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A computer-aided approach

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Pixel-level image analysis to derive the broncho-artery (BA) ratio employing HRCT scans: A computer-aided approach

Sami Azam, Sidratul Montaha, A.K.M. Rakibul Haque Rafid, Asif Karim, Mirjam Jonkman, Friso De Boer, Gabrielle McCallum, Ian Brent Masters, Anne B Chang

ABSTRACT

Bronchiectasis in children is a major health issue which can be life-threatening if not diagnosed and effectively treated. In the diagnosis of bronchiectasis, an increased broncho-arterial (BA) ratio is considered a significant marker. The BA ratio is measured by evaluating BA pairs, using high-resolution computed tomography (HRCT) scans. Detecting BA pairs automatically is challenging due to the complex characteristics of BA pairs and the ambiguous appearance of the bronchi. This study proposes an effective computerized approach to detect BA pairs and assess BA ratio using HRCT scans of children and employing computer-aided techniques and novel custom-build algorithms. Attention is given to reconstructing broken bronchial walls and identifying discrete BA pairs using custom-built kernel based and patch-based algorithms for pixel-level image analysis. To detect BA pairs, the lung region is segmented in the HRCT slices and image preprocessing techniques, including noise reduction, binarizing, largest contour detection and a hole-filling algorithm, are applied. A histogram analysis method is introduced to clean the images. A kernel-based algorithm is proposed to reconstruct the pixel distribution if the bronchial wall is so that the bronchi can be detected precisely. Potential arteries are detected using balanced histogram thresholding, morphological opening and an approach based on four conditions related to the object area circularity, rectangular boundary box ratio and enclosing circle area ratio. Potential bronchi are detected through matching of object coordinates with potential arteries, hole-filling and four condition based approaches. The potential BA pairs are detected by matching the coordinates of potential bronchi with those of potential arteries as the artery and bronchus are adjacent to each other in BA pairs. Finally, from the potential BA pairs, actual BA pairs are identified using a custom-built patch algorithm. The study is conducted using 2471 HRCT slices of seven children, obtained from the Royal Darwin Hospital, Australia. The BA ratio is derived based on the ratio of diameters, major axis lengths, minor axis lengths, area, convex hull and equivalent diameter where the BA ratios are respectively 0.51–0.65, 0.49–0.59, 0.59–0.77, 0.25–0.42, 0.29–0.47, 1.5–2 and 0.50–0.65.

Introduction

Bronchiectasis, a chronic respiratory syndrome, is a descriptive term for the medical condition of periodic wet cough, airway inflammation, bronchial wall thickening and irregular bronchial dilatation (Reiff et al., 1995; Chang et al., 2021). Interrupting the cycle of infection at a primary stage with appropriate treatment may halt disease progression and prevent further pulmonary damage (Chang et al., 2021). Bronchiectasis is infrequent in children, however, if it occurs it results in significantly morbidity and mortality. In infants and younger children, bronchiectasis is associated with a prolonged neutrophilic inflammatory and secretory response inside the airways, causes a wet sounding cough, while in older children, mucopurulent sputum expectoration occurs. Though there is a correspondence between bronchiectasis in children and adults, significant distinctions can be found as well. Bronchiectasis has been observed in infants of 10 weeks old having cystic fibrosis (CF) (Fantino et al.,...
Bronchiectasis unrelated to CF is also considered as a major lung condition among both children and grown-ups (Chang & Bilton, 2008). The pathophysiology of bronchiectasis has complex characteristics yet is readily affirmed by CT. The disease can be identified using chest computed-tomography (CT) scans and up-to-date CT scanners with advanced imaging technologies facilitate identification of pulmonary structures, including arteries and bronchi, with comparatively high accuracy (Nardelli et al., 2018). Thin-section CT scans can provide clinically relevant pathological changes related to bronchiectasis (Bhalla et al., 1991) where the BA pair looks like a signet ring. Most bronchiectasis research has been conducted for adult patients instead of children and it is questionable whether the diagnostic findings are applicable to young patients (Redding, 2009). An increased broncho-arterial (BA) ratio or bronchial dilatation is considered as one of the main CT markers for bronchiectasis (Wu et al., 2021; Kuo et al., 2017). Bronchial dilatation occurs when the size of the bronchus becomes larger than its accompanied pulmonary artery. Though the threshold for bronchial dilatation is defined as a BA ratio larger than 1. (Diaz et al., 2017), in children, the ratio is often smaller. Matsuzaka et al. (2003) observed that for the patients in the age range of 20–40 years, the average BA ratio was 0.609 ± 0.05 where patients aged more than 65 years have an average BA ratio of 0.782 ± 0.08. Kapur et al. (2011) recommended redefining the cutoff of bronchial dilatation for children as they found the threshold BA ratios in the range of 0.437–0.739. Therefore, determining the cutoff BA ratio associated to the bronchiectasis in children has become a major research interest. To determine the BA ratio accurately, precise identification of BA pairs is crucial but yet challenging. Interpretation of chest CTs can be time consuming, tedious and error-prone (Perez-Rovira et al., 2016). Due to recent advancement of artificial intelligence (AI) in medical imaging, an automated computer aided approach could be highly beneficial and aid clinicians in detecting BA pairs and deriving the BA ratios with less effort (Naseri et al., 2018). However, analyzing CT scan data through automated techniques can also be challenging due to the presence of noise, artifacts, cardiac motion, partial volume effects, damaged bronchial walls and uneven pixel intensities in different images (Prasad et al., 2008). With the help of image preprocessing techniques and pixel by pixel image analysis, these challenges can be addressed. This research aims to present a novel automated computer aided approach to detect BA pairs from CT scans and to derive the BA ratio through effective image pre-processing algorithms and pixel by pixel image analysis. BA pairs are detected and extracted from the HRCT scans, employing image pre-processing techniques and custom-built algorithms and the BA ratio is evaluated. This research focuses on restoring the pixel distribution of broken bronchial walls, identifying discrete BA pairs and maximizing detection of bronchi through novel custom-built algorithms. A dataset HRCT comprising a total of 2471 HRCT slices of seven children, collected at Royal Darwin Hospital, is used for this research. The approach includes (i) lung region segmentation, (ii) image cleaning, (iii) broken bronchial wall reconstruction, (iv) potential artery detection, (v) potential bronchi detection, (vi) potential BA pair detection, (vii) discrete BA pair detection and (viii) BA ratio measurement and assessment. The lungs regions are segmented from the CT scans by applying a suite of image preprocessing algorithms. After segmentation, the images are cleaned and denoised using a custom histogram analysis-based approach. In CT scans, the bronchial wall often appears to have a non-uniform pixel distribution, referred to as broken bronchial wall, which may interfere with the detection process. To resolve this issue, a custom kernel-based algorithm is proposed using a pixel-by-pixel iteration to find regions where the bronchial wall is broken and to subsequently reconstruct the bronchial wall. Potential arteries are identified using image preprocessing techniques and a condition-based approach using thresholds for image features such as object area, circularity, rectangular bounding box ratio and enclosing circle ratio. Potential bronchi are extracted by identifying the contours of potential adjacent arteries as a bronchus should be adjacent to an artery. The potential bronchi detection process is further optimized using the hole-detection and hole-filling method and a condition-based approach similar to the detection of arteries. Potential BA pairs are extracted by matching the coordinates of potential bronchi with potential arteries. To remove incorrectly identified BA pairs, a custom patch-based operation is carried out. The bronchial wall and its surrounding area are divided into several patches and a pixel-based operation is conducted. Conditions are applied to find actual bronchi and discrete BA pairs. The BA ratio is derived for the discrete BA pairs using image features such as diameter, major axis length, minor axis length, area and convex hull.

The main contributions of this research are summarized as follows:

- Unlike various hungry data driven based approaches the proposed method utilizes far less resources. Data driven algorithms require a large annotated dataset. The proposed approach requires less data as it makes use of experimentally derived parameters based on the properties of a BA pair.
- The proposed approach comprises of image processing methods, thresholding techniques and custom developed algorithms which do not require a large amount of computational time and resources.
- In CT scans, broken bronchial walls are often observed. As broken bronchial walls may interfere with bronchus detection process, a custom kernel-based algorithm is proposed using a pixel by pixel iteration to find regions where the bronchial wall is broken and to reconstruct the bronchial wall within these regions.
- The proposed approach involves identifying and analyzing discrete BA pairs in a similar way as clinicians to determine the BA ratio. A kernel-based algorithm is developed to detect the discrete BA pairs automatically.

The BA ratio is derived for the discrete BA pairs using not only the traditional diameter approach, but also image features such as major axis length, minor axis length, area and convex hull. Through these, a wider range of BA pair measurements are explored. This may provide more insight and lead to alternative ways to derive the BA ratio.

**Literature review**

In recent years, detecting BA pairs and computing the BA ratio has been a topic of in medical and computer science based research. Using electronic calipers with HRCT scans, the BA ratio was measured by Kapur et al. (2011) to identify bronchiectasis in children. The average BA ratio was calculated and the assessment of the correspondence with age was presented to determine the cutoff value for bronchiectasis. Bedi et al. (2018) proposed a simplified radiological score for HRCT scans, based on the Bhalla and Reifl scoring system. They analyzed bronchial dilatation and lack of tapering using statistical measures such as Receiver-operating characteristic (ROC) analysis, One-way ANOVA test, Mann-Whitney U test, kappa coefficient etc. Naseri et al. (2018) introduced two techniques to identify Airways and lung vessels in HRCT scans: threshold-based and model-based. The Laplacian of Gaussian (LoG) algorithm was employed to preprocess the images. A number of image enhancement methods including Frangi filter, connected components labeling (CCL), morphological hole-filling, and edge detection and a threshold-based technique were employed to detect airways and vessels. The output obtained from threshold-based technique was used to train a model and the parameters were optimized using the particle swarm optimization (PSO) method. Prasad et al. (2008) presented a novel approach in detecting abnormal broncho-vascular (BV) pairs form HRCT images, in three stages: detecting potential BV pairs, detecting distinct BV pairs and conducting a severity assessment. The abnormal pairs were detected through multi-view learning and active learning methods. The severity assessment was carried out deriving BA ratios based on the features of minor axis length and object area. Gao & Liu...
imaging features might result in a more comprehensive evaluation of the
this issue. Most research rely on diameter based measurements only for
pixel by pixel investigation should therefore been carried out to address
with bronchus detection process, making it difficult and error-prone. A
analysis and an adaptive multi-scale cavity algorithm. A graph-cut based
levels, they evaluated and categorized the wall thickness. Several image
preprocessing techniques and machine learning algorithms were applied
by Meng et al. (2017) for the segmentation of airway tree using CT scan
images. The image preprocessing techniques included Hessian based
and an adaptive multi-scale cavity algorithm. A graph-cut based
algorithm was proposed to achieve a cohesive airway tree. An auto-
mated approach to segment the airway and arteries from CT scans,
comprising different image preprocessing algorithms, was proposed by
Pererez-Rovira et al. (2016). The algorithm included Hessian eigenvalue
analysis, graph-cut, thresholding, morphological operations and region
growing. Prasad & Sovnya (2004) applied morphological operations
and a binary thresholding method to segment the lung areas from CT
scans. All the objects of less than 5 pixels were detected and eliminated
in order to remove noise and artifacts. The bronchi were identified using
a region-growing algorithm. Co-training and active learning approaches
were employed for the detection of BV pairs using relational based and
detected BA pairs using an automated approach from CT scans. A local
intensity gradient algorithm and a rule-based classification method were
applied to identify the bronchi. The adjacent arteries were detected
using a region growing algorithm equipped with leaking correction.
Azam et al. (2023) experimented with four image preprocessing based
approaches to detect BA pairs for the classification of lung diseases: a
Hessian-based method, a region-growing method, a clustering-based
method and a color-coding-based method. They obtained the best
outcome while applying the clustering-based method. In order to assess
the bronchial dilatation, Busayarat & Zrimec (2005) applied several
image preprocessing and machine learning techniques to detect BA
pairs. A knowledge-guided template matching method was employed to
identify the artery adjacent to a bronchus. This artery was segmented
employing the seeded region growing method. Chabat et al. (2001)
proposed an automated approach for the detection of bronchi in order
to assess BA abnormalities, including bronchial dilatation and wall thick-
ening. An edge-radius-symmetry (ERS) transform was employed to
analyze the gradient maxima and minima within local polar coordinates.
Geometric transformation was used to identify bronchi having an
ecliptic shape. The adjacent arteries of the bronchi were identified
through template matching.

Although detection of BA pairs in HRCT images is a challenging task
as the BA pairs are relatively small objects, there is limited research on
fully automated BA pair detection systems along with BA ratio mea-
surement. Most studies lacked sufficient image preprocessing, resulting
in ambiguous assessment of the BA ratio. Moreover, the normal BA ratio
in adults and children is different and no study was found of a BA
detection system solely focusing on CT scans of children. This gap has
been addressed in this research. Though, the importance of detection
and analysis of discrete BA pairs is recognized in literature, an auto-
mated system to identify discrete BA pairs is currently not available. The
bronchial lumen and bronchial wall often have an uneven pixel distrib-
ution and the bronchial wall often seems incomplete due to low pixel
intensities in some regions. These broken bronchial walls may interfere
with bronchus detection process, making it difficult and error-prone. A
pixel by pixel investigation should therefore been carried out to address
this issue. Most research rely on diameter based measurements only for
deriving BA ratio. Developing other means of deriving BA ratio such as
the ratio of object areas may provide more insight to doctors and might
lead to more suitable measures of the BA ratio. As considering additional
imaging features might result in a more comprehensive evaluation of the
BA ratio, this study looks at a number of features such as diameter, area,
circularity, and convex hull.

Dataset description

In this research, a dataset of HRCT scans of seven children is used.
The age range of the children is from 1 year 10 months to 3 years 2
months all having symptoms indicative of bronchiectasis. The images
were collected at Royal Darwin Hospital, Australia, using a Philip In-
genuity Core CT scanner. The dataset includes a total of 2397 HRCT
slices, where patient 1 has 429 HRCT slices, patient 2 has 465 HRCT
slices, patient 3 has 553 HRCT slices, patient 4 has 689 HRCT slices
and patient 5 has 261 HRCT slices. The proposed algorithms and comput-
erized approach are applied to all the slices. Example images for the
seven children are shown in Fig. 1.

Patient information such as age, name, and date of birth was
removed before conducting the further experiments of this study, in
addition, all HRCT scans were converted into 512×512 gray scale im-
ages. The name of the ethics committee for this dataset is HREC, Menzies
School of Health Research and approval code for this dataset is HREC–07/63 which was issued on 22nd April 2022.

Proposed methodology

The main objective of this research is to detect and segment the BA
pairs using lung HRCT images through automated process and assess the
BA ratio. All the HRCT scans of DICOM format are converted into 2D
slices of Portable Network Graphics (PNG) format. Lung segmentation is
conducted in six steps: denoising the image, binarizing the image,
largest contour detection, inverting the image, hole-filling and extract-
tion of the lung regions. A suite of image preprocessing methods,
including total variation denoising, conditional alpha beta correction,
Otsu thresholding, largest contour detection, hole-filling algorithm and
morphological operations, are applied. The segmented images are then
cleaned employing histogram analysis. In the CT scans, the bronchial
wall often has a non-uniform pixel distribution. A custom-build algo-
rihm is proposed to reconstruct the bronchial wall based on kernel
operations. Three kernels are used. The missing information of the
broken wall is detected through pixel by pixel iteration and updated
accordingly. To detect potential arteries, bright regions of the CT scans
are extracted first, employing balanced histogram thresholding and
connected component analysis. The arteries tend to be brighter on a CT
scan than the surrounding lung tissue, so they have a higher intensity
level. Four conditions based on contour area and circularity (area,
circularity, rectangular bonding box ratio and enclosing circle ratio) are
applied to the bright connected components to identify potential ar-
terries. The area threshold range is based on the possible sizes of arteries.
The remaining three conditions (circularity, rectangular bonding box
ratio and enclosing circle ratio) are used to determine whether the ob-
jects have a circular shape, as would be expected of arteries. The co-
ordinates of the potential arteries are then matched with other objects in
the cleaned CT scan images, to find potential bronchi. The hole-filling
method and four conditions, similar to those described above, are
applied to identify potential. Potential BA pairs are extracted by
matching the coordinates of potential bronchi with potential arteries.
Discrete BA pairs are identified and false BA pairs are detected and
removed through a custom patch based operation. In this process, the
surrounding area of the bronchial wall is checked through pixel by pixel
iteration. For discrete BA pairs, the BA ratio is calculated based on
different imaging features including diameter, major axis length, minor
axis length, area, equivalent diameter and convex hull.

Lung region segmentation

Precise identification of BA pairs is quite challenging due to their
complex structures, broken edges, and uneven intensity distributions.
For a better outcome, the two lung regions are extracted first from the CT scans. Fig. 2 illustrates the lung segmentation process.

First, total variation denoising is applied to remove noise from the images while preserving the edge details of the objects (Fig. 2-IMG2). To enhance the CT scans, the brightness and contrast levels of the images are adjusted with the conditional alpha beta correction method of OpenCV (Fig. 2-IMG3). The algorithm works dynamically, depending on the mean pixel value of a particular image, the alpha and beta enhancement factors are chosen. The Otsu thresholding technique is then applied to convert the images into a binary (black and white) format, see Fig. 2-IMG4. After binarizing, an unwanted curved line can be seen in lower region of some of the images. In order to remove such unwanted objects, largest contour detection technique is employed (Fig. 2-IMG5). In the next step, the images are inverted which causes the lung regions to become white and the surrounding area to become black (Fig. 2-IMG6). To turn all the pixels outside of the lungs the black, flood fill algorithm is applied from all four corners of the image. In this way the lung area in the middle is isolated (Fig. 2-IMG7). Some tiny objects are still found inside the lungs. These are removed using a morphological reconstruction technique (Fig. 2-IMG8). Thus, a binary mask is created.
achieved containing only the lung parts. This is then merged with the original image, resulting in segmented lung regions (Fig. 2 - IMG9).

**Image cleaning based on histogram analysis**

After lung region segmentation, the images are cleaned and noise and unwanted pixels are removed using a histogram plot based thresholding approach. The images are first converted into 2D array and a histogram plot is generated. The threshold value to clean the images is determined based on the histogram outline. Fig. 3 depicts the process.

After the plot is generated, it is found that pixel values of 0 are so frequent that the distribution of other pixel values can be hardly analyzed. In Fig. 3 - IMG1, pixels having value 0 are denoted as Segment 1 and pixels having intensity values above 0 are denoted as Segment 2. For a better interpretation, Segment 1 is eliminated and another histogram is generated, as shown in Fig. 3 - IMG2. It can be seen from IMG2 that after discarding the pixels of Segment 1 (pixels having a value of 0), pixels of Segment 2 (pixels with a value above 0) are clearly visible. From Fig. 3 - IMG2, the histogram height is determined. Based on the histogram’s height, the plot is horizontally divided in three sections: upper density, middle density and lower density. The starting point of (pixel quantity) of the upper density is denoted as the threshold for pixel quantity (TPQ). Using the value of TPQ, the pixel value threshold (PVT) is determined, as can be seen at Fig. 3 - IMG3. In IMG3, the pixels values (PV) for which the total number is larger or equal to TPQ, are isolated (pixels within the red box in IMG3). The pixel having the highest intensity value within the red marked box, is considered as PVT. This is the final threshold value and all the pixels having intensity less than PVT are eliminated from the image. For the specific example of Fig. 3, where the plot is divided into three sections, using the height of the histogram, the TPQ is found to be 3478. Based on the value of TPQ, the PVT is found to be 20 which is the pixel having highest intensity value in the range within the red box.

Fig. 4 shows the output after discarding the pixels below the threshold value.

It can be observed from Fig. 4 that after removing pixels based on the threshold value of TPQ, the image looks noise-free and clean. Determining the threshold value to remove noise is a dynamic process.

**Broken wall reconstruction**

In bronchial walls, the pixel distributions are often non-uniform and the bronchial wall appears broken. This might lead to misidentification of BA pairs. Fig. 5 shows an example of a broken bronchial wall where the broken border pixel is marked red.

In order to retain as much bronchial wall information as possible, kernel-based pixel reconstruction operations are developed. All the pixels of the clean CT scan are iterated over, according to some predetermined kernel conditions. The broken wall pixels are reconstructed by updating the broken pixels with a pixel value of the original

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**Fig. 3.** Histogram based image cleaning process.  
**Fig. 4.** Resultant image after the histogram based cleaning process.
image, based on the coordinates. Here, a total of three kernels, a horizontal \(7 \times 1\) kernel, a vertical \(1 \times 7\) kernel and a deciding \(3 \times 3\) kernel (Fig. 6) are utilized for the kernel operations.

The horizontal kernel contains a total of seven pixel positions, denoted as \(H1, H2, H3, HM, H4, H5\) and \(H6\). Similarly, the vertical kernel positions are named \(V1, V2, V3, VM, V4, V5\) and \(V6\). Lastly, the deciding kernel has a total of nine pixel positions, named \(A1, A2, A3, A4, AM, A5, A6, A7\) and \(A8\). While iterating with these kernels, the iterated pixel stays in the middle position, \(HM, VM\) and \(AM\) for the horizontal, vertical, deciding kernels respectively, and gets updated if necessary. While iterating through the pixels, the pixel is put through the kernel operation, if two main following conditions are met:

- The iterated pixel \(= 0\) in the clean image (Fig. 7-IMG1).
- The iterated pixel \(> 0\) in the original image (Fig. 7-IMG2).

If these two conditions are met, the horizontal kernel and the deciding kernel check if the surrounding pixels meet some predefined conditions, as shown in Fig. 8.

There are five conditions for the horizontal kernel, based on the pixel positions of this kernel:

\[
A = \{H1, H2, H3, H4, H5, H6\} \text{ such that } \forall a \in A, a = 0
\]

\[
A = \{H1, H2, H3, H5, H6\} \text{ such that } \forall a \in A, a = 0
\]

\[
A = \{H1, H2, H4, H5, H6\} \text{ such that } \forall a \in A, a = 0
\]

\[
A = \{H2, H3, H4, H5, H6\} \text{ such that } \forall a \in A, a = 0
\]

\[
A = \{H1, H2, H3, H4, H5\} \text{ such that } \forall a \in A, a = 0
\]

These condition state that for all variables a in the set \(A\), \(a = 0\). Here, the universal quantifier symbol "\(\forall\)" indicate that the condition applies to all elements in the set \(A\). If any of the five conditions are met, the deciding kernel checks the following condition:

\[
B = \{A2, A7\} \text{ such that } \forall b \in B, b = 0
\]

If this condition is true, then the iterated pixel at the HM position of the horizontal kernel is updated. An example of this operation is illustrated in Fig. 9.

IMG1 of Fig. 9 illustrates an enlarged image of a bronchial wall where the wall appears broken (blue circled black pixel). While iterating through the blue circled pixel, the two main conditions,

- The iterated pixel \(= 0\) in clean image (Fig. 9-IMG1).
- The iterated pixel \(> 0\) in the original image (Fig. 9-IMG2).

are satisfied, hence the horizontal kernel is applied, as shown in IMG2 (Fig. 9). It can be observed that pixels \(H1, H2, H3, H4, H5\) and \(H6\) are non-zero which satisfies one condition for this kernel (Fig. 9-IMG3). The surrounding pixel area is then checked by the deciding kernel (IMG 3 of Fig. 9), where pixels \(A2, AM\) and \(A7\) are zero pixels, thus satisfying the deciding kernel conditions. As the deciding kernel conditions are satisfied, the iterated blue circled pixel is updated with the pixel value of the original image of the same coordinate (Fig. 7-IMG5). If the horizontal kernel conditions are not met, the iterated pixel is checked with the vertical kernel and another deciding kernel with a different set of conditions, as shown in Fig. 10.

Similar to the horizontal kernel, there are five conditions for the vertical kernel

\[
A = \{V1, V2, V3, V4, V5, V6\} \text{ such that } \forall a \in A, a = 0
\]

\[
A = \{V1, V2, V3, V5, V6\} \text{ such that } \forall a \in A, a = 0
\]

\[
A = \{V1, V2, V4, V5, V6\} \text{ such that } \forall a \in A, a = 0
\]

\[
A = \{V2, V3, V4, V5, V6\} \text{ such that } \forall a \in A, a = 0
\]

\[
A = \{V1, V2, V3, V4, V5\} \text{ such that } \forall a \in A, a = 0
\]

If any of the above conditions are true, a deciding kernel will further check the following conditions:

\[
B = \{A4, A5\} \text{ such that } \forall b \in B, b = 0
\]

If these conditions are met, the iterated VM pixel will be replaced with the pixel value of the original image, similarly to the horizontal kernel. If these conditions are not fulfilled, the pixel will be left unchanged. As a result of this process, a clean CT scan can be achieved with fewer broken bronchial walls which can help to detect the bronchi more precisely.

**Potential artery detection**

**Balanced histogram thresholding and morphological opening**

In CT scans of the lungs, usually the arteries are found to have the brightest intensity levels. A balanced histogram thresholding algorithm can be applied to extract these bright areas of the CT scans. The
algorithm works by automatically determining a threshold value, balancing the pixel distribution of the image histogram. After applying the technique, the image is turned from grayscale to a binary image. Fig. 11 shows the output binary image after applying the balanced histogram thresholding technique.

In the output image, the brightest regions, which can be potential arteries, remain. Morphological opening with a kernel size of $3 \times 3$ is applied to remove tiny noise from the image, if existing (Montaha et al., 2021).

**Condition based potential artery detection**

To detect and extract the potential arteries, a condition based technique is carried out. First, connected component analysis is applied to find all the connected components of the image. From the connected components, the potential arteries are identified based on the four conditions listed in Table 1.

The conditions are applied using an AND operation, which means that an object which meets all four conditions, it will be considered as a potential artery, else it will be discarded. The mathematical expression can be stated as Eq. (1):

$$\text{If Condition 1} \land \text{Condition 2} \land \text{Condition 3} \land \text{Condition 4} = \text{TRUE}$$

Object = Potential artery

It can be anticipated that objects with a pixel size $<10$ are too small and objects with a pixel size $>300$ are too large to be potential arteries. For Condition 1, the threshold range of object area is denoted as area $>
Arteries tend to appear as near circular shapes in CT scans. For Condition 2, the threshold of object circularity is denoted as 0.3. Connected components having circularity \( \frac{\text{Area}}{\text{Perimeter}^2} \geq 0.3 \) are retained. The circularity of the connected component is calculated using Eq. (2) (Zdilla et al., 2016).

\[
\text{Circularity} = 4\pi \frac{\text{Area}}{\text{Perimeter}^2}
\tag{2}
\]

For Condition 3, a rectangular bounding box is drawn surrounding each connected component of the image. The co-ordinates to draw the bounding box are defined in such a way that the enclosing bounding box has the minimum area while covering the object entirely. The more circular an object is, the closer this enclosing bounding box will be to a square. The width to height ratio is computed using Eq. (3).

\[
\text{BBR} = \frac{W}{H}
\tag{3}
\]

where, BBR refers to the bounding box ratio, \( W \) is the width of the bounding box and \( H \) denotes the height of the bounding box. The largest side of the bounding box is considered as the height and the smallest side is defined as the width. To detect potential arteries, the width to height ratio threshold is set to 0.4 which means that objects for which BBR > 0.4 will be retained.

For Condition 4, a circle is drawn surrounding each connected component. The ratio of the area of the connected component to the area of the enclosing circle is derived using Eq. (4).

\[
\text{ECR} = \frac{O}{E}
\tag{4}
\]

where, ECR is the enclosing circle ratio, \( O \) is the object area and \( E \) refers to the enclosing circle area. In this case, the larger the value of ECR is, the more circular an object will be. To determine potential arteries, the ECR threshold is set to 0.4 which indicates that objects for which ECR > 0.4 will be retained. The four conditions are illustrated in Fig. 12.

The process of selecting potential arteries is illustrated in Fig. 13.

As can be seen from Fig. 13, objects with an area \( < 10 \) are too small and objects with an area \( > 300 \) are too large. Regarding Condition 2, objects with a circularity \( < 0.4 \) are not circular enough. For Condition 3, the circular an object is, the more BBR value will be closer to 1. Likewise, for Condition 4, the more circular an object is, the closer the ECR value will to 1. For both Condition 3 and 4, objects with threshold values above 0.4 may be potential arteries. The threshold range for all of the four conditions is set through experimentation, so that all potential arteries can be obtained without losing important information. The conditions are applied through an AND operation, which means that if an object meets all four conditions, it will be considered as a potential artery, else it will be discarded. In Fig. 13, an example is shown of a potential artery (IMG2) as well as discarded objects (IMG3). Fig. 14 shows the updated clean CT scan (IMG3) after removing the discarded objects (IMG2) from the clean CT image.

### Potential bronchi extraction

In this process, the potential bronchi are identified. First, the connected components are derived from the updated clean CT scan image (IMG2 of Fig. 15). The coordinates of the potential arteries (IMG3 of Fig. 15) are matched with the contours of connected components. If the coordinate of a potential artery matches coordinates of a contour of a connected component, the connected component will be identified (IMG4 of Fig. 15) and extracted (IMG5 of Fig. 15), else the connected

---

**Table 1**

Conditions for selecting objects as potential arteries.

<table>
<thead>
<tr>
<th>No.</th>
<th>Name</th>
<th>Description</th>
<th>Threshold</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Object area</td>
<td>If object area ((OJ)) is within a certain threshold range ((TR)): ( \text{Object} = \text{Potential artery} )</td>
<td>( 10 ) pixels (&lt; \text{area} &lt; 300 ) pixels</td>
</tr>
<tr>
<td>2</td>
<td>Object circularity</td>
<td>If object circularity ((OC)) ( &gt; ) threshold value ((TV)): ( \text{Object} = \text{Potential artery} )</td>
<td>( \text{circularity} &gt; 0.3 )</td>
</tr>
<tr>
<td>3</td>
<td>Rectangular bounding box</td>
<td>If width to height ratio ((\text{WHR})) ( &gt; ) TV: ( \text{Object} = \text{Potential artery} )</td>
<td>( \text{rectangular bounding box ratio} &gt; 0.4 )</td>
</tr>
<tr>
<td>4</td>
<td>Enclosing circle</td>
<td>If the ratio of ( OJ ) and enclosed circle area ((\text{ECA})) ( &gt; ) TV: ( \text{Object} = \text{Potential artery} )</td>
<td>( \text{enclosing circle ratio} &gt; 0.4 )</td>
</tr>
</tbody>
</table>
component will be discarded. Fig. 15 illustrates the process of extracting contours step by step.

In Fig. 15, IMG 2 shows the connected components and IMG3 shows the binary mask of potential arteries. After matching the coordinates of the objects of IMG2 and IMG3, the relevant contours are identified in IMG4. Afterwards, the identified contours are extracted.

To identify potential bronchi, another process is conducted (Fig. 16). The output image obtained from the previous step (IMG5 of Fig. 15) is converted to a binary mask (IMG2 of Fig. 16) and a morphological hole-filling algorithm is applied (IMG3 of Fig. 16). The algorithm identifies all

---

**Fig. 12. Potential arteries selection conditions.**

**Fig. 13. Potential artery selection process.**
the holes of the image and fills them with the surrounding pixel value (Montaha et al., 2022). The first binary mask (before filling holes) is subtracted from the hole-filled binary mask. In the resultant image, only the filled holes remain (IMG4 of Fig. 16). One of the features of bronchi is that they tend to be circular, similar to arteries. Therefore, the same four conditions used to detect potential arteries can be applied to detect potential bronchi. The threshold values for the conditions are kept the same as for the potential artery selection process. The conditions are again applied using an AND operation. Fig. 16 illustrates the process with step by step outputs.

In Fig. 16, IMG 2 shows the binary mask of output image of the previous step which is converted into a binary mask. From IMG3, it can be seen that after applying hole-filling algorithm, all the holes present in the image are filled with a pixel value of 255. IMG2 is subtracted from
Fig. 16. Potential Bronchi mask generation.

Fig. 17. Potential BA pair extraction.
IMG3 resulting in IMG4 where only the filled holes remain. The four conditions are then applied to IMG4. After conducting the condition-based approach, in the resultant image (IMG5) only the objects which meet the four conditions remain. These are considered as potential bronchi.

Extraction of potential BA pairs through coordinate matching

From the preceding steps, two binary masks: a potential artery mask (IMG2 of Fig. 13) and a potential bronchus mask (IMG5 of Fig. 16) are obtained. Potential BA pairs are detected and extracted by matching the coordinates of the objects of these two masks. The potential BA mask is then merged with the extracted contours image (IMG5 of Fig. 17), resulting in an output image with the potential BA pairs. Fig. 17 showcases the entire process with step-by-step outputs.

After merging IMG1 with IMG2 based on coordinates of the objects, IMG3 in Fig. 17 is the resultant image with potential BA pairs. It can be seen from IMG3 that two contours have been discarded as the coordinates of these two contours do not match with the coordinates of the contours of IMG2. In IMG4, the bronchi are marked with a red color and the corresponding arteries are marked with a blue color. Using the coordinates of the BA mask of IMG4, potential BA pairs are extracted from the extracted contours image (IMG1 of Fig. 17).

Bronchial wall identification

After the process of potential BA pair extraction, some falsely detected or non-discrete BA pairs can be observed. Fig. 15 is an illustration of such occurrences.

In some cases, false bronchus detection can happen when multiple artery-like objects can be seen together, creating a small bronchus-like hole. Some false bronchus detections can be caused by the non-uniform pixel distribution characteristics of CT scans. In other cases, a bronchus adjacent to multiple artery-like objects (IMG2 of Fig. 18) or an artery adjacent with multiple bronchus-like objects can be observed (IMG3 of Fig. 18). To resolve this issue, the structural characteristics of a discrete BA pair are analyzed. Typically, a discrete BA pair has only one bronchus attached to only one artery rather than to multiple objects. Non-discrete BA pairs can be detected and discarded by filtering out the BA pairs with two adjacent objects where one is the artery and the other one is the bronchus. Moreover, in CT imaging, a bronchus has a defined bronchial wall with pixel intensities higher than the surrounding area of the bronchus and appearing as a ring-like structure. Fig. 19 shows a discrete BA pair in CT scan.
discrete BA pair.

Using this knowledge, objects which are incorrectly detected as bronchi are eliminated through the bronchial wall area identification technique. In this method, the pixel distribution of bronchial wall of the detected BA pairs as well as surrounding area of the bronchial wall are analyzed in order to properly identify a bronchus with defined bronchial wall. Fig. 20 depicts the bronchial wall identification process.

In this process, instead of analyzing all the pixels of bronchial wall and the surrounding area, a total of eight patches, as shown in Fig. 21, are analyzed, named up, up-right, right, down-right, down, down-left, left and up-left. This minimizes the computational complexity of the algorithm.

Each patch starts from the edge of the inner bronchial region and reaches outwards towards the surrounding area through the bronchial wall. The patches are ten pixels in height and four pixels in width. In other words, each patch starts from the inner bronchial region edge, and then goes outwards for ten pixels. The patches have been assigned names based on their height, from level 1 to level 10 (Fig. 21). The patches are four pixels in width (Fig. 21).

The patch mechanism is designed based on observed characteristics of the bronchial walls.

- The bronchial wall has a maximum thickness of five pixels (counting from the edge of the inner bronchial region). Therefore, the area of wall will not extend more than level 5 of patches (left patch of Fig. 18).
- A defined bronchial wall has similar pixel distribution along all sides (up, up-right, right, down-right, down, down-left, left and up-left). Therefore, for the same patch level, a similar pixel distribution can be expected.
- The intensity of the pixels surrounding of bronchial wall is less than the intensity of the bronchial wall pixels. Therefore, level 6 to level 10 of the patches, which are usually on the outside of the bronchial wall tend to show a drop in pixel intensity.

Using these properties, we can develop some conditions to determine if a potential bronchus has a defined bronchial wall, which indicates that it is correctly identified. After applying the patches to the bronchial wall, each patch covers four pixels in width and 10 pixels in height. At each level, the intensity of the four pixels is averaged. The pixel analysis of each patch starts from level 1 and a pixel analysis point (PAP) is allocated at level 1. The pixel intensity value of level 1 is then compared with level 2. If the intensity of level 1 is larger than or similar to level 2, the PAP is allocated to level 2. Here, similar means that the difference between Level 1 and Level 2 is $\leq 10$. Level 2 is then compared with level 3 and so on. If in any case, a similar or higher pixel intensity cannot be found on the higher level, the PAP will remain on the previously allocated level. If the PAP does progress beyond level 5, it can be assumed that, in that particular patch no bronchial wall like pixel distribution can be observed. Five or more adjacent patches with a PAP below level 6 indicates the presence of a well-defined bronchial wall and a correctly detected bronchus. If, for a particular bronchus, a PAP below level 6 is not found in at least five patches, the bronchus will be considered falsely detected and the BA pair will be discarded.

Analysis of results

The previously described BA pair segmentation approach was applied to HRCT lung scans of seven patients. The number of detected discrete BA pairs is shown in Table 2.

Table 2 lists the total number of slices for each patient along with the number of detected discrete BA pair from both lungs. It is noticeable that the number of detected BA pairs is larger in the right lung while compared to the left lung for all patients. The largest number of BA pairs is found towards the lower region of the lungs (slice number $> 260$). The results of the BA pair detection process using our proposed approach has been validated by the medical expert who has served as a co-author of this paper and investigated the entire study. It was found that our proposed approach identified all the BA pairs that the medical specialist annotated, a 100 % accuracy when compared with the medical specialist’s annotations. Examples of 10 detected discrete BA pairs are visualized in Fig. 22 where the BA pairs are selected randomly from various slices of patient 1.

To find the BA ratio, experiments with multiple types of
measurements are conducted in an automated process. Firstly, multiple diameters for each of the bronchi and arteries are measured. Taking multiple diameters is necessary as the objects are not perfect circles. Here, a total of four diameters are measured and averaged. For the bronchi, diameters are measured for the inner area (inside the bronchial wall). The major axis length and minor axis length of the bronchi and arteries are also calculated. The method to find the BA ratio based on various diameters is presented in Fig. 23.

Through the center points of the bronchi and arteries, four diameters with 45-degree angles between them are measured. As illustrated in Fig. 23, the four bronchial diameters are denoted as BD1 (bronchus diameter 1), BD2, BD3 and BD4 whereas the four diameters of the arteries are denoted as AD1 (artery diameter 1), AD2, AD3 and AD4. The diameters measured in pixels (px) and the average bronchus diameter (ABD) and the average artery diameter (AAD) are calculated. The BA diameter ratio (BADR) is calculated by dividing the ABD by the AAD, see Eq. (5).

$$BADR = \frac{ABD}{AAD}$$ (5)

Table 3 shows the values of four diameters and the average diameters of bronchi and arteries, along with the BA ratio based on the average diameters for the five randomly selected BA pairs depicted in Fig. 24. The bronchus diameter of the bronchi is denoted as BD, artery diameter is denoted as (AD), the average bronchus diameter is denoted as ABD, the average artery diameter is denoted as AAD and the BA ratio is denoted as BADR.

The BA diameter ratios listed in Table 3 (BADR) are derived from BD1-BD4 and AD1-AD4 which refer to various diameter measurements of bronchi and arteries respectively. It is observed that BA ratio for the first three pairs ranges from 0.51 to 0.58. For the last two pairs, the BA ratio is above 0.60.
In order to compare the values obtained by automated computerized measurements, shown in Table 3 with human observation based measurement, the same BA ratios are measured with the image analysis tool ‘Sante Dicom Viewer’. Multiple diameter measurements are taken in pixel format and the results are shown in Table 4.

Tables 3 and 4 show that similar diameters and a similar BA ratio was found across all BA pairs. The BA ratios are in the range 0.50–0.64 and 0.51–0.65 for automated (Table 3) and human observer based measurements respectively.

In the next experiment, the major axis length and minor axis length were derived. The major axis length is denoted as BM_axis and AM_axis for bronchi and arteries respectively, and the minor axis length is denoted as BMi_axis and AMi_axis. The BA ratio is derived using the major axis diameters (MADR) and the minor axis diameters (MiADR), utilizing Eq. (6) and Eq. (7), respectively.

\[
\text{MADR} = \frac{\text{BM}_{\text{axis}}}{\text{AM}_{\text{axis}}} \tag{6}
\]

Table 3
BA ratio calculation utilizing various diameters through a computerized technique.

<table>
<thead>
<tr>
<th>BA Pair</th>
<th>BD1</th>
<th>BD2</th>
<th>BD3</th>
<th>BD4</th>
<th>ABD</th>
<th>AD1</th>
<th>AD2</th>
<th>AD3</th>
<th>AD4</th>
<th>AAD</th>
<th>BADR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>6.01</td>
<td>6.02</td>
<td>8.03</td>
<td>7.00</td>
<td>6.77</td>
<td>10.03</td>
<td>14.04</td>
<td>14.13</td>
<td>15.06</td>
<td>13.31</td>
<td>0.51</td>
</tr>
<tr>
<td>2</td>
<td>7.01</td>
<td>7.19</td>
<td>8.03</td>
<td>9.04</td>
<td>7.82</td>
<td>9.06</td>
<td>17.05</td>
<td>13.03</td>
<td>15.00</td>
<td>13.53</td>
<td>0.58</td>
</tr>
<tr>
<td>3</td>
<td>5.37</td>
<td>4.20</td>
<td>7.19</td>
<td>7.15</td>
<td>5.98</td>
<td>14.09</td>
<td>7.08</td>
<td>12.01</td>
<td>12.13</td>
<td>11.32</td>
<td>0.53</td>
</tr>
<tr>
<td>4</td>
<td>7.02</td>
<td>7.03</td>
<td>8.00</td>
<td>9.17</td>
<td>7.80</td>
<td>9.02</td>
<td>13.06</td>
<td>12.06</td>
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<td>12.04</td>
<td>0.65</td>
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<tr>
<td>5</td>
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<td>7.01</td>
<td>8.01</td>
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<td>9.00</td>
<td>14.00</td>
<td>12.00</td>
<td>14.00</td>
<td>12.25</td>
<td>0.61</td>
</tr>
</tbody>
</table>

Table 4
Five randomly selected BA pairs.

Fig. 23. Process of deriving the BA ratio utilizing multiple diameters.

In order to compare the values obtained by automated computerized measurements, shown in Table 3 with human observation based measurement, the same BA ratios are measured with the image analysis tool ‘Sante Dicom Viewer’. Multiple diameter measurements are taken in pixel format and the results are shown in Table 4.

Table 5
BA ratio calculation utilizing major axis length and minor axis length.

<table>
<thead>
<tr>
<th>BA Pair</th>
<th>BM_axis</th>
<th>AM_axis</th>
<th>MADR</th>
<th>BMi_axis</th>
<th>AMi_axis</th>
<th>MiADR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>7.87</td>
<td>15.87</td>
<td>0.49</td>
<td>6.87</td>
<td>11.62</td>
<td>0.59</td>
</tr>
<tr>
<td>2</td>
<td>8.7</td>
<td>18.1</td>
<td>0.48</td>
<td>7.36</td>
<td>10.68</td>
<td>0.68</td>
</tr>
<tr>
<td>3</td>
<td>7.46</td>
<td>15.6</td>
<td>0.47</td>
<td>5.58</td>
<td>9.02</td>
<td>0.61</td>
</tr>
<tr>
<td>4</td>
<td>8.66</td>
<td>15.13</td>
<td>0.57</td>
<td>7.85</td>
<td>10.33</td>
<td>0.75</td>
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<tr>
<td>5</td>
<td>9.62</td>
<td>16.26</td>
<td>0.59</td>
<td>7.78</td>
<td>10.07</td>
<td>0.77</td>
</tr>
</tbody>
</table>

Table 5
BA ratio calculation utilizing major axis length and minor axis length.

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<tr>
<th>BA Pair</th>
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<td>10.07</td>
<td>0.77</td>
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</table>

In order to compare the values obtained by automated computerized measurements, shown in Table 3 with human observation based measurement, the same BA ratios are measured with the image analysis tool ‘Sante Dicom Viewer’. Multiple diameter measurements are taken in pixel format and the results are shown in Table 4.

Tables 3 and 4 show that similar diameters and a similar BA ratio was found across all BA pairs. The BA ratios are in the range 0.50–0.64 and 0.51–0.65 for automated (Table 3) and human observer based measurements respectively.

In the next experiment, the major axis length and minor axis length were derived. The major axis length is denoted as BM_axis and AM_axis for bronchi and arteries respectively, and the minor axis length is denoted as BMi_axis and AMi_axis. The BA ratio is derived using the major axis diameters (MADR) and the minor axis diameters (MiADR), utilizing Eq. (6) and Eq. (7), respectively.

\[
\text{MADR} = \frac{\text{BM}_{\text{axis}}}{\text{AM}_{\text{axis}}} \tag{6}
\]

Fig. 24. Five randomly selected BA pairs.

Table 3
BA ratio calculation utilizing various diameters through a computerized technique.

<table>
<thead>
<tr>
<th>BA Pair</th>
<th>BD1</th>
<th>BD2</th>
<th>BD3</th>
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<td>12.00</td>
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<td>12.25</td>
<td>0.61</td>
</tr>
</tbody>
</table>
miADR = \frac{\text{BMI}_{\text{axis}}}{\text{AMI}_{\text{axis}}} \tag{7}

Table 5 lists the values of the major axis length and the minor axis length for the bronchi and arteries of five BA pairs, along with BA ratio, based on major axis length and the BA ratio based on minor axis length (Fig. 24). The major axis lengths are denoted as BM_{\text{axis}} and AM_{\text{axis}}, for bronchi and arteries respectively, and the minor axis lengths are denoted as BM_{\text{i-axis}} and AM_{\text{i-axis}}. The BA ratio based on major axis length is denoted as MADR and the BA ratio based on minor axis length is denoted as MiADR.

It can be observed from Table 5 that, for the five BA pairs shown, the BA ratio based on major axis length and minor axis length show a similar pattern to the BA ratios based on diameters. The first three BA pairs have a smaller BA ratio than the last two BA pairs. The MADR is lower than the MiADRs. However, using major axis length and minor axis length, a larger BA ratio is found compared to using diameters, for all the BA pairs.

Similar to average diameter measurements (Table 4), the values of computerized measurement of Table 5 were compared with human observation based measurement. The measurements were taken in pixels using the medical imaging analysis tool ‘Sante Dicom Viewer’ and the results are shown in Table 6.

It can be observed from Tables 5 and 6 that, a similar BA ratios can be observed across all BA pairs whether the major and minor axis diameters are measured with electronic calipers (Table 6) or in an automated manner (Table 5). This further demonstrates that the automated diameter measurement and BA ratio calculation are close to human measurements.

Additionally, four other imaging features are used to derive BA ratios (Fig. 25).

The bronchial inner area (BAr) and the area of the arteries (AAr) are derived and BA area ratio (BAAR) is calculated. The number of pixels contained within an object is considered as the area measurement. Utilizing Eq. (8), BAAR is calculated.

\[
\text{BAAR} = \frac{\text{BAr}}{\text{AAr}} \tag{8}
\]

Furthermore, the convex area of both bronchi (BCAr) and arteries (ACAr) are found and the BA ratio based on convex hull area (CAr) is calculated using Eq. (9).

\[
\text{CAr} = \frac{\text{BCAr}}{\text{ACAr}} \tag{9}
\]

The BA ratio using the equivalent diameters (EDR) of bronchi (BED) and arteries (AED) are also derived. Here, the equivalent diameter is calculated using Eqs. (10) and (11).

\[
\text{BED} = \sqrt{4 \times \text{BAr}} / \pi \tag{10}
\]

\[
\text{AED} = \sqrt{4 \times \text{AAr}} / \pi \tag{11}
\]

The EDR is derived using Eq. (12).

\[
\text{EDR} = \frac{\text{BED}}{\text{AED}} \tag{12}
\]

Table 7 presents the values for area, convex hull area and equivalent diameter for bronchi and arteries and the BA ratios using these four features for BA pairs depicted in Fig. 25. BAr denotes the bronchus area, Aar denotes the artery area, R1 denotes the BA ratio based on area, BCAr denotes the bronchial convex hull area, ACAr denotes the arterial convex hull area, R2 denotes the BA ratio based on convex hull areas, BED denotes the equivalent diameter of the bronchi, AED denotes the equivalent diameter of arteries and R3 denotes the BA ratio based on equivalent diameter.

It can be seen from Table 5 that, a much lower BA ratio is obtained using area and convex hull. However, across all three BA ratios of Table 5, a common pattern can be observed: BA pair1 > BA pair4 > BA pair2 > BA pair1 > BA pair3. This pattern is similar to the pattern of BA ratios based on diameter, major axis length and minor axis length shown in Tables 3 and 4.

Automated medical analysis methods need to be evaluated and validated by medical professionals. In this case, the outcome of the proposed approach has been validated by a medical specialist with subject specific knowledge. To ensure the effectiveness of the proposed BA pair detection method, a dynamic approach is introduced which can adapt to different CT slices rather than applying fixed parameter values. Some key parameters are pre-defined, however, in particular the parameter values utilized in the four conditions applied to detect potential arteries and bronchi which are based on the characteristic and appearance of arteries and bronchi in CT scans. In addition, the kernels used for the broken wall reconstruction process use a pre-defined value indicating the limit of the thickness of the bronchial wall. In order to validate the proposed method, the outcomes of the BA pair detection process are examined by a medical specialist with extensive knowledge of the subject. The resulting BA ratio is also evaluated through comparison with manual measurements utilizing a medical imaging analysis tool. This evaluation approach helps to evaluate the effectiveness of the method. To diagnose bronchiectasis, BA ratio is regarded as the most effective marker due to the occurrence of the disease the structure of the BA pairs changes. Hence, to determine the changes of BA pair, BA ratio is derived and based on a threshold bronchiectasis is determined. It has been found in the literature that to determine bronchiectasis both in adults and children BA ratio is the most significant marker. To precisely diagnose the bronchiectasis in children, deriving BA ratio optimally is important. For adults and children, the threshold of BA ratio differs. Hence, this study presents an automated method to detect BA pairs and measure BA ratio. As the BA ratio of children is a topic of debate, we
have attempted to quantify the ratio as accurately as possible. From this concern, along with diameter-based BA ratio other imaging feature-based techniques are adopted. The resulting BA ratio is also evaluated through comparison with manual measurements utilizing a medical imaging analysis tool. This evaluation approach helps to evaluate the effectiveness of the method.

**Comparison with existing methods**

Several studies have experimentally found BA ratios related to the diagnosis of bronchiectasis in adults as well as children. The BA ratios identified in these studies, along with the age group, are listed in Table 8.

Table 8 lists various studies conducted with diverse age groups resulting in a range of BA ratios. Although there is some debate regarding the cutoff value of the BA ratio for children, the value seems to be lower in children than in adults. Most articles involve an age group, which makes it difficult to generalize the results. For instance, Matsuoka et al. conducted experimentation with patients in three age groups, 21–40 years, 41–64 years and older than 64 years. The BA ratio (based on diameter) was measured using electronic calipers at the segmental and sub-segmental levels of the apical and posterior basal segments. As no difference exists between the right and left lung, only the right lung was considered for the analysis. They found different BA ratios for the different age groups and concluded that the impact of age should be considered while diagnosing bronchiectasis. Likewise, Berend et al. included patients ranging from 16 to 60 years which is a diverse group. They found BA ratios in the range of 0.4–0.95, where higher BA ratios were typically observed in older patients (study 5 of Table 8). The internal diameter of the bronchus was compared with three different diameters of the artery (internal, external medial, and external adventitial). Thia et al., determined the occurrence of bronchial dilatation and air tapering in newborn infants with CF and evaluated the reproducibility of scoring system Brody-II. Kapur et al., measured airway lumen and vessel diameters of the upper and lower lobes of the lungs using electronic calipers and calculated the mean BA ratio. According to their hypothesis, BA ratio in children is typically lower than the adults. In the similar study of Chalwadi et al., an attempt was made to find the BA ratio in children that reflects bronchiectasis. After computing the BA ratio, the mean BA ratio was calculated for each lobe and which was later indexed by age. Wu et al., computed BA ratio from different points including inner bronchial diameter, outer bronchial diameter and arterial diameter and a total of 6 measurements were obtained. Some studies focused on children, teenagers, and adolescents aged 0–20 years (study 3,4 of Table 8). They found BA ratios ranging from 0.4 to 0.9. None of these studies solely focused on a particular category of patients. Various studies indicate that there are differences in the BA pairs and BA ratios of children and adults. Conducting experiments with a particular age group may lead to more outcomes specific for that age group. These studies were based on medical research and inspired by their investigation and findings we have conducted an automated approach in the diagnosis of bronchiectasis in children. In addition, the evaluation of BA ratio has been shown using the diameter only in the prior studies. On the other hand, our study proposes an automated approach where the BA ratios are evaluated using diameter, object area, perimeter etc. Thus, a more comprehensive experiment has been presented from where along with looking into the diameter-based BA ratio measurement the radiologists can also consider the other measurement techniques for a thorough investigation. The fact that these studies found similar BA ratios as the proposed approach of this paper is an indication of the effectiveness of the proposed approach.

The main contribution of this study over the existing methods is this research is solely based on the analysis of bronchiectasis in children whereas most other studies worked with young/adult subjects. In this research, a step-by-step approach is taken to detect the BA pairs, mimicking the clinicians’ diagnostic process. Key properties related to the appearance of BA pairs in HRCT scans are used for discrete pair identification, identifying BA pairs with a poorly defined bronchial wall, and different BA ratio measures are all integrated in the proposed approach. Moreover, the study focuses on identifying the discrete and precise BA pairs those radiologists consider. In some cases, an artery can be attached to a hole like object which may not be a bronchus at all. Together, they might be detected as a BA pair by an automated system. In most studies, there is no counter measure for such false detection of BA pairs. This research addresses the issue with a bronchial wall identification process in which falsely detected bronchi are neutralized. The majority of the studies relating to the identification of BA pairs did not include adequate image preprocessing, which might lead to imprecise interpretation. The distribution of pixels in the bronchial lumen and bronchial wall is often unbalanced. Due to this, BA pair recognition is challenging and error-prone which is not addressed in the existing works. In this research, the algorithms are developed based on pixel-by-pixel analysis of BA pairs. Our method is robust even with few data and computationally efficient due to the integrating of pixel-by-pixel approach and image preprocessing algorithms. A variety of parameters such as diameter, area, circularity, and convex hull are used to compute the BA ratio since taking into account more imaging properties can lead to a more thorough evaluation of BA pairs. The BA pairs and BA ratio derived in the study are validated by expert radiologists which assess the compatibility of the proposed methods. These differences make the study stand out from other studies regarding automated BA detection and BA ratios.

**Time cost analysis**

To overcome the challenge of balancing performance and time cost in BA pair detection, integration of hardware acceleration technologies can be explored. These technologies, such as Graphics Processing Units
method, from start to finish takes less than 1500 ms per image, which is applicable in various contexts.

detection algorithms into the clinical workflow and increase their possible to significantly reduce the time cost of BA pair detection quite promising, as the process is running on windows 10 operating pair measurement process take less than 100 ms each. The proposed image in order to derive a suitable outcome. Most of the processes take the longest time of 290 ms as it needs to analyze all the pixels of the detection of BA pair and BA ratio measurement, a thorough analysis of the time costs associated with all the process is conducted (Table 9). The

<table>
<thead>
<tr>
<th>Process no</th>
<th>Process</th>
<th>Time taken /slice (milliseconds)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>CT scan segmentation</td>
<td>250</td>
</tr>
<tr>
<td>2</td>
<td>Image cleaning</td>
<td>290</td>
</tr>
<tr>
<td>3</td>
<td>Broken bronchial wall</td>
<td>230</td>
</tr>
<tr>
<td>4</td>
<td>Potential artery detection</td>
<td>210</td>
</tr>
<tr>
<td>5</td>
<td>Potential bronchous detection</td>
<td>180</td>
</tr>
<tr>
<td>6</td>
<td>Potential BA pair detection</td>
<td>90</td>
</tr>
<tr>
<td>7</td>
<td>Discrete pair detection</td>
<td>110</td>
</tr>
<tr>
<td>8</td>
<td>BA pair measurement</td>
<td>80</td>
</tr>
<tr>
<td>9</td>
<td>Entire method: process 1 to 8</td>
<td>1440</td>
</tr>
</tbody>
</table>

(GPUs), Tensor Processing Units (TPUs), and memristor circuits, provide computational power and parallel processing capabilities that might enhance the efficiency of a computerized approach. In terms of speed and energy efficiency, compact Extreme Learning Machine (ELM) architectures with spintronic memristor-based synaptic circuits have shown a performance boost compared to Von Neumann computer architectures (Dong et al., 2021). Additionally, memristor circuit-based Internal Cascaded Neuromorphic Computing Systems (ICNCS) have demonstrated improved accuracy and time efficiency (Dong et al., 2023). In order to increase the performance and energy efficiency in any computerized system, the potential of nanotechnology, energy-efficient circuits, and neuromorphic systems has been investigated (Dong et al., 2023). The classification of human emotions has been made more accurate and efficient computationally by energy-efficient memristive sequencer networks based on memristor circuits (Ji et al., 2023). Multimodal neuromorphic sensory-processing systems with memristor circuits provide a practical and affordable method for building smart homes (Dong et al., 2023).

To assess the viability and efficacy of the proposed approach for the detection of BA pair and BA ratio measurement, a thorough analysis of the

It can be observed from Table 9 that the image cleaning process takes the longest time of 290 ms as it needs to analyze all the pixels of the image in order to derive a suitable outcome. Most of the processes take very little time, less than 250 ms. The potential BA pair detection and BA pair measurement process take less than 100 ms each. The proposed method, from start to finish takes less than 1500 ms per image, which is quite promising, as the process is running on windows 10 operating system with an older Intel core i5 4th generation CPU and 8GB of RAM.

By leveraging these hardware acceleration technologies, it might be possible to significantly reduce the time cost of BA pair detection without compromising performance and further improve efficiency while moving the project to real life implementation. As a result, real-time analysis may be possible, making it easier to incorporate BA pair detection algorithms into the clinical workflow and increase their applicability in various contexts.

Discussion

Reconstructing the broken region of a broken bronchial wall, employing a custom kernel-based algorithm, helps to detect BA pairs more precisely. After detecting potential BA pairs using a computerized approach, a patch algorithm is developed to accurately identify discrete BA pairs. The BA ratio is calculated employing several diameters, contour area and convex hull. It was found that for all features, the BA ratios followed a similar pattern: BA pair 5 > BA pair 4 > BA pair 2 > BA pair 1 > BA pair 3. However, for different features, a different range of BA ratios is observed. For example, when using average diameter, minor axis length, minor axis length and equivalent diameter, a higher BA ratio is obtained when using area or convex hull. Moreover, though the measurement technique is quite similar, for different diameter-based measurements, different BA ratios are generated. This leads to the question whether BA ratio assessment using diameter is an effective approach. On the other hand, the area of an object is measured considering all the pixels of an object and convex hull represents the shape of an object. As bronchi and arteries have a non-uniform pixel distribution and are not perfectly circular, diameter-based BA ratio evaluation might not be the most effective approach. Instead, area-based techniques can be explored as area measurement represents the entire object and might lead to a more accurate BA ratio assessment. The BA pairs and BA ratio derived in the study are validated by expert radiologists. In this regard, along with the automated analysis of BA ratio, other two step verifications are conducted (i) evaluation of BA ratio through manual measurement and (ii) evaluation of BA ratio through validated by experts. In both cases, similar outcomes are perceived which further validates the robustness of the proposed approach.

There has been much advancement in the field of medical research through various data driven algorithms. Automated detection of BA pairs in CT slices is quite challenging as it involves finding the small ORIs (BA pairs) in an overwhelming number of similar looking objects and noise. In this regard, integrating accurate definitions of the geometric properties and nature of BA pairs and developing the processes around these definitions is the key to BA pair detection. Although deep learning and other data driven algorithms are very promising, to locate such a small ROI from several background objects presented in the CT slices, a large number of CT slices with proper annotation is required to expect any usable outcome. Building a large dataset comprising of CT scans with BA pair ground truth annotation is a very tedious task, especially with data from children. In our process, the properties of BA pairs are applied in the algorithm, along with a set of defined rules to detect BA pairs. We utilized several image processing algorithms and various custom algorithms. Combining multiple processes in an innovative arrangement made it possible to accomplish these difficult tasks. The lung segmentation process comprises of some image processing and thresholding algorithms that are arranged and tuned, so that the desired segmentation can be produced precisely without losing any relevant information. A custom image cleaning algorithm is developed to clean the CT slices through a dynamic thresholding approach. The value is automatically adapted to the CT slice. In the potential artery and bronchus detection process, geometric features of bronchi and arteries are utilized to determine the thresholds. A combination of four features (area, circularity, bounding box ratio, enclosed area ratio) is considered to determine if a particular object is a potential bronchus or artery. Considering four factors instead of one only increases the chance of accurately finding BA pairs. A coordinate matching algorithm is utilized to extract BA pairs accurately. Detecting discrete BA pairs is one of the main goals of this research as clinicians rely on discrete BA pairs to find the BA ratio. A custom developed algorithm is proposed which identifies discrete BA pairs taking the nature of bronchial wall and the surrounding area of BA pair into account. All these custom algorithms are derived based on properties of the BA pairs and developed through extensive experimentation. Unlike various data driven based approaches the proposed method utilizes relatively limited resources.

Conclusion

The primary objective of this study is to propose an automated approach based on pixel-level image analysis to segment BA pairs from children’s HRCT scans and to calculate the BA ratio using image preprocessing methods and novel custom-built algorithms. Several
processes are introduced: histogram-based image cleaning, reconstructing broken bronchial walls, potential artery detection, potential bronchus detection, potential BA pair detection and discrete BA pair identification analyzing the bronchial wall. Custom built kernel and patch-based algorithms are used to reconstruct the broken bronchial wall and identify discrete BA pairs. This helps to detect the BA pairs more precisely. Through these approaches, discrete BA pairs, verified by a medical specialist, can be identified in both lungs. BA ratios, based on various diameter and imaging features were derived. Equivalent diameter-based BA ratios and average diameter based BA ratios provide similar outcomes. For our future research work, an efficient deep learning model may be developed and trained with a large HRCT dataset with annotated BA pairs. To acquire this large annotated dataset, the proposed BA pair detection approach of this study can be employed as through this approach BA pairs can be detected despite a non-uniform pixel distribution of HRCT scans. This approach may assist doctors and increase the efficiency of bronchiectasis diagnosis.

CRediT authorship contribution statement

Sami Azam: Conceptualization, Supervision, Project administration, Writing – review & editing. Sidratul Montaha: Methodology, Investigation, Writing – original draft, Writing – review & editing. A.K.M. Rakibul Haque Rafid: Methodology, Investigation, Software, Visualization, Writing – original draft. Asif Karim: Data curation, Writing – review & editing. Mirjam Jonkman: Supervision, Writing – review & editing. Friso De Boer: Supervision, Writing – review & editing. Gabrielle McCallum: Supervision, Data curation, Writing – review & editing. Ian Brent Masters: Data curation, Resources, Writing – review & editing. Anne B Chang: Supervision, Writing – review & editing, Project administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

References


