Carina Landmark Detection in ICU Images via Integrating Geometrical and Thoracic Anatomy Based Features

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Abstract

Carina is a useful and reliable radiological landmark for detection of accidental arterial placement of central venous catheters and can provide essential groundwork for successful automation of various open problems such as segmentation, registration of anatomical structures. A fully automatic approach for the detection of carina landmark in ICU images is presented in this paper. It integrates shape based geometrical quantification features with thoracic anatomy based features to deal with the complexity of carina appearance in ICU images, from highly visible to invisible with occlusion. Accuracy and robustness of the proposed method has been validated by hundreds of images from real ICU patients.

1. Introduction

Clinical evaluation of patients in an Intensive Care Unit (ICU) often relies on diagnostic images, such as portable chest radiographic images, for example. It has been noted that chest radiographs can be helpful in the ICU to indicate significant or unexpected conditions requiring changes in patient management.

Patient treatment includes the ability to detect the proper positioning of the tip of a tube that has been inserted into the patient. Proper tip positioning can help to insure delivery or disposal of liquids and gases to and from the patient during a treatment. Improper tip positioning, on the other hand, can cause patient discomfort, can render a treatment ineffective, or can even be life-threatening.

Reliable and accurate detection of carina landmark can help to detect and identify ET (endo-tracheal) tube tip positioning. However, the carina is often overlaid by other surrounding anatomies, rendering it's a challenging to detect it in chest X-ray images. Automated detection can be even more challenging; techniques for computer aided carina detection (CACD) have proved to be error-prone and often less accurate than desirable, making it difficult to detect tube and tip mal-positioning in some cases. Thus, there is a need for a detection method with improved accuracy for locating landmark in digital radiographic images.

A fully automatic CACD algorithm in ICU images is presented in this paper. To the best of our knowledge, this is the first automatic CACD algorithm using ICU X-ray images. The algorithm extracts features quantifying both carina's geometrical pattern and its anatomy dependency with thoracic anatomy for confirmation, hence overcoming the difficulty in detecting low visible or invisible carina in ICU images.

The rest of the paper is organized as follows: section 2 describes the framework of proposed CACD algorithm in detail. Experiments are carried out in section 3. Finally, section 4 concludes the results.

2. Method

There are 3 steps of the proposed method as shown in Fig 1. First, the raw image is preprocessed via contrast enhancement, de-noising and background removal, and then a region of interest (ROI) is extracted from the enhanced chest X-ray image. The ROI contains some critical anatomical regions for carina detection and estimation, including spine, trachea, carina, aortic knob (AK), etc. Second, a multi-constraints based detector is applied to roughly detect locations of carina candidate, the constraints used include template based shape constrain and neighboring anatomy (AK) dependency. Finally, a trained LDA classifier is used to eliminate false positives from initial suspicious candidates based on defined features.
2.1 Carina ROI extraction and enhancement

Starting from original input chest X-ray image, the region that contains anatomy is extracted for further processing [1] and refined neighboring region around carina (carina ROI) is then estimated based on the understanding of chest anatomy.

2.1.1 Trapezoid lung ROI estimation. The most indicative regions for carina detection need to be defined on the primary anatomy in chest X-ray image to capture relevant region, i.e. the lung region.

The implementation of lung ROI extraction starts with the detection of the midline of key chest anatomies (lung and spine) using multi-scale medial axis (MMA) extraction [2, 3]. Then, an intensity profile of the midline is computed and analyzed to search for the location of lung region. Using the detected location of lung as reference, a ROI is defined to enclose the lung region with the size of the region proportional to the width of the chest. The defined lung ROI provides a good initialization for detecting carina ROI. This is because carina is always located between left and right lungs. Fig 2 is an illustration of major steps in trapezoid lung ROI extraction. Fig 2(a) shows the input image. Fig 2(b) shows the estimated middle lines for spine (in red), left (in blue) and right lungs (in green). Fig 2(c) shows the estimated trapezoid shape from middle lines extracted in Fig 2(b). Fig 2(d) shows the trapezoid lung ROI overlaid on input image.

2.1.2 Carina ROI estimation and enhancement. Carina ROI was further estimated within the range of extracted trapezoid lung ROI, aiming to include all necessary anatomy, such as: spine, trachea, AK, and exclude irrelevant anatomy. In anatomy, the carina is the position where the trachea starts to bifurcate. Since the trachea is located within or very close to spine in chest X-ray images, thus carina ROI is defined as a rectangle region with the spine as its long axis with the upper and low edges of lung ROI as its upper and low bounds, respectively. The width of carina ROI is set empirically based on the size of lungs. Fig 3(a) is an illustration of carina ROI extraction. The blue trapezoid is lung ROI and the red rectangle is the extracted carina ROI. Fig 3(b) shows the extracted carina ROI after enhancement by CLAHE [4]. The red curve on the upper half of the image shows the rough location of trachea, the location where the trachea bifurcates is the location of carina, the blue contour on the right of the image shows the AKs.

2.2 Suspicious carina candidate detection

In chest X-ray images, the visibility of carina has large variation, as illustrated in Fig 4, from highly visible (Fig 4(a)) to barely visible (Fig 4(b)) and to invisible (Fig 4(c)). It is thus very hard to detect it purely based on its imaging profile. Experienced radiologists usually use neighboring anatomy or other information to locate where the carina is. Activated by this observation, we first use two different approaches to detect suspicious carina candidates with different degree of visibility in chest X-ray images separately, then combine them together based on their detection confidence to generate an integrated suspicious candidate detection results. The two independent approaches are

- Template matching based carina detection.
- Anatomy dependency based carina estimation.

2.2.1 Template matching based carina detection. The anatomy of carina is a cartilaginous ridge within the trachea that runs between the two primary bronchi at the site of the trachea bifurcation at the lower end of the trachea. When projected on chest X-ray images, if visible, it has a geometrical pattern to be the connection of three branches (the trachea and bifurcation), as shown in Fig 5(b). Based on this knowledge, a template (Fig 5(a)) matching based
An approach is used to recognize possible carina pattern in chest X-ray images. The enhanced carina ROI image is first binarized using Sauvola’s local binarization method [5]. A template matching is then used to recognize potential carina locations in carina ROI image. Fig 5(a) shows the standard template, \( r \). A parameter set, \( \theta \) \( \theta'=[s, \phi] \), specifies the geometric parameters of the template (i.e., the scale \( s \) and rotation \( \phi \)). The deformable template used in matching can be given as

\[
f(r, \theta) = f \left( \frac{1}{s} M(\phi) r \right)
\]

where

\[
M(\phi) = \begin{bmatrix}
\cos(\phi) & -\sin(\phi) \\
\sin(\phi) & \cos(\phi)
\end{bmatrix}
\]

The template matching result can then be given as

\[
F = \arg \max_{r, \theta} \left\{ f(r, \theta) \otimes I_{binary} \right\}
\]

where \( I_{binary} \) is the binary image generated by local thresholding, \( \otimes \) is the convolution operation, \( C \) is a normalization factor.

Fig 5 shows some of the major steps in template matching based carina detection. Fig 5(a) is the base template used; Fig 5(b) is the carina ROI with trachea and bifurcate delineated (red dotted lines); Fig 5(c) is the binary image by local thresholding; Fig 5(d) is the feature map by template matching which shows the magnitude of feature while recognizing template-alike pattern from the binary image in Fig 5(c), referred to as \( F_{cd} \), the right side of Fig 5(d) shows the color map which indicates that the location corresponding to carina in Fig 5(d) has the highest feature value.

![Figure 4. Carina with different visibilities](image)

![Figure 5. Template matching based suspicious carina candidate detection](image)

### 2.2.2 Anatomy dependency based carina estimation

Similar to the approach of carina detection described in section 2.2.1, a template matching was used to detect AK within carina ROI, which is further utilized to estimate carina location within the ROI.

AK (circle in Fig 6), is then used to estimate carina location. Once AK’s radius and location is determined, spine line and construction line (dotted line passing through the center of AK template) can be traced. Construction line extends through the center of the matched AK template circle and intersects with the spine middle line at angle within a predetermined range. For carina detection, these lines intersect substantially at a 45° angle, i.e., at an angle between 54° and 36°, more preferably between 50° and 40°, and most preferably as close to 45° as possible.

By using a combination that detects and traces the midline of spine and detects the AK as bench-mark features, less visible carina can be estimated, thereby providing complementary information to the carina template based approach as described in section 2.2.1.

#### 2.2.3 Integration of carina detection & estimation

Approaches described in sections 2.2.1 and 2.2.2 provide complementary information in locating carina, however, features generated by them locate in different space and need to be normalized to the same feature space. To do this, features from carina estimation is transformed to the feature space of carina detection via using the construction line described in section 2.2.2, i.e. feature value on location \( C_{aortic_knob} \) is transformed to \( C_{potential\_carina} \) in Fig 6. After this transformation, another feature map similar to Fig 5(d) is generated for the estimation of carina location in carina ROI, referred to as \( F_{ce} \).

A final single feature map, \( F_c \), is constructed by combining information from \( F_{cd} \) and \( F_{ce} \), i.e., for a certain pixel \( (x, y) \) in carina ROI, its feature value on \( F_c \) is computed as:

\[
F_c(x, y) = \sqrt{F_{cd}(x, y)F_{ce}(x, y)}
\]

A list of suspicous carina candidates can then be selected by thresholding \( F_c \).

![Figure 6. Carina estimation via detecting AK](image)

### 2.3 Classification based false positive elimination

#### 2.3.1 Feature definition and extraction

Two features are extracted from \( F_{cd} \) to characterize carina visibility for each carina candidate. They are

1. The maximum value, \( m_{cd} \), within the boundary of each suspicious carina candidate’s small neighboring ROI (snROI) on \( F_{cd} \). snROI(c) denotes a \( w \times w \) square region centered at candidate \( c \), the size \( w \) is predetermined based on the a prior knowledge of carina size.
2. The entropy of values, $\eta_{cd}$, within each suspicious carina candidate’s snROI on the feature map. The first feature conveys information describing the likelihood of the presence of the carina pattern within a certain candidate’s snROI, the second feature quantifies the inconsistency of carina pattern within a certain candidate’s snROI. Suppose that the carina geometrical pattern can be perfectly described by the template defined in section 2.2.1, then the matching procedure performed within a certain candidate’s snROI can always find fully or partially matched carina geometrical pattern, thus produces a large maximum value, while other types of tissue snROI can only generate small maximum value due to the lack of matched carina pattern. Similarly, the entropy feature turns to be low for other types of tissue candidates due to the lack of matched carina pattern. The template matching procedure can typically be inconsistent within the boundary of true carina snROI and thus generate large entropy feature values.

Similarly, two features, $m_{ce}(c)$ and $\eta_{cd}(c)$, can be computed from $F_{ce}$ to characterize AK visibility.

2.3.2 Classification of carina using LDA. LDA classifier is used to determine a certain testing candidate’s class category based on extracted features and training dataset.

3. Experimental results

Figure 7 shows 3 representative carina detection results with carina visibility decreased from Fig 7(a) to (c). Ground truth region (red circle) is defined (red “+”) by experienced radiologist and surrounded by a red circle of 1mm in radius. The blue “*” shows the location of computer detection. AA regions are marked as blue circle centered with a blue “+”. The intersection between AA and center line is shown as blue squares.

4. Conclusion

This paper presents a methodology for integrating geometrical and anatomy a priori knowledge for the detection of carina in chest X-ray images, which is a well-known challenging topic. To the best of our knowledge, this is the first approach in detecting carina in chest X-ray images and provides accuracy and robust detection results. The 4 features delivered by this algorithm can provide good discriminate ability between carina candidates and false positives. The efficiency and efficacy of the proposed method are demonstrated with the results obtained by applying the method to 270+ chest X-ray images.

5. Acknowledge

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References