Enhanced airway-tissue boundary segmentation for real-time magnetic resonance imaging data

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Abstract

This paper introduces an algorithm for robust segmentation of airway-tissue boundaries in the upper airway images recorded by the real-time magnetic resonance imaging. Compared to the previous method by Proctor et al. [1], the present algorithm performs image quality enhancement, including pixel sensitivity correction and grainy noise reduction, followed by robust estimation of airway path between the vocal tract walls. The accuracy of the tissue boundary segmentation was evaluated in terms of root-mean-squared-error as well as statistics (mean and standard deviation) of error for specific region in the vocal tract. Results suggest that the proposed algorithm shows significantly less estimation error than the previous method [1], especially for the front cavity and the lower boundary.

Keywords: real-time magnetic resonance imaging, image segmentation, automatic tracking, vocal tract analysis

1. Introduction

Real-time Magnetic Resonance Imaging (rtMRI) [2] is an important tool for studying human speech production. The rtMRI provides the entire mid-sagittal view of the upper airway of a subject. The airway-tissue boundary segmentation in the MR images is often required as a pre-processing for the analysis and modeling of the vocal tract movements [3] and of the morphological structure of the vocal tract [4]. Performing this segmentation automatically is essential for analyzing the upper airway image by Ohman [7]. This paper presents an algorithm for more robust segmentation of the MR images, which includes (1) retrospective pixel intensity correction of the MR images, (2) detection of the front-most edge of the lips and the top of the larynx, (3) segmentation of airway-tissue boundary in the vocal tract, and (4) measurement of the distance between the upper and lower boundaries. The current method improves the robustness of the airway-tissue boundary estimation over the previous method [1] by using a combination of data-driven way of pre-processing of the MR images, robust airway path estimation, and model-based weighted linear curve fitting.

2. Methods

2.1. Pre-processing of MR images

The MR images in rtMRI data often suffer from grainy noise and non-uniform field sensitivity of the tissues, depending on recording configuration [2]. Figure 1 (a) shows an example of the MR images in the USC-EMO-MRI corpus [5], which was recorded at an image frame rate of 23.18 frames/sec and a spatial resolution of 68 \times 68 pixels. The present algorithm uses a multi-resolution approach to minimizing the effects of the noise, artifacts, and non-uniform field sensitivity of the tissues. The details of the approach are as follows.

1. Create a field sensitivity map, denoted by $S$, of an original MR image using a morphological closing operation, followed by 2-dimensional median filtering. Figure 1 (b) shows the sensitivity map of the image in Figure 1 (a). The morphological closing operation selectively exclude low-intensity pixels (of grainy noise or artifacts in general) in the airway region when creating $S$.

2. Create the set of edge points, as in Figure 1 (c), of the sensitivity map using the Canny edge detector [6] implemented in MATLAB. Likewise, create the set of edge points of the original image. Let $E_D$ and $E_{SM}$ denote the sets of edge points of the sensitivity map and the original image, respectively.

3. Create the head and neck boundary line $E_H$ by finding the left-most points of $E_D$ and $E_{SM}$. Then, create a binary image, denoted by $B$, of the head-neck region by setting the pixel intensity to be 1 for pixels in the right side of $E_H$ in each row and setting the pixel intensity to be 0 otherwise, as in Figure 1 (d).

4. Multiply the pixel intensity of the original image and the inverse of the pixel intensity of $S$ for non-zero elements in $B$, while setting the non-tissue pixel intensity to be zero. Figure 1 (e) shows the result image, denoted by $C$.

5. Perform a sigmoid warping of the pixel intensity in $C$ for suppressing grainy noise as well as highlighting tissue. Figure 1 (f) shows the final image.

3. Construction of grid lines

In order to detect the lips, the larynx, and the airway-tissue boundaries, the present algorithm constructs grid lines, adopting from the previous method [1]. The previous method is motivated by the analysis of the upper airway image by Ohman. The grid construction method requires four manually chosen anatomical landmarks near the larynx, the highest point on the palate, the alveolar ridge, and the center of the lips, in one of the MR images. See [1] for the details of grid construction that we follow. The differences from the previous method are (i) that
4. Lips and Larynx detection

For each frame, the initial and the final grid lines correspond to the locations of the top of the larynx and the front-most edge of the lips, respectively. Since these articulatory positions vary slowly and smoothly over time, the present algorithm finds each of their optimal positions by constraining rapid change of the estimated locations of them.

Assume \( q_i \) is a state at instance \( t \). \( N \) denotes the number of states. \( S_{q_{i-1},q_i}^L \) denotes the transition score from \( q_i \) to \( q_j \). \( S_{q_i}^U \) is the likelihood score (of the observation) for \( q_i \). \( P_i \) is the prior score of \( q_i \). \( K \) is the number of instances. \( Q \) denotes a sequence of states \( q_1, q_2, \ldots, q_K \), one state for each instance. The objective score \( J \) of \( Q \) is defined as follows:

\[
J = \left( P_1 S_{q_1}^L + w S_{q_2, q_1} \right) + \left( \sum_{u=2}^{K-1} S_{q_u}^L + w S_{q_u+1, q_u} \right)
\]

(1)

where \( w \) is a weighting factor for \( S_{q_2, q_1} \). The optimal sequence \( Q^* \) is obtained by finding \( Q \) associated with the minimum \( J \):

\[
Q^* = \arg \min_{\{q_1, q_2, \ldots, q_K\}} J
\]

(2)

5. Airway-path detection

The key idea behind improving airway-tissue boundary segmentation is to find an accurate and possibly approximate airway path in the upper airway first, from which the optimal airway-tissue boundaries can be determined easily and more robustly. The optimal airway paths passing through all grid lines in an MR image are determined by finding the paths of the minimum score, using the Viterbi algorithm. For this problem, each possible path in a grid line corresponds to a state, while each grid line corresponds to an observation. \( q_i \) corresponds to the \( i \)-th bin, where \( q_{K/2} \) is placed at the center of the grid line. \( S_{x,y}^L \) is the Euclidean distance between bins \( x \) and \( y \). \( S_{x,y}^T \) is the maximum pixel intensity of all pixels in the grid line \( x \). Note that the length and width of searching region for the lip detection are specified by users.

For the top of the larynx, \( q_i \) corresponds to the \( i \)-th grid line where \( q_{K/2} \) is placed on the grid line of the larynx landmark (the first grid line in Fig. 2). \( S_{x,y}^T \) is the same as defined for lips detection. Let \( D_{x}^L \) be the mean of the first-order derivatives of pixel intensities of \( x \), computed along the grid lines. Then, \( S_{x,y}^T = D_{x}^L \times W_{x} \), where \( W_{x} \) is an optional weighting term which gives more weight on higher grid line. \( W_{x} \) often helps for better estimation, especially when the lower part of the larynx in MR images protrudes. This algorithm detects the point where the pixel intensity increases the most, searching from the top grid line.

The length and the width of searching regions (grid lines) for the lip detection and the larynx detection are specified by users. \( w \) is set to be 1 for these problems. One example of lips and larynx detection results is shown in Figure 3 (a).
four bins were used for the estimated airway path in Figure 3 (b). Neighbors in the range of four instances, eight grids a
by forcing the intensity of the present pixels of fully close
inside the upper airway when a part of vocal tract is fully clo
sity values. Also, the smoothing assists the airway path to s
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found that this smoothing is effective for reducing the esti
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closest lower boundary point regardless of their grid line.
The estimated airway-tissue boundary points are smoothed
by the robust local regression using weighted linear least squares and a 1-st degree polynomial model, implemented in MATLAB, for each image frame. Figure 3 (c) illustrates the smoothed airway-tissue boundaries. Finally, a distance function for the airway-tissue boundaries is obtained by computing the Euclidean distance (in pixel unit) between the upper and lower boundaries or between the upper boundary point and the closest lower boundary point regardless of their grid line. It was observed that the later (green line in Fig. 4) is less erroneous, in particular near the lip region, than the former (blue line in Fig. 4). The initial boundary point for computing the distance function is in the grid line of the estimated larynx. The final boundary point is in the grid line of the first local minimum distance from the final grid line. Figure 4 illustrates a distance function in the upper airway. The software package which contains the MATLAB codes for the present algorithm and the subsets of data for demonstration is freely available at http://sail.usc.edu/old/software/rtmri_cseg.

6. Airway-tissue boundary segmentation

Two airway-tissue boundaries, i.e., the upper and lower boundaries of the vocal tract walls, are determined at the first bins whose pixel intensity is over a certain threshold in the upper direction and lower direction, respectively. The threshold was set to be 0.5, where the maximum pixel intensity of each MR image is 1.

The estimated airway-tissue boundary points are smoothed by the robust local regression using weighted linear least squares and a 1-st degree polynomial model, implemented in MATLAB, for each image frame. Figure 3 (c) illustrates the smoothed airway-tissue boundaries. Finally, a distance function for the airway-tissue boundaries is obtained by computing the Euclidean distance (in pixel unit) between the upper and lower boundaries or between the upper boundary point and the closest lower boundary point regardless of their grid line. It was observed that the later (green line in Fig. 4) is less erroneous, in particular near the lip region, than the former (blue line in Fig. 4). The initial boundary point for computing the distance function is in the grid line of the estimated larynx. The

Figure 3: Estimated vocal tract parameters: (a) estimated locations of forward-most edge of the lips (yellow color) and top of the larynx (cyan color), (b) airway path (cyan color), (c) airway-tissue boundaries (red line for lower boundary, green line for upper boundary).

Optionally, our algorithm performs a smoothing of the pixel intensity matrix (observations) using the mean of the 25% and 75% quantiles of the intensity values of neighboring pixels. We found that this smoothing is effective for reducing the estimation error caused by the low-intensity pixels outside the vocal tract walls, because this smoothing tends to increase their intensity values. Also, the smoothing assists the airway path to stay inside the upper airway when a part of vocal tract is fully closed, by forcing the intensity of the present pixels of fully closed region to be low (because the past and future pixel intensities are low). Neighbors in the range of four instances, eight grids and four bins were used for the estimated airway path in Figure 3 (b). \( w \) in eqn. 1 was set to be 3.

7. Evaluation of estimated airway-tissue boundaries

The estimated airway-tissue boundaries are evaluated against manually annotated tissue boundaries. For this purpose the annotators were instructed to sketch the lower and upper vocal tract walls using a continuous curve. For each of lower and upper boundaries, the Euclidean distance between each estimated boundary point and the closest point in the reference boundary for the estimated point is measured.

The statistics (mean and standard deviation) of the distance values are computed for each sub-region in the vocal tract and each phone. The sub-regions of the present algorithm are (1) grid lines 1 ~ 19 for pharyngeal region, (2) grid lines 20 ~ 52 for velar and dorsal constriction region, (3) grid lines 53 ~ 67 (alveolar ridge landmark) for the hard palate region, and (4) grid lines 68 ~ 77 for labial constriction region. The sub-regions of the previous algorithm are also determined in a similar way. The previous algorithm does not include the lip detection, thus large estimation error is observed in the grids after the lip landmark. For a fair comparison, the final grid line for analysis is fixed to the lip landmark point.

The palatal and dental corrections, and the mean pharyngeal wall were used as pre-processing for the baseline system [1]. See [1] for more details. For the present algorithm, the mean of the estimated boundary in the palatal region and the vertical position of the palate landmark is used in the final upper boundary. The reason for the palatal corrections in both algorithms is that the soft tissue in the hard palate region often shows significantly lower pixel intensity than other tissues, thus not sufficiently contrasted to the airway.

The list of phones used for evaluation is \{B, F, G, IY, K, M, N, NG, P, UW, V\}. Producing speech sound for these phones involves highly constricted or fully closed articulatory gestures, where the error of the estimated airway-tissue segmentation tends to be high. For each phone, 10 phone instances were randomly selected in a male subjects’ data in the USC-EMO-MRI corpus. The acoustic phone boundary of each phone instance is obtained using an adaptive speech-text alignment tool, SaliAlign [8]. The image frames within the starting and final times with one marginal frame in each side were selected. In
vocal tract region than the baseline algorithm. In sum, the proposed algorithm generates more accurately more accurate airway-tissue boundaries than the baseline algorithm. These results suggest that the proposed algorithm generates significantly more accurate airway-tissue boundaries than the baseline algorithm. In sum, the proposed algorithm generates more robust airway-tissue boundaries regardless of the phone and the vocal tract region than the baseline algorithm.

**8. Conclusion and future work**

The present algorithm estimates the airway-tissue boundaries from a robustly estimated airway path in each enhanced MR image. According to the quantitative evaluation on the estimated boundaries, the estimation error is significantly reduced by the present algorithm than the previous method [1] in terms of RMSE (2.56 to 0.71 for the lower boundary; 2.13 to 0.93 for the upper boundary). A major advantage of the proposed method over the baseline is robustness across different regions in the vocal tract. The proposed algorithm also extracts the positions of the front-most edge of the lips and the top of the larynx automatically. This helps constrain the search space of the airway-tissue boundaries, resulting in more robust boundary estimation. In addition, with the algorithm one can estimate the length of the vocal tract above the larynx.

Automatic head movement correction for each MR image is an on-going work that we would like to use for more robust and convenient tissue boundary estimation. In addition, this approach also calls for a preprocessing technique that is better suited to this imaging modality.

**9. Acknowledgements**

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**10. References**


