SEGMENTATION OF OBSTRUCTED AIRWAY BRANCHES IN CT USING AIRWAY TOPOLOGY AND STATISTICAL SHAPE ANALYSIS

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ABSTRACT

Chest pathology can lead to airway branch obstruction, and segmentation of the airways beyond obstructions is a challenge. We propose a novel method that automatically identifies points of obstruction using airway topology and statistical shape analysis and segments disconnected branches. The point of obstruction is used to define an allowed region for the airway beyond the obstruction in order to direct the segmentation. This method can be used to extend standard airway segmentation approaches and was evaluated using 42 chest CT scans of paediatric patients with tuberculosis. The algorithm was compared to manually labelled obstructions, and identified 24 of the 26 obstructed branches (where the 2 missing branches would likely be identified with more training data for the left main bronchus) and identified 18 of the 19 disconnected airway regions.

***Index Terms*—** object segmentation, pattern recognition, support vector machines

1. INTRODUCTION

Automated airway analysis has the potential to be an important tool in the detection and treatment planning of disease. A key identifier of primary tuberculosis (TB) in children, for example, is airway stenosis caused by enlarged lymph nodes [1, 2]. These lymph nodes can compress the airways or cause herniation of the airways [3]. In severe cases, a branch can be completely obstructed.

There are a number of existing airway segmentation methods [4, 5, 6, 7, 8, 9]. However, these generally focus on healthy adult airways and do not consider obstructions. In order to minimise the likelihood of segmentation of non-airway regions these methods generally require the airway to be completely connected. This is often performed using a region growing step from a seed point in the trachea. If a method is to be effective for the analysis of pathological airway trees then the method must be robust enough to segment branches beyond complete obstructions.

A few methods do not require the airways to a connected structure and instead rely on the filtering step to minimise leaking. Sonka et al. [6] propose a rule-based method that uses airway grey-scale, size and vessel adjacency to classify airways. They produce two representations: a 3D connected region and a representation that includes disconnected regions that are also classified as airways. Kitasaka et al. [10] use filters to enhance tubular structures in the image. Both these methods show potential to segment disconnected airway structures but also result in considerably increased leaking because non-airway disconnected structures are also included [10, 6]. Kitasaka et al. [10] mentions that structures of a similar intensity and shape such as the oesophagus are included, and suggest statistical shape analysis as a possible approach to remove these objects.

We propose a method that takes into account the airway tree topology and branch shape in order to identify and segment missing branches. This analysis layer is added to a previously tested segmentation algorithm [9]. The goal of this method is not only to improve the segmentation but also to link the missing branches to the branching structure of the airway tree – to allow further airway evaluation. The method is used in conjunction with a specific airway segmentation algorithm in this paper but has the potential to be applied to most airway segmentation algorithms, including the two previously discussed methods.

The algorithm is applied to a paediatric chest CT dataset of patients with airway compression caused by TB. The size of paediatric airways means that the airways are a lower resolution than can be achieved with adult patients. The lower resolution along with increased risk of movement artefacts means that fewer generations can be extracted compared to

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adult airways. Therefore, to perform a meaningful analysis it is essential that as many generations as possible are extracted – in particular complete obstructions.

2. METHOD

The segmentation algorithm that this method builds on is a morphology based algorithm [9]. The morphological filtering is applied in the axial, sagittal and coronal planes, to enhance circular shaped objects, using a range of kernels of a similar size to bronchi cross sections. A region growing method starting from the trachea is then used to identify the connected airway region. This segmentation procedure has two outputs: a number of possible airway locations identified using the filtering and the 26-connected airway region seeded at the trachea.

Next the medial line is identified and used for branch labelling. Palagyi et al. [11]'s skeletonisation method is used for the extraction of the medial line. This algorithm uses a iterative thinning approach while preserving the branching structure of the airways. The 1-voxel thick centreline is then used to detect branch points by finding the connectivity of each point and finally assign a label to each branch. Heuristics are then used to identify each branch and assign the anatomical name of the branch.

Point distribution models consist of a set points that represent each object in the dataset, where a point on one object has a corresponding point on each other object in the dataset [12]. This is a challenge for the airways because other than the branching structure there are no obvious anatomical landmarks. Correspondence was established using the centreline and branch points as a reference. The centreline was sampled equidistantly along each branch and, at each point, the intersection between the airway surface and the plane orthogonal to the centreline was found – from which corresponding points could be found.

2.1. Detection and segmentation of missed branches

The previous steps find a suitable point representation so that shape analysis can be performed to find obstructed branches. Three steps are used to detect new branches:

- Identify the existence of an obstruction
- Find the position of the obstruction
- Find airway beyond the obstruction

Obstructions can be separated into two categories: obstructions that occur late enough in the branch for the obstructed branch to be distinguished from the parent branch (which we will define as *incomplete branches*), and obstructions that occur close enough to the beginning of the branch for there to be no identifiable new branch on the main airway tree (*missing branches*). The separation between these categories is dependent on the sensitivity of the skeletonisation procedure to detect new branches. However, the more sensitive the skeletonisation procedure is to false branching, the greater the chance that false branching will occur.

Incomplete branches are easier to detect than *missing branches*. An obstructed branch is assumed to be present when a branch has no child branches. Identification of obstruction is more complicated for *missing branches*. In our algorithm, statistical shape analysis is used to distinguish normal branches from branches that include the "stump" from a missing child branch. Principal component analysis (PCA) is applied to the dataset and the first four modes are used as a feature vector for classification. Branches in the dataset are manually labelled and used to train a support machine classifier (SVM). This trained classifier is used to identify obstructed branches. An analysis of the radius of the branch is then performed to detect the position of obstruction for those branches that have been identified as containing missing child branches.

Once the obstructed branches have been identified and the point of obstruction found then the next step is to identify the airway beyond the obstruction (*disconnected airway region*). A cylinder defined by the point of obstruction and the direction of the branch is defined. Segmented objects that intersect the cylinder are identified and labelled. In most cases only one object is found, however, if more than one exists, a set of heuristics based on size and compactness are used to identify the correct object. Figure 1 shows the steps used in the algorithm.

2.2. Dataset

The dataset consists of 49 chest CT scans from Tygerberg Hospital, Western Cape, South Africa. These are paediatric patients diagnosed with definite or probable TB from positive culture or scope and CT findings. The median age of a patient in the dataset is 14 months and the maximum and minimum age is 108 months and 2 months, respectively. The scans were acquired on a number of units with voxel size varying from 0.3-0.4 mm in the XY plane and 0.7 -1.0 mm in the Z direction. This dataset contains various degrees of stenosis including complete obstructions. The age of the patients concerned meant that the airways are much smaller than adult airways, and therefore, with fewer branches segmented. Seven cases were removed from the dataset: 3 because of severe movement artefacts, 2 because of scan errors and 2 because a tube in the trachea affected the trachea shape. The algorithm was tested on the remaining 42 cases. Obstructions

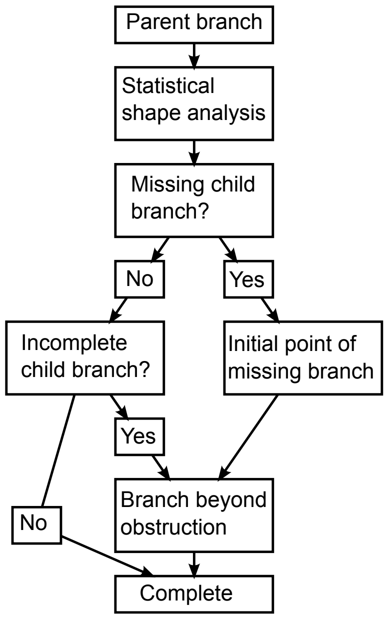


Fig. 1. Diagram showing the procedure to identify missing child branches

and disconnected airway regions were manually labelled from the segmentation. These were also verified using the greyscale CT scans. These manually labelled images were used for training the SVM and for comparison.

3. RESULTS AND DISCUSSION

The segmentation method has been previously examined [9] and this paper focuses on statistical shape analysis to detect and segment obstructed branches (Figure 2 demonstrates the segmentation method on a previous adult dataset and shows branch labels [9]).

The method was tested on branches where there was a clinical focus for detecting TB from lymphadenopathy and, therefore, where there were a number of obstructions present. Therefore, the trachea, right main bronchus (RMB), left main bronchus (LMB), right upper lobe bronchus (RUL) and bronchus intermedius (BI) were considered (as shown in Figure 2). A dataset of 42 patients was used and these cases were manually labelled as a reference. 2 cases had a missing LMB, 3 cases had a missing RUL and 9 cases had a missing BI. 1 case had an incomplete LMB, 1 case had an incomplete RMB, 3 cases had an incomplete BI and 7 cases had an incomplete RUL. The skeletonisation and false branch pruning procedure is automated but in 4 cases false branches still occurred and were manually removed.

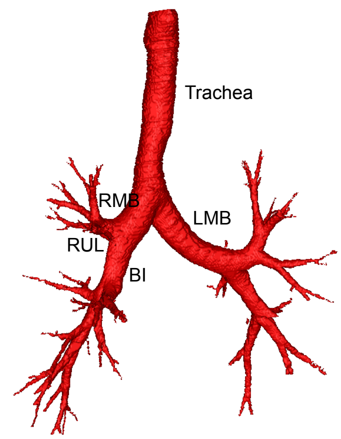


Fig. 2. Reference image of adult airway segmentation

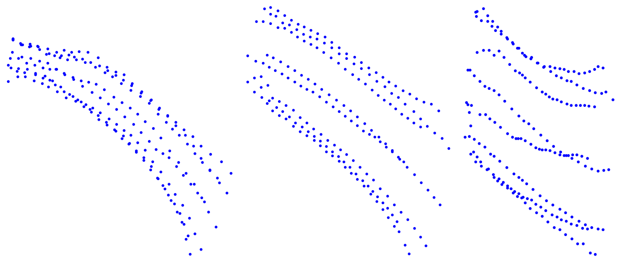
3.1. Detection of missing and incomplete branches

Shape analysis was performed on each individual branch to find missing child branches. Shape analysis was applied to the RMB to detect missing RUL and BI, and shape analysis was applied to the trachea to detect missing LMB and RMB. The first 4 PCA modes were used as a feature vector and SVM with a polynomial kernel was used as a classifier. SVM was implemented with PrTools [13]. The first 4 modes accounted for 65% of the RMB variation in the dataset. Figure 3 shows the point representation of the RMB and the shape variation along first PCA mode. Figure 5 shows the point representation of the airway and the identification of the obstruction start point. Figure 4 is a plot of the dataset in feature space for the RMB and Trachea. The plot uses multidimensional scaling (MDS) to present the 4 dimensions as a 2D plot. The 3 classes for the RMB could be separated well using the 4 PCA modes where the classes represented: 1) RMB, 2) RMB with RUL "stump" or 3) RMB with BI "stump". Using SVM with leave-one-out testing, all the RMB were classified correctly as shown in Table 1. This method was also applied to the trachea to identify missing LMB (as shown in Figure 4). The results look promising, however, with only two obstructed LMB cases and no obstructed RMB cases, a classifier could not be trained.

True Labels	Estimated Labels			
	1	2	3	Totals
1	28	0	0	28
2	0	3	0	3
3	0	0	9	9
Totals	28	3	9	40

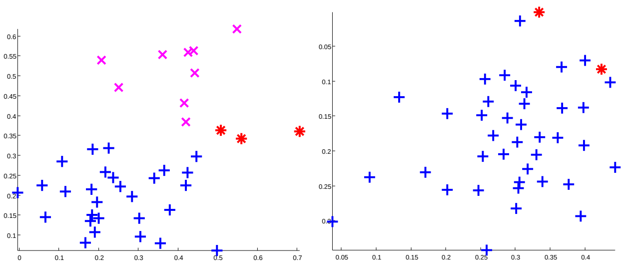
Table 1. Leave-one-out cross validation of SVM for the RMB

After missing child branches are identified, the algorithm checks the child branches of the remaining airways for fur-



(a) -ve (b) Mean RMB (c) + ve

Fig. 3. Variation along the first PCA mode of RMB



(a) RMB (b) Trachea

Fig. 4. MDS reduction to 2 dimensions of 4 dimensional feature space

ther branching. If not then the child branches are incomplete (see Figure 1). All cases where the branches had not been labelled as missing (by the classifier in the previous step) were checked and obstructions were detected for all cases (see Table 2).

3.2. Segmentation of disconnected airway regions

Table 2 shows the total number of cases with obstructions (*missing branches* and *incomplete branches*) and the total number of cases with disconnected airway regions. In some cases for RUL there are no disconnected branches after obstruction (see Table 2). In these few cases the possibility of small branching could not be excluded but were not identifiable during manual labelling. Two airways with obstructed LMB are not listed as being identified for the LMB. The statistical shape method is likely to work for these branches, however, there was not enough data to train and test the model on this branch (see Figure 4). Assuming correct classification of all three LMB then the second step extracted all three disconnected airway regions correctly. Obstructions and disconnected branches for all 12 cases of the BI branch were identified correctly. “false obstructions” were identified in 3 cases where the airway was not discontinuous in the scan but was not segmented completely because of severe stenosis. This algorithm was also able to identify these disconnected regions that were missed by the original segmentation algorithm. Figure 6 shows branch labelling of the original

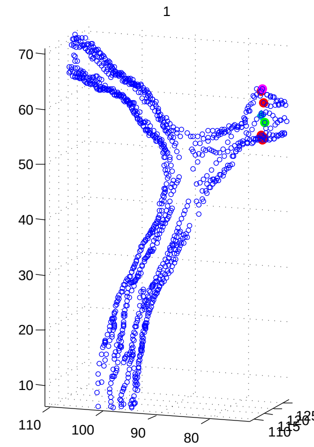
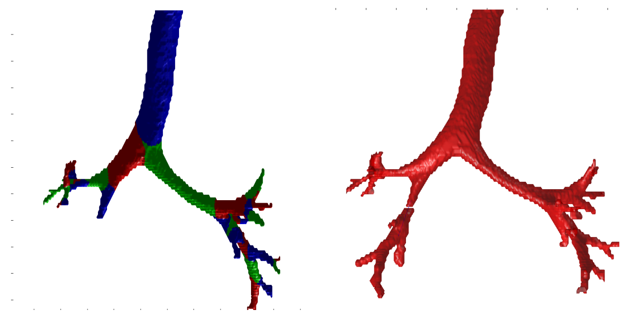


Fig. 5. Point model with identified obstruction

connected region and the addition of the disconnected region. Figure 7 shows example segmentations of disconnected airway regions.



(a) Branch labelling (b) Disconnected airway region

Fig. 6. Branch labelling and identification of obstructed branch

In summary, this method automatically identified 24 of the 26 obstructed branches. Two branches could not be classified because of a lack of data. 18 of 19 disconnected airway regions were segmented.

4. CONCLUSION

Airway segmentation beyond obstructed regions will improve the effectiveness of segmentation procedures for severe pathology and will improve the viability of automated airway analysis. We have presented a method that uses the airway topology and shape to identify disconnected airway regions – and can be applied to these existing methods. This improves upon previous methods that did not take into account the relationship between the main airway tree and the disconnected airway regions, and applies statistical shape analysis for the first time to this problem. In addition, the topological

	Manual labelling			Automated detection	
Branch	Obstructed branch	Disconnected region	False Obstructions	Obstructed branch	Disconnected region
LMB	3	3	0	1 [a]	3
RMB	1	1	0	1 (+1 error) [b]	1
BI	12	12	3	12	12
RUL	10	3	0	10	2

[a] 2 excluded branches are likely to be detected by the SSM but classification could not be performed for these 2 cases because of lack of training data
[b] 1 branch was misclassified because of a lack of child branches

Table 2. Manually and automated labelling of obstructions and disconnected branches (no. of airways)

(a) BI obstruction

(b) LMB obstruction

Fig. 7. Segmenting past complete obstruction

relationship between the main tree and disconnected airway region is also found, which will aid further airway analysis.

5. REFERENCES

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