Illustration of the obstacles in computerized lung segmentation using examples

Xin Meng

Department of Structural Biology, University of Pittsburgh, Pittsburgh, Pennsylvania 15213

Yongqian Qiang

Department of Radiology, The First Affiliated Hospital of Medical School of Xi'an Jiaotong University, Xi'an, Shaanxi 710061, China

Shaocheng Zhu

Department of Radiology, Henan Provincial People's Hospital, Zhengzhou 450003, China

Carl Fuhrman

Department of Radiology, University of Pittsburgh, Pittsburgh, Pennsylvania 15213

Jill M. Siegfried

Department of Pharmacology and Chemical Biology, Hillman Cancer Center, Pittsburgh, Pennsylvania 15213

Jiantao Pu^{a)}

Departments of Radiology and Bioengineering, University of Pittsburgh, 3362 Fifth Avenue, Pittsburgh, Pennsylvania 15213

(Received 17 April 2012; revised 4 June 2012; accepted for publication 26 June 2012; published 25 July 2012)

Purpose: Automated lung volume segmentation is often a preprocessing step in quantitative lung computed tomography (CT) image analysis. The objective of this study is to identify the obstacles in computerized lung volume segmentation and illustrate those explicitly using real examples. Awareness of these “difficult” cases may be helpful for the development of a robust and consistent lung segmentation algorithm.

Methods: We collected a large diverse dataset consisting of 2768 chest CT examinations acquired on 2292 subjects from various sources. These examinations cover a wide range of diseases, including lung cancer, chronic obstructive pulmonary disease, human immunodeficiency virus, pulmonary embolism, pneumonia, asthma, and interstitial lung disease (ILD). The CT acquisition protocols, including dose, scanners, and reconstruction kernels, vary significantly. After the application of a “neutral” thresholding-based approach to the collected CT examinations in a batch manner, the failed cases were subjectively identified and classified into different subgroups.

Results: Totally, 121 failed examinations are identified, corresponding to a failure ratio of 4.4%. These failed cases are summarized as 11 different subgroups, which is further classified into 3 broad categories: (1) failure caused by diseases, (2) failure caused by anatomy variability, and (3) failure caused by external factors. The failure percentages in these categories are 62.0%, 32.2%, and 5.8%, respectively.

Conclusions: The presence of specific lung diseases (e.g., pulmonary nodules, ILD, and pneumonia) is the primary issue in computerized lung segmentation. The segmentation failures caused by external factors and anatomy variety are relatively low but unavoidable in practice. It is desirable to develop robust schemes to handle these issues in a single pass when a large number of CT examinations need to be analyzed. © 2012 American Association of Physicists in Medicine. [<http://dx.doi.org/10.1118/1.4737023>]

Key words: lung segmentation, challenge, computer-aided diagnosis, computed tomography (CT)

I. INTRODUCTION

Significant efforts^{1,2} have been dedicated to the development of computerized schemes in aiding detection, diagnosis, and quantitative analyses of lung abnormalities depicted on computed tomography (CT). The motivation arises from the prevalence of lung disease and the high resolution of CT in manifesting normal and abnormal lung structures in significant details. At the same time, the high resolution typically leads to the production of hundreds of images in a single ex-

amination, making it very challenging and time-consuming to manually identify regions-of-interest and perform quantitatively analyses, especially when a large dataset is involved. In particular, manual operations often introduce a large inter- and intraoperator variability.³⁻⁵ Hence, computerized analysis of CT examinations is widely recognized as an efficient way in aiding diagnosis and investigation of lung diseases.

When performing computerized analysis, automated lung volume segmentation is often applied as a preprocessing step. The aim is not only to narrow the search/analysis space for

TABLE I. Summary of the collected lung CT examinations by study and/or program.

	SCCOR (COPD)	SARP (asthma)	LTCR (ILD)	PE	Pneumonia	HIV	SPORE (cancer)	Healthy	LIDC	Total
No. of Exams	923	296	90	174	5	100	232	50	898	2768
No. of subjects	707	156	90	174	5	100	112	50	898	2292

computer-aided diagnosis scheme, but also to improve efficiency, accuracy, and consistence of the quantitative analyses. At first glance, given the relative low density of lung parenchyma, a straightforward solution is the application of a thresholding operation. However, in reality, due to the anatomical variability across subjects and the presence of various diseases, a simple thresholding procedure is often not sufficient and may cause obvious over- or undersegmentation of the lung volume.⁶ In particular, it is difficult to determine an optimal threshold. Improper threshold selection may lead to an inconsistent segmentation that ultimately affects the accuracy of the quantitative analysis in particular when the lung volume is involved. Although a large number of lung segmentation methods^{7–13} have been developed in the past, most of them are designed for specific applications, which may limit its robustness and generality. For example, when detecting pulmonary nodules, the lung volume segmentation scheme needs to properly include pleural nodules in order to reduce the potential false negative,^{14,15} while for volumetric quantification of emphysema, the ignore of pleural nodules may not have obvious impact on the final analysis or conclusion due to its relative small volume. When identifying an airway tree, the trachea region needs to be preserved;¹⁶ while the trachea has to be removed when the objective is to identify individual pulmonary lobes.^{17,18} When performing regional/local analysis, it is often required to have the right/left lungs separated and labeled.^{19,20} In summary, to the best of our knowledge, none of the available approaches is capable of handling all potential issues in a single pass within a unified framework,

particularly in the presence of severe lung diseases. Given the increasing importance of quantitative lung CT image analysis in disease diagnosis, it may be helpful to explicitly know the underlying obstacles that challenge a robust and consistent lung segmentation.

In this study, we attempt to summarize the challenges facing automated lung segmentation using a number of examples. These examples are identified after the application of a generic thresholding-based method to a large diverse database of chest CT examinations (>2700). These examinations are collected from various sources and cover a wide range of diseases, such as chronic obstructive pulmonary disease (COPD), human immunodeficiency virus (HIV), asthma, interstitial lung diseases (ILD), and lung cancer. We expect that such a test may relatively comprehensively identify the potential “obstacles” in computerized lung segmentation. The segmentation issues will be illustrated using classified examples.

II. MATERIALS AND METHODS

II.A. A large diverse database

In the past few years, we have collected a large number of chest CT examinations from several ongoing research projects at our institute and those available in the National Biomedical Imaging Archive (NBIA) at the National Cancer Institute (NCI). Funded by the National Institutes of Health (NIH), the involved research projects include the Specialized Center of Clinically Oriented Research (SCCOR), the

FIG. 1. Illustration of the thresholding-based lung segmentation scheme used in this study: (a) a CT examination, (b) the result after the application of a thresholding operation, (c) the result after nonhuman body region removal, (d) the result after human body removal, (e) the result after trachea removal, (f) right and left lung labeling, (g) vessel inclusion, and (h) three-dimensional lung volume.

TABLE II. Distribution of the failed cases in segmentation by study and / or program.

	SCCOR (COPD)	SARP (asthma)	LTCR (ILD)	PE	Pneumonia	HIV	SPORE (cancer)	Healthy	LIDC	Total
No. of Exams	27	11	14	9	5	4	16	2	33	121
Failure ratio (%)	2.9	3.7	15.6	4.6	100	4	6.9	4	3.7	4.4

Severe Asthma Research Program (SARP), the Lung Tissue Research Consortium (LTRC), and the Specialized Programs of Research Excellence (SPORE) in Lung Cancer. In addition, we collected around 898 CT examinations from a public database named Lung Image Database Consortium (LIDC) at the NBIA.^{21,22} The LIDC dataset is the result of a multiinstitutional effort funded by NIH. Totally, there have been 2768 examinations acquired from 2292 subjects. These examinations cover a wide range of diseases, including lung cancer, COPD, HIV, pulmonary embolism (PE), pneumonia, asthma, and ILD. Because these examinations were acquired from various sources with different research/clinical backgrounds, the CT acquisition protocols, including dose, scanners, reconstruction kernels, and presence of diseases, vary significantly. For example, the section thickness of these examinations ranges from 0.625 mm to 5.0 mm, and the in-plane pixel size from 0.50 mm to 1.0 mm. Hence, our established database has a relatively large diversity in size, acquisition protocol, and disease. Testing using such a diverse dataset may lead to a relatively objective and thorough performance assessment of a lung segmentation scheme.

II.B. Automated lung volume segmentation scheme

In order to identify the “obstacles” in lung segmentation, we used a simple thresholding-based approach to process the collected dataset. The motivation stems from the fact that the thresholding-based approach has no bias in nature in regard to the applications and is widely used as a preprocessing step

FIG. 2. An example in the failure category “C1.” The indicated juxtapleural nodule is missed.

to obtain initial lung region in most available lung segmentation approaches.^{7–13} Given the “neutral” characteristic of the thresholding-based approach, we expect to obtain a relatively complete picture of the “difficult” cases in lung segmentation without consideration of any specific clinical application (background). Here, the “difficult” does not mean that the identified cases cannot be successfully segmented by other sophisticated approaches but by the traditional thresholding-based approach.

The thresholding-based approach is simple in both methodology and implementation. Here, we only provide a brief description of our implementation (Fig. 1). First, a thresholding operation is used to identify the region with low densities [Fig. 1(a)]. The threshold is selected adaptively from a histogram as described in Ref. 6. Second, small nonbody regions, such as these in Fig. 1(b), are removed by a simple size-based filtering operation. Only the small regions located within low density regions are filtered out. This operation is to assure that nonbody regions are fused with each other in space. Third, as shown in Figs. 1(c) and 1(d), a flooding operation is taken to remove the nonlung region. The left upper corner [i.e., point (0, 0, 0)] is simply selected as the seed point. Fourth, the trachea regions are removed in a slice-by-slice manner by identifying small regions that are located between two large regions (i.e., the right and the left lungs) [Figs. 1(d) and 1(e)]. In practice, if it needs to retain the trachea, this step can be simply skipped. Fifth, the right and the left lungs are labeled using the patient position information stored in the DICOM header. In the DICOM standard, there are tags that provide information about patient position and orientation relative to a CT scanner. For example, possible patient position tags include: HFP = head first-prone, HFS = head first-supine, HFDR = head first-decubitus right, HFDL = head first-decubitus left, FFP = feet first-prone. Using these tags will lead to the identification of the right and left lungs. Finally, whereas the thresholding operation removes regions with relatively high densities, the vessels are missed in the segmentation [Fig. 1(f)]. If an application needs the vascular tree, an intuitive solution is the application of a conventional close morphological operation. The example in Fig. 1(g) is the result after the application of the morphological operation. The identified three-dimensional (3D) lung volume is shown in Fig. 1(h).

II.C. Identification of failure cases

In order to identify the failed cases, we asked an image analyst to look through the results after the application of the above described thresholding-based segmentation scheme to

FIG. 3. An example in the failure category “C2,” where the right and left lungs are attached when a thresholding procedure is applied.

the collected chest CT examinations and identify those that are not properly segmented. The computerized scheme was applied to these examinations in a batch manner with the same parameters. Whereas the lung boundaries are actually well defined in CT examinations, we do not ask a radiologist to initially read the large volume of results. This image analyst has an experience of at least three years in lung CT image analyses and has sufficient knowledge for this specific task. Thereafter, a radiologist (>30 years experience) was asked to read the failed cases and classify them into different categories (subgroups).

III. RESULTS

Totally, there are 121 examinations labeled subjectively as “failures.” These are classified into the 11 subgroups as listed in Table II, and their distributions in terms of diseases are summarized in Table III. For clarity purpose, each of the 11 subgroups (i.e., C1–C11) is explained using an example (i.e., Figs. 2–12). It can be seen from Table II that the failure ratios are relatively high in the presence of specific diseases, such as ILD, pneumonia, and lung cancer, corresponding to a failure ratio of 15.6%, 100%, and 6.9%, respectively. For other types

of diseases, the failure ratios are relatively similar, ranging from 2.9% to 4.6%. As shown in Table III, most failed cases are located in the category of “C1.” Actually, all juxtapleural nodules are missed by the thresholding-based approach. “C2” is the subgroup with the second highest failure number, corresponding to a failure ratio of 30.6%.

These subgroups from “C1” to “C11” are classified further into three broader categories: (1) category “B1”: failure caused by diseases, including “C1,” “C3,” “C8,” “C9,” and “C10,” (2) category “B2”: failure caused by anatomy variability, including “C2” and “C5,” and (3) category “B3”: failure caused by external factors, including “C4,” “C6,” “C7,” and “C11.” Their distributions are shown in Table IV. The segmentation failures occur frequently in the presence of lung diseases (category “B1”). There are a certain number of segmentation failures caused by anatomy variability. In contrast, there are few failures caused by external factors.

IV. DISCUSSION

In this study, we attempted to comprehensively identify the potential “obstacles” (Figs. 2–12) in automated lung segmentation. We note that our emphasis is not on the development

FIG. 4. An example in the failure category “C3.” In this example, the presence of mucus makes part of the left major bronchus not depicted on CT images. (a) and (b) Two neighboring image slices of the CT examinations. It can be seen that the left major bronchus is depicted on a slice (a) but disappears on the next neighboring slice (b).

FIG. 5. An example in the failure category “C4.” In this example, the improper field-of-view makes the algorithm fail to identify the parenchyma regions, because the parenchyma is fused with the external nonlung regions in space.

of a novel lung segmentation scheme. A unique characteristic of this study is the use of a large diverse dataset of chest CT examinations (>2700). These examinations are collected from various sources and cover a wide range of diseases and acquisition protocols. In identifying the “obstacles,” we used a “neutral” thresholding-based approach with the motivation of avoiding the “involvement” of any additional specific procedure in lung segmentation. Given the large diverse dataset and a “neutral” algorithm, we believe that a relatively comprehensive set of failed case could be identified. Awareness of these failures (examples) listed in Figs. 2–12 may be useful for facilitating the development of a robust and consistent computerized lung segmentation scheme.

FIG. 6. An example in the failure category “C5.” In this example, the left lung was removed because of the existence of lung cancer. When labeling the right and the left lungs, the computer algorithm fails because the left lung cannot be found.

FIG. 7. An example in the failure category “C6.” In this example, the right and left lung are incorrectly labeled. The patient position/orientation information is not available in the DICOM header of this specific case.

Our experiments show that a thresholding-based approach is not a robust solution to lung segmentation. As shown by the results in Tables II and III, most failures are caused by specific lung diseases, such as pulmonary nodules, severe pneumonia, and ILD. The severe ILD or pneumonia typically causes the missing of a large portion of the lung volume and at the same time may divide the lungs into isolated parts (Figs. 9 and 10). When performing the segmentation, it is a challenging task to automatically identify the missed regions and smoothly include them using contours that faithfully fit the “true” lung boundaries. Wang *et al.*¹⁰ developed a texture-based method to segment the lungs in presence of severe ILD. Although they claimed that their methods could obtain a mean overlap rate of 96.7%, this texture-based method may not work for the example in Fig. 10, because there is little “textural” information in the diseased region for analysis. Alternatively, Prasad *et al.*⁸ took advantage of the curvature of the ribs for lung segmentation in the presence of ILD. However, if ILD occurs in a region close to the spine, this method may fail because their assumption “the curvature of the ribs and the curvature

FIG. 8. An example in the failure category “C7” where the metal spray effect in (a) leads to the inclusion of some nonlung region as shown in (b).

TABLE III. Distribution of the failed cases in segmentation by the 11 classified subgroups.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	Total
No. of exams	52	37	1	2	2	1	2	5	14	3	2	121
Failure ratio (%)	43.0	30.6	0.8	1.7	1.7	0.8	1.7	4.1	11.6	2.5	1.7	100

Note: “C1”: juxtapleural nodule; “C2”: right and left lung attachment; “C3”: mucus in main bronchi; “C4”: improper CT scan; “C5”: absence of a lung due to thoracotomy; “C6”: prone-supine position in CT scan; “C7”: metal spray effect; “C8”: severe pneumonia; “C9”: severe interstitial lung disease (ILD); “C10”: Chilaiditi syndrome; “C11”: damage of image slices.

FIG. 9. An example in the failure category “C8.” A large part of the right lung is missed due to the presence of severe pneumonia.

FIG. 10. An example in the failure category “C9.” A large part of the right lung is missed due to the presence of severe interstitial lung disease (ILD).

of the lung boundary around the ribs to be very close” will not hold. To date, we do not find any method that is capable of robustly identifying lung volume in presence of severe ILD or pneumonia. Although we have a large number of CT examinations from a COPD study, our experiments show that the existence of COPD has little impact on the lung segmentation. This may be attributed to the fact that unlike other diseases (e.g., pneumonia and ILD) COPD does not lead to lung damages with high densities. In practice, due to the popularity of the above mentioned diseases, specific attention is necessary to handle this segmentation issue. In the past, there are a number of methods developed for the inclusion of regions caused by one specific disease (e.g., pleural nodules¹⁴) in lung segmentation, but they may not be used directly for the inclusion of other diseases [e.g., ILD (Ref. 10)]. As compared to ILD, it is relatively easy to handle juxtapleural nodules because their shapes and sizes vary slightly. As reported in Ref. 14, 100% of the juxtapleural nodules were successfully included in the

lung segmentation. The piecemeal manner of handling lung segmentation may be suitable for specific application but not for a general purpose.

In this study, the CT examinations were collected from various sources. Their acquisition protocols, such as dose, scanners, reconstruction kernels, are different. Whether this variation may potentially cause segmentation issues is not clear. In our practice, we do not find failures caused by the variations in acquisition protocols. This may be attributed to the obviously low density of the lungs. Although lung segmentation failures caused by external factors (e.g., category “C11” in Fig. 12) are relatively rare, it does not mean that a computer algorithm should ignore it, because errors from human beings are always unavoidable in practice. For example, the patient position information for the example in Fig. 7 is missed in the DICOM header of the associated CT examination. Proper handling of these exceptions is desirable in practical application. Instead of using the DICOM header, anatomy

FIG. 11. An example in the failure category “C10.” In this example, there is an obvious Chilaiditi syndrome, or presence of gas in the right colic angle between the liver and the right hemidiaphragm. Due to its attachment to the right lung in image space, the gas region in hepatic flexure of colon is incorrectly included as part of the right lung.

information (e.g., the global shape of the human lungs) may be explored as an alternative solution to robustly determine the patient position/orientation.

As compared to the external factors, there are relatively more failures caused by anatomy variability. Unlike the external factors, such issues cannot be avoided. In this category, the attachment between the right and the left lungs occur frequently on CT images. In theory, even a single voxel (image noise) may lead to such an attachment when a flooding operation is used. For this issue, a simple solution is the application of the conventional open morphological operation. However, the morphological operation is typically time-consuming. In addition, whereas the junction region between the right and the left lungs varies in size, it may not be easy to select an optimal kernel size for the morphological operation. In the past, there have been a few investigations on how to separate the right and left lungs. A widely employed idea is to locate the anterior and posterior junction locations of the right and

TABLE IV. Distribution of the failed cases in segmentation.

	“B1”: failure caused by diseases	“B2”: failure caused by anatomy variability	“B3” failure caused by external factors	Total
No. of exams	75	39	7	121
Failure ratio (%)	62.0	32.2	5.8	100

the left lungs by studying the connectivity between sequential CT image slices.^{9,19,23–25} Thereafter, either a straight line²³ or a morphological operation⁹ is used to separate the junction. In particular, Park *et al.*¹⁹ proposed to use dynamic programming to perform the separation. When the junction of the right and the left lungs are small, the above mentioned approaches should be able to achieve a reasonable accuracy; otherwise, it will be difficult to identify the exact boundary between the right and the left lungs.

In practice, the above mentioned issues (e.g., diseases, anatomy variability, and external factors) may occur at the same time in the same patient. It is extremely necessary to develop computerized lung segmentation schemes to robustly handle the presence of these diseases simultaneously in a transparent manner. Although we attempted to resolve these segmentation issues in a single pass instead of in a piece-meal manner using a shape break-and-repair strategy,²⁵ there is still obvious undersegmentation in volume, especially when there is severe disease such as ILD. In addition, this scheme is not efficient because of the involvement of a 3D freeform surface fitting operation, largely limiting its application in practice. Given the potential challenge in resolving these issues simultaneously, instead of performing the segmentation in a fully automatic manner, an alternative choice is to provide a mechanism for a user to interactively select a proper method for specific failure. However, this method is only suitable for situations where only a few examinations are involved.

We are aware of the limitations of this study. First, an image analyst instead of a radiologist was asked to initially look through the segmentation results. In fact, it is ideal for a radiologist to perform this task. However, due to the large number of CT examinations (>2700) involved in this study, it is

FIG. 12. An example in the failure category “C11,” where a slice of image is damaged. This issue causes the fusion of the lung region with the outside nonlung region, ultimately leading the failure in lung volume identification.

time-consuming and expensive to ask a radiologist to do so. Considering that it is not difficult for an image analyst with basic knowledge of lung CT images to visually identify the lung boundary, the potential problem caused by this limitation should be small. Hence, an experienced radiologist was asked to only verify the initially identified failed cases and classify them into different categories. Second, although we use a large diverse dataset in this study to identify the potential failed cases in lung segmentation, there may still miss unknown types of lung segmentation failures because the dataset may not be large enough to covers all kinds of cases. Third, despite its large size, the collected dataset may actually over-represent some types of diseases (e.g., lung cancer). Hence, the reported values (e.g., failure ratios in Tables I and III) may not be true or remain the same for other datasets. We note that our primary objective is to identify the types of lung segmentation failures instead of presenting a statistical analysis of these failures.

V. CONCLUSION

We attempt to identify potential issues in computerized lung segmentation. Totally, 2768 examinations were collected from various sources and a thresholding-based method was applied to these cases. The failed examinations were subjectively identified and classified into 11 subgroups and 3 broad categories. Each subgroup is illustrated using an example. Finally, we discussed these failures and potential solutions for the lung segmentation. Awareness of these issues (obstacles) may be helpful for developing robust computerized lung segmentation schemes and accelerating their application to the investigation and quantification of lung diseases.

ACKNOWLEDGMENTS

This work is supported in part by Grant Nos. R01 HL096613, P50 CA090440 from National Heart, Lung, and Blood Institute, National Institutes of Health (NIH), to the University of Pittsburgh, The Bonnie J. Addario Lung Cancer Foundation, and the Pittsburgh and the SPORC in Lung Cancer Career Development Program. Dr. Xin Meng and Dr. Yongqian Qiang contributed equally to this work.

^{a)} Author to whom correspondence should be addressed. Electronic mail: jip13@pitt.edu

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