Automated anatomical labeling of bronchial branches using multiple classifiers and its application to bronchoscopy guidance based on fusion of virtual and real bronchoscopy

Shunsuke OTAa, Daisuke DEGUChib, Takayuki KITASAKAa,b, Kensaku MORIa,b, Yasuhito SUENAGAA,a,b, Yoshinori HASEGAWAc, Kazuyoshi IMAIZUMIc, Hirotugu TAKABATAKEd, Masaki MORIf, and Hiroshi NATORIf

aGraduate School of Information Science, Nagoya University, Nagoya, Japan
bMext Innovative Research Center for Preventive Medical Engineering, Nagoya University, Nagoya, Japan;cSchool of Medicine, Nagoya University, Nagoya, Japan;dSapporo Minami Sanjo Hospital, Sapporo, Japan;ecSapporo-Kosei General Hospital, Sapporo, Japan;fKeiwakai Nishioka Hospital, Sapporo, Japan

ABSTRACT

This paper presents a method for automated anatomical labeling of bronchial branches (ALBB) extracted from 3D CT datasets. The proposed method constructs classifiers that output anatomical names of bronchial branches by employing the machine-learning approach. We also present its application to a bronchoscopy guidance system. Since the bronchus has a complex tree structure, bronchoscopists easily tend to get disoriented and lose the way to a target location. A bronchoscopy guidance system is strongly expected to be developed to assist bronchoscopists. In such guidance system, automated presentation of anatomical names is quite useful information for bronchoscopy. Although several methods for automated ALBB were reported, most of them constructed models taking only variations of branching patterns into account and did not consider those of running directions. Since the running directions of bronchial branches differ greatly in individuals, they could not perform ALBB accurately when running directions of bronchial branches were different from those of models. Our method tries to solve such problems by utilizing the machine-learning approach. Actual procedure consists of three steps: (a) extraction of bronchial tree structures from 3D CT datasets, (b) construction of classifiers using the multi-class AdaBoost technique, and (c) automated classification of bronchial branches by using the constructed classifiers. We applied the proposed method to 51 cases of 3D CT datasets. The constructed classifiers were evaluated by leave-one-out scheme. The experimental results showed that the proposed method could assign correct anatomical names to bronchial branches of 89.1% up to segmental lobe branches. Also, we confirmed that it was quite useful to assist the bronchoscopy by presenting anatomical names of bronchial branches on real bronchoscopic views.

Keywords: bronchus, anatomical labeling, bronchoscopy guidance, virtual bronchoscopy, chest CT image, multi-class AdaBoost

1. INTRODUCTION

To make the bronchoscopy much safer and effective, virtual bronchoscopy system (VBS) becomes very common tool to guide a bronchoscopist. In the pneumology, a bronchoscope is a quite useful tool for diagnosis of inside the bronchus. A bronchoscopist inserts the bronchoscope into a bronchus through a mouth or a nose, and diagnoses inside a bronchus with looking at a TV monitor which displays the bronchus lumen. However, since the bronchus has a complex tree structure, a bronchoscopist easily gets disoriented and loses the way to a target location. Therefore, VBS assisting a bronchoscopist has been developed. Figure 1 shows an example of VBS. As seen in
Fig. 1, VBS can display the various kinds of information, such as organs existing beyond the bronchus wall, the current location and orientation of a bronchoscope, the outside view of a bronchus region and the path to the position where the biopsy will be performed\textsuperscript{1,2}. Such information is generated by using a 3D CT image taken in prior to bronchoscopy.

Path planning is a crucial task to perform bronchoscopy smoothly and safely\textsuperscript{3-5}. In prior to bronchoscopy, a bronchoscopist usually generates an optimal path using VB images generated from CT images of a patient. The path is represented by the anatomical names of bronchial branches that the bronchoscope will visit. However, since the bronchus has a very complex tree structure, a bronchoscopist sometimes gets disoriented. Therefore, it is desired to develop a guidance system providing the information of the insertion direction of the bronchoscope by displaying the anatomical names of the observing branch and its child branches (Fig. 1).

As mentioned above, anatomical names of bronchial branches are quite useful information to assist a bronchoscopist. Anatomical names of bronchial branches should be labeled before the bronchoscopy to guide him/her using them. However, since the bronchus has a complex tree structure consisting of a lot of branches, it is heavily time-consuming task to label them manually. Therefore, we develop a method for automated anatomical labeling of bronchial branches (ALBB) extracted from three dimensional (3D) CT images. Several groups proposed methods for automated ALBB\textsuperscript{6-8}. They performed automated ALBB based on model-matching approach. Mori et al.\textsuperscript{6} prepared one branching-pattern model containing anatomical names. The model has information about running directions, parent branch names and parent-child relationships. They performed ALBB by selecting the most suitable branch information from the model for each branch. The problem of this method was that it was possible to deal with variations of branching-patterns. Kitaoka et al.\textsuperscript{7} proposed ALBB using a weighted maximum clique search approach. However since they also prepared only one branching-pattern model, it is still difficult to deal with variations of branching pattern. While Mori et al.\textsuperscript{8} utilized multiple branching-pattern models for each part of the bronchus (right upper lobe, right middle and lower lobes, left upper lobe and left lower lobe). By utilizing several branching-pattern models, they became to be able to deal them. However, they did not consider variations of running directions of bronchial branches. Since the running directions of bronchial branches differ greatly among individuals, they could not perform ALBB accurately when running directions of bronchial branches are different from those of their models. Also, in generally, model-matching approach requires preparing a lot of branching-pattern models to deal with various branching-patterns. However, it becomes difficult to select suitable model as the number of models increase, because the number of models having similar branching-patterns also increase. Though machine-learning approach also requires a lot of datasets to classify unknown datasets correctly, it can construct powerful classifier learning features well when there are a lot of
datasets. Therefore, we consider the ALBB as a problem that each bronchial branch is classified into the category (bronchial name) to which it belongs, and perform ALBB employing the machine-learning approach. Also, to deal with variations of running directions of bronchial branches, we construct classifier learning variations of running-directions of bronchial branches. Since the bronchus consists of hundreds of branches with unique anatomical names, our problem is formulated as a multi-class classification problem in which each bronchial branch is to be assigned to each class corresponding to its anatomical name. We utilize multi-class AdaBoost technique to construct classifiers. Multi-class AdaBoost\textsuperscript{11–13} is a powerful tool for a multi-class classification problem. Li et al.\textsuperscript{13} utilized error-correcting-code (ECC) to reduce multi-class classification problem to binary classification problem. They updated ECC by a technique named “repartitioning” to be more classifiable. They showed experimentally that their algorithm is very efficient and outperforms existing multi-class boosting technique. Therefore the proposed method utilizes the multi-class AdaBoost technique proposed by them. Also, we develop a method to overlay bronchial names on a real bronchoscopic (RB) view using the ALBB results.

In Section 2, we describe the detailed procedures of the proposed method. Section 3 shows experimental results of the proposed method. Then we discuss about the results of the proposed method in Section 4.

2. METHODS

2.1 Overview

In this section, we describe details of the proposed method in two parts. The first part shows a method for labeling anatomical names to bronchial branches automatically. The second part shows a method for displaying bronchial names on RB views. Figure 2 shows the processing flow of the proposed method. Automated ALBB is considered as a procedure that classifies a feature vector extracted a bronchial branch into category (=its bronchial name). The proposed method employs the machine-learning approach, and assigns an anatomical name to each bronchial branch by using the classifier constructed from training datasets. Multi-class AdaBoost technique is used for constructing classifiers, and bronchial features, such as the length and running directions of bronchial branches are calculated for learning classifiers. Finally, we utilize anatomical names of bronchial branches obtained by ALBB for the bronchoscopy guidance system. The proposed method overlays the anatomical names of currently observing branch and its child branches onto RB views. Here, the observing branch is identified as the closest branch from the RB camera. To compute the closest branch, the position of the RB camera is estimated by the method proposed in the reference\textsuperscript{9}.

2.2 Definition

Figure 3 illustrates an example of a bronchial tree structure. In this figure, a tree structure is represented as a set of connected lines corresponding to the bronchial branches \( b_i \) (\( i = 1, \ldots, M \) : \( M \) is the number of branches). In particular, \( b_1 \) denotes the root of the tree structure. Also, the coordinates of the start and the end points of \( b_i \) are represented as \( S(b_i) \) and \( E(b_i) \), respectively. \( N(b_i) \) is a name of \( b_i \), and \( P(b_i) \) is a parent branch of \( b_i \). From these definitions, sibling branches of \( b_i \) are defined as

\[
B(b_i) = \{ b_j \mid (b_j \neq b_i) \land P(b_j) = P(b_i) \}.
\] (1)
Figure 3. An example of the tree structure of a bronchus region. Tree structure is represented by lines. Red lines represent $C(b_1) = \{b_2, b_3\}$ and green lines represent $D(b_2) = \{b_4, b_5, b_8, b_9, b_{10}, b_{11}\}$

Also, $C(b_i)$, which represents child branches of $b_i$, is represented as

$$C(b_i) = \{b_i; N(b_i) = N(P(b_i))\}, \quad (2)$$

and $D(b_i)$, which represents descendant branches of $b_i$, is defined recursively as

$$D(b_i) = C(b_i) \cup \{b_i; b_i \in D(b_k), b_k \in C(b_i)\}. \quad (3)$$

By using above definitions, relationships between branches shown in Fig. 3 can be described, for example, as $P(b_2) = b_1$, $B(b_2) = \{b_3\}$, $C(b_1) = \{b_2, b_3\}$ and $D(b_2) = \{b_2, b_4, b_5, b_8, b_9, b_{10}, b_{11}\}$.

2.3 Extraction of a tree structure of bronchial branches

The first step of the proposed method is extraction of the bronchi region and analysis of its tree structure from the 3D CT image. A bronchi region is extracted by Kitasaka’s method. They extract bronchi regions by region growing using branch-by-branch VOI (Volume of Interest) placement technique. This method can detect the bifurcation points of bronchial branches during extraction procedure of the bronchi region. The tree structure is obtained by connecting detected bifurcation points. The proposed method uses the extracted tree structure for automated ALBB and displaying anatomical names of bronchial branches on the RB views.

2.4 Anatomical labeling of bronchial branches

2.4.1 Construction of classifiers using multi-class AdaBoost

The construction process of classifiers consists of two parts: (a) feature calculation of bronchial branches and (b) construction of classifiers utilizing multi-class AdaBoost technique. We consider the ALBB as a problem that each bronchial branch is classified into the bronchial name which it belongs to. Therefore, we try to solve this problem by constructing classifiers that output anatomical names of bronchial branches by employing the machine-learning approach. Generally speaking, the computational resources and complexity grow as increasing the number of classes or categories that should be classified. Therefore, the reduction of the number of classes is very important for constructing classifiers. To reduce the number of classes, we eliminate candidate branches based on the parent branch name. Detailed procedures are described in the following parts.

(a) Feature calculation of bronchial branches In the proposed method, the following four features of a bronchial branch $b_i$ are calculated: (i) length $l_i$, (ii) running direction $d_i$, (iii) relative position $e_i$ from the parent branch, and (iv) average direction of the child branches $m_i$. The feature $m_i$ can represent a region the branch $b_i$ dominates. These features are computed as

$$l_i = \| E(b_i) - S(b_i) \|, \quad (4)$$
\[ d_i = \frac{E(b_i) - S(b_i)}{\|E(b_i) - S(b_i)\|}, \quad (5) \]

\[ e_i = E(b_i) - S(P(b_i)), \quad (6) \]

\[ m_i = \sum_{b_k \in D(b_i)} (E(b_k) - E(b_i)) \quad (7) \]

Patient’s position and orientation may be different from those of others. Such shift of patient’s body position and orientation affects running direction of bronchial branches and generates individual differences of them. To reduce individual differences caused by shift of patient’s body and orientation, the proposed method introduces two normalization methods: (1) global normalization and (2) local normalization. In the rest of this part, we describe the algorithms of both normalizations. In the rest of this part, we describe the algorithms of both normalizations. Here, \( e_y = (0, 1, 0) \) and \( e_z = (0, 0, 1) \) indicate y- and z-axis of the CT coordinate system, respectively. Also, “\( \times \)” is the outer product of vectors and “\( \cdot \)” is the inner product of vectors.

[Global normalization]

Global normalization process makes the plane defined by the right and the left main bronchi equal to that of the plane defined by \( e_z \) and \( e_y \). This process reduces the variations of the patient’s position and orientation.

[Step 1] \( b_l \leftarrow \) Left main bronchus and \( b_r \leftarrow \) Right main bronchus.

[Step 2] Calculate a quaternion \( Q \) which represents the global normalization by Eq. (8). Quaternion \( Q \) makes the plane defined by the vectors \( v_l = (E(b_l) - S(b_l)) \) and \( v_o = v_l \times (E(b_r) - S(b_r)) \) equal to that of the plane defined by \( e_z \) and \( e_y \).

\[ Q = (w_2 w_1 - v_2 \cdot v_1, w_2 v_1 + w_1 v_2 + v_2 \times v_1), \quad (8) \]

where \( w_1, w_2, v_1 \) and \( v_2 \) are calculated as

\[ w_1 = \sqrt{\frac{1 + (e_z \cdot v_l)}{2}}, \quad (9) \]

\[ w_2 = \sqrt{\frac{1 + (e_y \cdot v_l)}{2}}, \quad (10) \]

\[ v_1 = \sqrt{1 - w_1^2} \left( \frac{e_z \times v_l}{\|e_z \times v_l\|} \right), \quad (11) \]

\[ v_2 = \sqrt{1 - w_2^2} \left( \frac{e_y'}{\|e_y'\|} \right), \quad (12) \]

In these equations, \( e_y' \) is a vector obtained from Eq. (13). Equation (13) represents the rotation of \( e_y \) using quaternion \((w_1, v_1)\)

\[
(0, e_y') = (w_1, v_1)(0, e_y)(w_1, -v_1) \\
= (0, (v_1 \cdot e_y)v_1 + w_1(e_y + v_1 \times e_y) - (w_1 e_y + v \times e_y) \times v_1) \]

\[ (0, e_y) = (w_1, v_1)(0, e_y)(w_1, -v_1) \\
= (0, (v_1 \cdot e_y)v_1 + w_1(e_y + v_1 \times e_y) - (w_1 e_y + v \times e_y) \times v_1) \]

(13)
Table 1. A branch correspondence table of relationships between the parent branch name and child branch names.

<table>
<thead>
<tr>
<th>Group</th>
<th>Parent name</th>
<th>Child names</th>
<th>Classifier</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Trachea</td>
<td>Right Main Bronchus</td>
<td>$H_1(x)$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Left Main Bronchus</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Right Main Bronchus</td>
<td>Right Superior Lobar Bronchus</td>
<td>$H_2(x)$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Right Intermediate Bronchus</td>
<td></td>
</tr>
</tbody>
</table>

[Local Normalization]

Local normalization process makes the normal of the plane defined by the parent branch and its sibling branch equal to that of the plane defined by $e_z$ and $e_y$. The quaternion representing the local normalization can be obtained using the same algorithm as the global normalization by replacing $b_i$ and $b_r$ with $P(b_i)$ and $B(P(b_i))$, respectively.

(b) Construction of classifiers with the AdaBoost technique The complexity of construction of classifier depends on the number of categories to be classified. Therefore, to reduce the complexity, the proposed method reduces the number of categories using a property that a child branch name is restricted by its parent branch name. We call this property as “parent-child relationship”. Specifically, the proposed method constructs a table called “branch correspondence table”, as shown in Table 1, in prior to construction of classifier. This table consists of four elements (Group, Parent Name, Child Names and Classifier). Here, Child Names belonging to Group $i$ are a set of candidate names that may become a child branch of a Parent branch belonging to same Group. By using the branch correspondence table, the proposed method reduces the number of candidates and tries to improve the accuracy of ALBB, and also reduces the computation time. The proposed method constructs classifier $H_i(x)$ which classifies child branches belonging to Group $i$. Here, $x$ is a feature vector extracted from the tree structure of the bronchus. $H_i(x)$ outputs an anatomical name from candidate names. The proposed method constructs the classifier using Multi-class AdaBoost technique. In the technique, the classifier is constructed by ensemble of weak-classifiers. Also, we use the classifier used in the reference as the weak-classifier. This weak-classifier determines the optimal threshold classification function, such that the minimum number of samples are misclassified, for each feature.

The algorithms for construction of the branch correspondence table and classifiers are described as follows. Figure 4 illustrates the processing flow of this procedure.

[Step 1] $i \leftarrow 1$
[Step 2] Select bronchial branches $\{b_c\}$ satisfying the condition $N(P(b_c)) = N(b_i)$ from all training datasets (red lines of Fig. 4). And append $N(b_i)$ and $\{N(b_c)\}$ to the branch correspondence table, as shown in Fig. 4.
[Step 3] Compute features from $\{b_c\}$.
[Step 4] Construct a classifier $H_i(x)$ to classify the child branches belonging to Group $i$ by using multi-class AdaBoost algorithm.
[Step 5] $i \leftarrow i + 1$.

2.4.2 Classification of bronchial branches

Figure 5 illustrates the processing flow of the classification procedure. At first, the root of the tree structure is labeled as TRACHEA. Then, child branches of TRACHEA are labeled by $H_1(x)$. In this way, the rest of all branches are labeled in the order of the depth first search. This procedure is repeated until all branches are labeled. The algorithm of the procedure is described as follows.
Figure 4. A flowchart of construction a correspondence table and classifiers. In the figure, RMB, LMB, RSLB and RIMB mean 'Right Main Bronchus', 'Left Main Bronchus', 'Right Superior Lobe Bronchus' and 'Right Inter Mediate Bronchus' respectively.

Figure 5. A schematic illustration of the flow of classifying bronchial branches. RMB and LMB mean 'Right Main Bronchus', 'Left Main Bronchus', respectively.

[Step 1] $i \leftarrow 1$ and $N(b_i) \leftarrow$ TRACHEA.
[Step 2] Select $b_{i+1}$ based on the way of the depth first search.
[Step 3] As shown in the center of Fig. 5, find a group $k$ whose parent name is $N(P(b_{i+1}))$.
[Step 4] Label $b_{i+1}$ by the classifier $H_k(x)$ which classifies child branches belonging to the group $k$.
[Step 5] $i \leftarrow i + 1$
[Step 6] [Step 2] to [Step 5] are repeated until all branches are labeled.

2.5 Anatomical name display on RB views

Our Bronchoscopy guidance system can overlay the anatomical names of bronchial branches onto RB views. Therefore, the proposed method displays the anatomical names of observing branch and its child branches using the result of ALBB, and helps a bronchoscopist to recognize the insertion direction of RB. At first, to display anatomical names of these branches, the position and orientation of the tip of the bronchoscope are estimated by Deguchi’s method. Then, the observing branch is identified by the closest branch from the RB camera.
position. In the proposed method, the distance \( D(b_i, p) \) between the branch \( b_i \) and the RB camera position \( p \) is calculated as

\[
D(b_i, p) = \begin{cases} 
\| p - S(b_i) \|^2 & \text{if } l < 0 \\
\| p - E(b_i) \|^2 & \text{if } l > \| E(b_i) - S(b_i) \| \\
\| p - S(b_i) \|^2 - l^2 & \text{otherwise}
\end{cases},
\]

where \( l \) is calculated as

\[
l = \frac{(p - S(b_i)) \cdot (E(b_i) - S(b_i))}{\| E(b_i) - S(b_i) \|}.
\]

The closest branch from \( p \) is obtained as

\[
b_j = \arg \min_{b_i} D(b_i, p).
\]

Next, to display the anatomical names of the closest branch and its child branches, 3D location \( L(b_j) \) of the branch \( b_j \) is calculated as

\[
L(b_j) = \frac{S(b_j) + E(b_j)}{2}.
\]

The 3D locations of \( C(b_j) \) are also calculated by Eq. (17). These locations are the middle point of the line that connects the start point and the end point of each branch, respectively. The 2D position for displaying anatomical names on the RB view is computed by projecting 3D locations based on camera parameters, such as the viewpoint and view direction.

### 3. EXPERIMENTS

We applied the proposed method to 51 cases of 3D CT datasets. The acquisition parameters of the CT datasets are: slice size: 512 × 512 [pixels], slices: 80 - 728, pixel size: 0.549 - 0.625 [mm/pixel], thickness: 1.0 - 2.5 [mm] and 0.5 - 2.5 mm reconstruction intervals. The following computer was used in the experiments: CPU: Quad-Core Intel Xeon 3.00 GHz × 2, Memory: 3GByte, OS: Microsoft Windows Vista. First of all, we extracted the bronchi region, the medial line and its tree structure from CT datasets by Kitasaka’s method. Then we manually corrected missing or incorrect branches. As a result, the datasets have 2236 bronchial branches, including 1852 bronchial branches up to segmental lobe branches. Then, all bronchial branches were anatomically labeled by 2 of the authors who have anatomical knowledge about the bronchus.

#### 3.1 Experiment of Automated ALBB

The performance of the ALBB was evaluated by leave-one-out scheme. The accuracy of ALBB was measured as \( N_a/N_s \), where \( N_a \) is the number of correctly labeled branches up to segmental lobe, and \( N_s \) is the total number of branches up to segmental lobe branches. The experimental results showed that the accuracy of the proposed method was 89.1%, while the accuracy of the previous method was 79.8%. Also, the average of computation time for construction of classifiers was 1.01[sec]. Results of the proposed and previous methods are shown in Fig. 6. In this figure, incorrect ALBB results are shown in red boxes. Table 2 shows the accuracy of ALBB in the right upper, right middle and lower, left upper, left lower lobes, and the others (trachea, right main bronchus, left main bronchus).

#### 3.2 Display anatomical bronchial name on the RB view

Figure 7 shows an example of display of bronchial names on RB views using a bronchoscope guidance system. The anatomical names can be displayed close to their bronchial branches, correctly.
Figure 6. Examples of ALBB by the previous\textsuperscript{8} and the proposed methods. Lines represent medial lines of bronchial branches. Anatomical names in red boxes show incorrect labeling results. (a) the results of ALBB for bronchial branches in right lower lobe, and (b) the result of ALBB for bronchial branches in left lower lobe. RMLB, RLLB and LLLB mean right middle lobe bronchus, right lower lobe bronchus and left lower lobe bronchus, respectively.

Table 2. Evaluation results of the proposed method for each lobe. (TR: Trachea, LM: Left main bronchus, RM: Right main bronchus, RU: Right upper lobe, RL: Right middle and lower lobe, LU: Left upper lobe and LL: Left lower lobe)

<table>
<thead>
<tr>
<th>The number of using datasets</th>
<th>The accuracy of ALBB[%]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>TR, RM, LM</td>
</tr>
<tr>
<td>Previous\textsuperscript{8}</td>
<td>25</td>
</tr>
<tr>
<td>83.5 Previous\textsuperscript{8}</td>
<td>51</td>
</tr>
<tr>
<td>Proposed</td>
<td>25</td>
</tr>
<tr>
<td>Proposed</td>
<td>51</td>
</tr>
</tbody>
</table>

Figure 7. Examples of displaying anatomical names of bronchial branches on the RB image. (a) Result for left upper lobe, and (b) Result for left lower lobe.
Table 3. Evaluation results of the proposed method when using one feature selected from 4 features.

<table>
<thead>
<tr>
<th>Feature</th>
<th>ALBB accuracy [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Length</td>
<td>48.8</td>
</tr>
<tr>
<td>Running direction</td>
<td>86.5</td>
</tr>
<tr>
<td>Relative position from the parent branch</td>
<td>85.0</td>
</tr>
<tr>
<td>Average direction of the child branches</td>
<td>88.5</td>
</tr>
</tbody>
</table>

![Figure 8. The accuracy of ALBB when the number of samples was increasing.](image)

4. DISCUSSION

As shown in Table 2, when using 51 datasets, the accuracy of the proposed method increased about 9.3% than the previous method. Since the previous method constructs the same number of models as the branching-patterns which the training datasets have, models having similar branching-pattern may increase. Therefore, it becomes difficult to select the model appropriately as training datasets increase. In contrast, the accuracy of the proposed method increases when the datasets increase. This is because the proposed method employs the machine-learning approach. In the machine-learning approach, the classifier learns the more variations of features as the training datasets increase, and gets to be able to classify the test dataset more accurately.

Also, we performed the ALBB using only one feature selected from 4 features, and evaluated the accuracy. The results showed that the feature $m_i$ (average direction of the child branches) contributes most to the accuracy of ALBB in 4 features. The accuracy when using each feature is shown in Table 3. This indicates that the region dominated by the child branches greatly influence the anatomical labeling of bronchial branch.

Furthermore, ALBB was also performed without the information of the parent-child relationships. As a result, the accuracy of ALBB was 51.7% and the average of computation time for construction of classifiers was 97.8[sec]. This result is quite poor and slower than the result mentioned in 3.1. This indicates that using the parent-child relationships can greatly increase the labeling accuracy and reduce the computation time for construction of classifiers. However, there is a problem in the use of the parent-child relationships. That is, when ALBB once failed, the ALBB to decendant branches of the mis-labeled branch are also failed. This greatly deteriorates the accuracy of ALBB. In future work, we need to develop a method which can deal with this problem.

In addition to this problem, the proposed method has following two problems. The first one is that the number of samples is quite small. In the experiments, we used 50 cases for training datasets. When employing the machine-learning approach, the number of training datasets should be more than hundreds. Therefore, we verified how the accuracy of ALBB changes as the number of training datasets increase. The graph in Fig. 8 shows the behavior of the accuracy of ALBB on increasing training datasets. When the number of training datasets was increased, the accuracy of ALBB became improved.

The second one is that features extracted from abnormal cases are very different from those extracted from normal cases. As seen in Fig. 9, the bronchial branches are distorted by a lesion. Figure 10 shows the distribution
of feature $m_i$ (average direction of the child branches). In Fig. 10, blue point represents the feature extracted from a case which is strongly influenced by a lesion. As seen in this figure, the average direction of the child branches extracted from abnormal case is different from that extracted from normal case. Therefore, to survey the influence of lesion on the accuracy of ALBB, the additional experiment of ALBB was performed using the datasets having no lesion. There is 5 datasets having no lesion in 51 datasets, and we use these datasets. The experimental result showed the accuracy of the ALBB was 81.7%. While, as seen in the Fig. 8, the accuracy when using 5 datasets selected from 51 datasets randomly was 71.9%. This indicates that the accuracy of ALBB may improve by selecting training datasets corresponding to the lesion position of the target datasets of ALBB.

Also, as seen in Fig. 7, anatomical names of bronchial branches are displayed on RB images. A bronchoscopist can recognize the current position and the insertion direction to which he/she would like to go by looking the bronchial name displayed on the RB images, and does not lose the way to the desired position. Also, the anatomical name corresponding to the observing branch is selected correctly when the viewpoint and direction change. Therefore, we confirmed presentation of anatomical names of bronchial branches on RB views is quite useful to assist the bronchoscopy.

5. CONCLUSIONS
This paper presented a method for automated ALBB. The proposed method constructed classifiers that output anatomical names of bronchial branches by employing the machine-learning approach. The classifiers were constructed by the multi-class AdaBoost technique. The proposed method was evaluated by leave-one-out scheme. As a result, the proposed method could assign correct anatomical names to bronchial branches of 89.1% up to segmental lobe branches. Also, we confirmed presentation of anatomical names of bronchial branches on real bronchoscopic views was quite useful to assist the bronchoscopy. Future work includes: (1) to solve
the problem that the ALBB to descendant branches are failed successively when ALBB once failed, (2) the experiment using a lot of datasets, and (3) research for new features for ALBB.

ACKNOWLEDGMENTS

This work was supported in part by the program of formation of innovation center for fusion of advanced technologies “Establishment of early preventing medical treatment based on medical-engineering for analysis and diagnosis” funded by MEXT.

REFERENCES


