration was $32 \times 0.625 \text{ mm}^2$. CT images were reconstructed to encompass the entire lung field using the GE “bone” kernel at 0.625 mm section thickness and 0.625 mm interval (without slice overlapping). The CT images were represented using a 512×512 pixel matrix with a pixel dimension ranging from 0.549 to 0.738 mm depending on participant body size.

After assembling the anonymized data set, two experienced board certified thoracic radiologists (28 and 13 yr of experience) independently reviewed and manually marked the complete and incomplete regions of each individual pulmonary fissure (the right major and minor fissures and the left major fissure) as depicted on coronal views in each of the 50 chest CT examinations. These markings were used as a “gold standard” in assessing the performance of the fully automated computerized scheme. As this is a very time consuming task to mark each of the images contained in the 50 high resolution chest CT examinations, we adopted a strategy of marking every seventh image depicting lung tissue after studying different sampling rates (i.e., every five, seven, and ten slices). All markings were made on the coronal views. We tested that “unmarked” fissures on in-between images could be estimated quite well by linear interpolation between the neighboring selected and marked images. A total of 2114 slices were marked manually on the 50 examinations by each of the two radiologists. For each case, the individual fissure integrity was estimated by calculating the ratio between the total length (L1) of the fissures marked as incom-

plete and the length (L2) of the marked complete fissures. The fissure integrities estimates based on radiologists’ markings were used to assess the agreement and/or discrepancy between the two radiologists (inter-reader variability) and were compared to the estimates of completeness as computed by the computerized scheme. Mean discrepancies (or errors) and standard deviations were calculated. Comparisons among the three matched measurement sets for each fissure in terms of estimated percent completeness values (two radiologist and the computerized system) were tested using a nonparametric Friedman’s test (two sided, $p < 0.05$) and paired sets (reader-reader and reader-computerized scheme) were tested using the Wilcoxon matched pairs signed rank test (two sided, $p < 0.05$). Spearman correlation coefficients were also computed to assess correlations between paired computed estimates generated from the radiologists’ markings and by the automated scheme. We note that none of the 50 CT examinations used in this experiment had been used during the development, prior testing, and parameter setting or training (refinement) of the automated computerized scheme.

III. EXPERIMENTS AND RESULTS

The estimated fissure integrity (completeness) levels for the 50 chest CT examinations by each of the radiologists and the computerized scheme are shown in Table I. The table provides percent integrity estimates for individual fissures in each case (i.e., the right major and minor fissures and the left major fissure). For the computerized scheme and the two radiologists, the mean percent integrity levels of the right major fissures were 82.89 ± 11.84 , 85.76 ± 8.15 , and 82.30 ± 9.34 , respectively; the mean percent integrity levels of the right minor fissures were 63.53 ± 22.51 , 66.65 ± 23.55 , and 62.30 ± 24.73 , respectively; and the mean percent integrity levels of the left minor fissures were 89.92 ± 8.99 , 89.10 ± 10.81 , and 88.59 ± 7.94 , respectively. There were statistically significant differences among the three matched measurement sets for each fissure (Friedman’s test, $p \leq 0.005$). Paired matched comparisons between the readers themselves and between each of the readers and the computerized scheme indicated that three of the four significant differences (Wilcoxon matched pairs signed rank test, $p=0.012$, $p<0.0001$, and $p<0.0001$ for the LMA, RMA, and RMI, respectively) were related to between reader differences. The other significant difference was between the computerized scheme and radiologist no. 2 for the LMA (Wilcoxon matched pairs signed rank test, $p<0.0001$).

For a typical chest CT data set consisting of approximately 450–600 images (with a slice thickness 0.625 mm), our scheme takes approximately 36 min to detect the fissures when using a desktop PC computer installed with an AMD Athlon™ 64×2 Dual 2.11GHz central processor and 2 GB RAM. The majority of the computational cost is spent on the pulmonary fissure detection (~ 10 min) and the lobe segmentation (~ 25 min), while the computational cost for the fissure integrity level estimation can be largely ignored (less than 1 min).

TABLE I. Individual fissure integrity (%) estimated by two radiologists and the computerized scheme and their means and standard deviations (M and S). RMA: Right major fissure; RMI: Right minor fissure; LMA: Left major fissure.

Case	Computerized scheme			Radiologist 1			Radiologist 2		
	RMA	RMI	LMA	RMA	RMI	LMA	RMA	RMI	LMA
1	81.47	57.68	96.01	77.81	50.73	95.33	76.02	25.09	96.66
2	82.55	50.33	96.21	90.82	58.82	95.85	95.31	55.29	96.89
3	67.59	13.91	49.58	73.68	00.00	72.50	79.71	00.00	83.35
4	71.71	53.55	97.80	85.24	68.93	95.31	80.62	68.43	95.90
5	66.90	29.61	80.08	72.96	42.32	75.67	69.84	32.10	69.79
6	92.57	60.78	77.33	91.27	60.63	71.73	86.75	41.53	73.30
7	91.74	61.23	86.37	79.22	52.41	85.23	78.27	44.95	85.54
8	58.42	74.64	91.21	83.77	89.87	93.34	77.41	82.49	90.97
9	70.72	72.77	90.24	80.05	82.57	84.15	80.33	78.59	81.73
10	87.81	55.34	90.66	78.07	50.81	84.74	79.17	49.74	89.95
11	98.74	50.92	94.61	85.18	45.48	93.28	82.31	35.10	94.86
12	92.99	62.29	94.78	97.94	50.75	96.89	95.60	48.54	93.92
13	78.46	00.00	90.55	78.22	00.00	91.42	74.34	00.00	88.49
14	97.15	65.47	95.86	96.22	64.55	95.66	94.21	53.04	91.89
15	98.92	98.13	95.26	98.06	97.68	97.87	94.72	94.12	94.12
16	76.42	58.61	97.28	79.12	59.18	96.84	73.70	49.40	91.55
17	78.49	76.41	93.90	89.74	82.91	87.90	82.78	67.95	93.57
18	84.37	64.43	93.22	94.97	76.67	96.23	85.40	76.42	93.28
19	91.59	72.80	93.54	87.45	65.93	96.68	80.25	54.11	90.91
20	97.02	84.38	94.50	94.29	92.71	95.47	94.12	91.81	93.79
21	90.88	79.96	89.65	97.45	85.34	96.27	93.43	82.38	87.01
22	71.43	58.63	90.27	81.36	70.64	93.90	80.71	62.40	88.57
23	90.39	83.87	74.19	92.56	94.10	96.68	80.19	83.44	91.80
24	97.58	84.29	92.39	96.98	58.48	96.49	97.46	66.15	96.26
25	88.13	70.63	95.68	87.28	49.02	83.12	86.25	52.42	95.98
26	68.56	55.91	96.69	76.44	73.27	96.84	68.13	64.09	95.87
27	89.31	65.13	93.11	78.83	76.72	93.65	83.75	78.59	93.61
28	63.47	61.44	98.80	87.19	57.50	96.35	84.37	46.61	95.40
29	73.96	70.73	97.73	85.11	70.50	93.04	80.81	77.85	93.95
30	63.41	12.04	90.87	75.25	64.36	89.34	59.13	52.72	84.08
31	97.74	94.13	92.36	96.71	97.16	94.03	94.49	94.36	92.67
32	98.08	94.82	95.16	97.81	97.68	96.61	94.33	94.33	89.84
33	91.34	73.31	89.84	92.19	81.58	86.31	85.22	84.47	78.26
34	93.38	94.17	90.95	87.53	92.67	89.55	86.71	95.96	89.12
35	86.82	58.63	81.31	96.42	59.63	83.05	89.39	47.22	79.41
36	92.11	96.89	88.36	92.01	96.22	81.31	83.99	85.01	74.41
37	60.05	42.15	89.18	67.36	37.31	86.71	53.97	22.50	79.62
38	75.47	93.41	93.50	86.57	87.73	94.68	79.93	79.85	92.17
39	80.23	73.92	90.37	86.07	73.99	86.29	87.30	72.98	87.53
40	84.67	54.50	94.25	80.09	50.57	95.57	77.70	44.08	92.43
41	90.60	70.02	94.18	83.15	78.17	84.35	80.05	73.99	81.71
42	87.94	60.52	94.3051	84.88	58.48	93.99	80.97	72.43	93.44
43	67.26	63.95	93.19	83.55	78.28	89.85	80.42	72.26	90.19
44	77.03	66.50	64.03	82.91	68.89	37.56	72.45	63.66	59.54
45	62.74	95.01	94.71	91.80	95.41	96.91	85.69	87.02	94.41
46	94.91	66.48	94.91	78.19	73.25	93.25	76.19	90.20	91.36
47	83.75	60.74	95.48	80.85	73.31	96.28	79.40	78.17	94.36
48	95.01	35.63	83.19	92.92	53.20	77.36	94.66	57.58	74.84
49	90.56	67.42	76.95	88.36	86.08	91.62	83.56	83.51	93.62
50	71.87	08.11	81.94	65.99	00.00	61.99	64.30	00.00	87.43
M and S	82.89 ± 11.84	63.53 ± 22.51	89.92 ± 8.99	85.76 ± 8.15	66.65 ± 23.55	89.10 ± 10.81	82.30 ± 9.34	62.30 ± 24.73	88.59 ± 7.94

Disagreement, or difference levels, between the computerized scheme and each of the radiologists as well as the inter-radiologists' disagreement levels are summarized in Table II. The Spearman correlation coefficients for paired estimates of percent completeness of specific fissures in the

50 examinations were all equal to or greater than 0.61 (Spearman, $p < 0.0001$). In general, the percent disagreements between the computerized scheme and the radiologists were similar in magnitude.

When comparing the results obtained by the computerized

TABLE II. Mean errors and standard deviations between our computerized scheme C and each of the two radiologists (R1 and R2).

	Right major fissure	Right minor fissure	Left major fissure
C vs R1	7.42 ± 6.54	8.64 ± 8.86	4.84 ± 6.21
C vs R2	7.11 ± 5.45	11.13 ± 8.20	4.54 ± 6.10
R1 vs R2	4.27 ± 3.32	7.02 ± 5.54	4.23 ± 4.93

scheme and the average of the estimated percent integrities of the two radiologists, the number of cases with percent integrity errors lower than 5% for the right major fissure, the right minor fissure, and the left major fissures was 24, 14, and 37, respectively, accounting for 48%, 24%, and 74% of the involved 50 cases. The number of cases in which disagreements exceeded 10% was nine, 20, and six, respectively, for the same fissures. As expected, the computerized scheme performed best on the left major fissures. This is most likely attributed to the relatively simple topology of the fissures in the left lung.

There were several cases (e.g., case nos. 8, 23, 25, 30, and 45) with estimation disagreements larger than 20%. The two primary reasons for these disagreements were: (1) The fissures were not fully detected or correctly segmented by the computerized scheme due to the presence of diseases (Fig. 11) and (2) individual fissures were incorrectly identified due to a complex topology of the fissures in the right lung (Fig. 12). Cases that can be classified as category (1) included case nos. 25 and 26. In case no. 23, the undersegmentation of the left major fissures does not affect the lobe segmentation but

it does affect the fissure integrity assessment. In case no. 30, the undersegmentation of the right fissures led to completely incorrect lobe segmentation (Fig. 11). Case no. 8 can be classified as a problem belonging to category (2).

IV. DISCUSSION

We developed a computerized scheme to automatically quantify the integrity (completeness) of pulmonary fissures depicted on high resolution CT images, and tested its performance on a relatively small albeit diverse data set of 50 high resolution chest CT examinations. To the best of our knowledge, there are no automated computerized schemes developed and tested in this manner using clinically acquired data sets. Our previously developed fissure/lobe segmentation schemes cannot be used for quantitatively assessing individual fissure integrity levels and significant improvements had to be made in this study to make it possible. These include: (1) The anisotropic morphological filtering for irregularities and “filling in holes” in the detected fissures; (2) a progressive shape decomposition strategy for individual fissure identification; (3) a uniform sampling strategy for improved interlobe surface fitting; and (4) a projection strategy for fissure integrity quantification while accounting for possible false positive fissure detection and identification.

We are well aware of the lack of a verified “ground truth” for an absolute assessment of the performance accuracy of this computerized scheme or any other similar scheme for that matter. This is why we resorted to using assessments of two experienced radiologists and compared the scheme per-

FIG. 11. Two examinations in which the estimation errors are caused by the undersegmentation of the pulmonary fissures due to presence of diseases (e.g., interstitial disease and severe emphysema). The top row shows the left lung of case no. 23 and the bottom row shows the right lung of case no. 30. The left column shows the sagittal views of the CT examinations. The middle column shows the detected fissures in overlay. The lobe segmentation results are shown in the right column.

FIG. 12. An examination (case no. 45) in which the estimation error is caused by incorrect individual fissure identification due to a complex topology of the fissures in the right lung. (a) The sagittal view of the CT examination, (b) the detected fissures in overlay, (c) the lobe segmentation results, and (d) the three-dimensional model of the pulmonary fissures in the right lung are shown, respectively.

formance with manual marking based estimates on a relative scale. Our initial results are quite encouraging in that the fully automated, objective, computerized scheme yielded disagreement levels with each of the individual radiologists that were similar in magnitude as inter-radiologists' levels of disagreement. As to the estimation of the complete fissures, we adopted a subjective approach in that the radiologists independently marked their own explicit perceptions of where incomplete fissures would have ended if they were complete. Hence, our gold standard is based on these subjective assessments by necessity.

The primary limitation of the proposed scheme is the lack of data on the robustness of the approach on examinations depicting severe lung diseases. The potential for incorrect identification of individual fissures is a concern. As our experiments showed, the presence of severe diseases (Fig. 11) and/or unique fissure configuration (Fig. 12) were the two primary reasons for inaccurate estimation of fissure integrity. The former may lead to the underestimation of the fissure integrity, albeit the final lobe segmentation may be accurate (e.g., case 23 in Fig. 11), while the latter may result in incorrect lobe segmentation, ultimately resulting in an incorrect estimation of the complete versions of the detected fissures. We note that in our study fissures depicted on CT images were fully detected in several of these "problem" cases (e.g., case 45 in Fig. 12). Although our experiments demonstrated that the proposed approach worked well in most of the tested examinations, we recognize that the employed approach, including the use of anatomical knowledge based refinements, was not sufficient to assure an errorless scheme for all cases. In practice, severely diseased areas may

result in additional complex regions that appear as surface shape like fissures but are actually not fissures, thus making it very challenging to identify individual fissures. This could result in an incorrect integrity assessment (Fig. 11). We are currently investigating different approaches to address these issues in the hope of achieving robust individual fissure identification in severely diseased cases.

V. CONCLUSION

We developed and tested an automated computerized scheme to quantitatively estimate the integrity or completeness of individual pulmonary fissures. The procedure includes anisotropic fissure "beautification," individual fissure identification, complete fissure estimation and representation, and quantitative integrity estimation. Assessment of the computerized scheme using 50 CT examinations showed the feasibility of using this approach, as it resulted in a relatively high performance level with reasonable robustness.

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