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Constructing 3D Models of the Pediatric Upper Airway from Long Range Optical Coherence Tomography Images

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ABSTRACT

Long-range optical coherence tomography has been developed to image the upper airway, obtaining high resolution, cross-sectional images of the hollow structure. The information obtained from the anatomical structure of the airway is important to objectively identify regions of airway obstruction. This paper describes a technique to create 3D reconstructions of the upper airway from LR-OCT images. Herein we outline the necessary steps to generate these 3D models, including image processing techniques, manual tissue segmentation in Mimics, anatomical curvature bending, and the final STL model rendition. These 3D models were used to qualitatively analyze structural changes before and after surgical interventions. The reconstructions could also be used for further computational fluid dynamics analysis.

Keywords: Optical coherence tomography, upper airway, 3D modeling, segmentation

1. INTRODUCTION

Obstructive sleep apnea (OSA) affects up to 3% of children and is characterized by prolonged partial upper airway obstruction and/or intermittent complete obstruction that disrupt normal ventilation during sleep^{1,2}. The first-line treatment for OSA is adenotonsillectomy, but the decision to proceed with surgery is based on subjective clinical impressions, most often without any imaging or objective criteria. Imaging modalities such as computed tomography (CT), x-ray cephalometry, or magnetic resonance imaging (MRI) have been used to acquire structural information about the airway³⁻⁵, but are not routinely ordered due to cost, radiation exposure, and/or need for sedation. Because OSA has been associated with significant morbidity in the pediatric population, there is a serious need for improving diagnostic tools and treatment for upper airway obstruction.

Recently, a new imaging modality, long-range optical coherence tomography (LR-OCT), has been developed to image the upper airway⁶⁻¹⁰. This tool utilizes non-ionizing infrared light to obtain high resolution, cross-sectional images of biological tissues. Incorporating a rotary fiber optic system with linear pullback, the hollow structure of the airway can be obtained by performing a helical scan. The upper airway, as defined from the hypopharynx (piriform sinus) to nostril, can be scanned in approximately 20 to 40 seconds, making this method an efficient means to visualize airway anatomy¹¹. The development of LR-OCT has proven to be useful for obtaining information on the anatomical structure of the airway in order to objectively identify regions of airway obstruction.

We describe in this paper a novel technique to create 3D reconstructions of the upper airway from LR-OCT images. These 3D models were used to qualitatively analyze changes before and after pediatric tonsillectomy and/or adenoidectomy. In addition, these models can be generated into standard tessellation language (STL) file types and processed for further computational fluid dynamics (CFD) simulations. Figure 1 shows a flow chart of the major steps of this reconstruction process. Modeling the airway is an important step in identifying regions of airway obstruction and may serve as a guide for more individualized clinical decisions.

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Figure 1. Flow chart highlighting the major steps for constructing 3D models of pediatric upper airways from OCT images.

2. IMAGE PROCESSING

2.1 Data Selection

The LR-OCT system provides an image stack of 300-1000 raw axial images (file type .bmp; 2000 x 2048 pixels) of the airway. These images are first represented in Cartesian coordinates, but can be converted into polar coordinates to provide a better anatomical representation of a cross-section (figure 2). In the sample cross-sectional image given, signals from the probe sheath, tissue, and endotracheal tube can be identified. Vertical and horizontal bands are also present, indicating residual noise from the LR-OCT probe.

Figure 2. Cartesian (a) and polar (b) representations of a cross-sectional image. Identified in both images are signals for tissue (T), endotracheal tube (ET), marking on endotracheal tube (M), probe sheath (S), and vertical and horizontal bands of noise (N).

Image stacks were analyzed and chosen for further processing and reconstruction based on the overall quality of the images. Factors influencing image quality decisions were high signal-to-noise ratio, good contrast of air-tissue interface, identifiable anatomical structures present in the data, and minimal loss or distortion of data. Shown in figure 3 are four images ranging from excellent to poor image quality.

In some cases, missing sections of tissue data are caused by a limited imaging range. Because OCT probes are handmade, the imaging range is variable and could be affected by the quality of the manufacturing process. Thus airways of a greater diameter cannot be fully captured when the probe is located eccentrically in the airway.

Figure 3. Examples of varying image qualities ranging from excellent to poor. (a) Excellent image quality – high signal-to-noise ratio, good contrast between areas of tissue and air, and no apparent data distortion. (b) Average image quality – presence of noise, but strong signal. (c) Below average image quality – signal is faint, but present. (d) Poor image quality – low signal-to-noise ratio, difficult to determine where signal is, presence of large streaks of noise causing missing data.

2.2 Converting to Polar Coordinates

LR-OCT images were processed for correct anatomical scaling in Cartesian coordinates. During the image acquisition process, the reference arm length of the OCT system was manually adjusted, resulting in variability among image stacks in the number of vertical pixels between the top of the image and the probe signal (figure 4a). In order to accurately render the images into a 3D model, this distance was standardized and corrected based on the actual inner diameter of the probe sheath (1.067 mm) and the approximate resolution of the LR-OCT system (8.8 $\mu\text{m}/\text{pixel}$). The average distance between the top of the image and the inner sheath surface (sheath radius) was corrected to be approximately 0.533 mm (half of the sheath diameter), or 61 pixels. The average vertical pixel distance of the image stack was measured within IrfanView (Irfan Skiljan, Wiener Neustadt, Austria), a graphic viewer, and pixels were added or cropped in MATLAB (Mathworks, Natick, MA). The processed linear image stack was then converted to a polar representation using MATLAB because the converted circular format (4096 x 4096 pixels) provided a better anatomic visualization of the airway. Figure 4 shows the differences in the polar images before and after cropping the raw linear image accurately.

Figure 4. Conversion from Cartesian coordinates to polar coordinates. (a) Cartesian image showing extra pixels at the top of the image. (b) Polar image when 4a is converted without cropping. (c) Polar image showing correct airway dimensions when 4a is converted after cropping at the green line.

2.3 Aligning Images

In some cases, a patient might present with significant tissue collapse due to the presence of large tonsils or adenoids. The enlarged tissue mass could compress the probe sheath and create friction against the probe, limiting smooth probe rotation. Changes to the probe's angular velocity could produce image artifacts such as distortion and stretching of the image, and inconsistencies in the angular position ("twisting") of the polar image stack (figure 5).

This problem was fixed by two different methods of aligning the image stack. The first method is an automated processing algorithm written in MATLAB that aligns linear data based on the cross correlation between images. Occasionally, misalignment due to high levels of noise in the images required further adjusting. Following this automatic alignment, a second method was implemented to manually adjust images in finer detail. This manual alignment was done in Amira (FEI Visualization Sciences Group, Burlington, MA), a medical imaging and processing program. Amira allows the user to manually adjust individual image slices according to the similarities of the grey intensities when adjacent slices overlap. Both methods allow the user to select anterior and posterior orientations. The aligned images were then resized to 512 x 512 pixels for faster processing. Batch process resizing was done in IrfanView.

Figure 5. Adjacent images in a stack that requires alignment. (a) Image in a stack that requires rotation in a clockwise direction. (b) Image in a stack at correct alignment. (c) Image in a stack that requires rotation in a counter-clockwise direction.

3. 3D RENDERING IN MIMICS

3.1 Importing Data

The axial image stack was imported into Mimics (Materialise, Leuven, Belgium), a medical imaging program, for segmentation and contouring. The image resolution for images at 512 x 512 pixels was set to a resolution of 70.4 $\mu\text{m}/\text{pixel}$ in the x and y directions. This resolution is calculated based on the known resolution of OCT in air. In the z direction, the resolution was set at 250 $\mu\text{m}/\text{pixel}$ between slices based on the set pullback speed of the OCT probe. After importing the data, the correct anatomic orientation was defined.

Because OCT images contain varying amounts of noise and artifacts, the "threshold" function in Mimics cannot be used for automatic segmentation. Thresholding is normally the first step to create a segmentation mask. It selects a lower and upper boundary range of the region of interest and all pixels with a grey value in that range are highlighted.

Since grey levels corresponding to the tissue may also correspond to noise, the threshold function in Mimics is not applicable. As a result, the tissue layer was manually contoured by creating a new mask with the segmentation threshold set at the lowest level so that no noise or tissue information is picked up. Any residual noise that was still present after creating a new mask was removed using the "multiple slice edit" function. This function allows changes made on one slice to be copied throughout the entire image stack to delete any remaining noise from the mask.

3.2 Segmentation and Contouring

In the “edit mask” function, the airway was manually traced with a circle brush at a size of 3 pixels. To segment out the tissue, the inner surface of the tissue lumen was delineated (figure 6) starting at the first sign of the piriform sinus and ending near the choana. Representative anatomical landmarks identified in OCT images are shown in figure 7.

Figure 6. Manual segmentation of an OCT image. (a) How the polar image appears in the Mimics interface. (b) Manual segmentation via contouring is applied using a new mask (green) that overlays the signal. (c) Exported mask containing the tissue contour as a black and white image.

In some slices, an endotracheal (ET) tube (figure 7a) was present. Contours were drawn around the back of the ET tube, making sure to avoid rendering the tube itself or the glare produced by the ET tube mark. In certain images where the back of the ET tube was not clearly shown, the tissue curvature around the ET tube was carefully estimated.

Figure 7. Identifiable anatomical landmarks throughout image stack. (a) ET tube (blue) and epiglottis (yellow). (b) Base of tongue. (c) Soft palate. (d) Adenoid region (post-surgery). (e) Choana.

3.3 Manual Interpolation

Occasional gaps in the data occurred for several reasons. The most common occurrence of missing tissue information came from signals lying outside the imaging window (Figure 8). This could be caused by an airway space too large to be detected by the LR-OCT probe or by the presence of the ET tube blocking the tissue signal. Other gaps could be the result of poor signal quality, high noise, or eccentric positioning of the probe in the airway lumen.

Figure 8. Cross sectional slices with missing tissue information. (a) Tissue signal outside imaging window. (b) Tissue signal blocked by presence of ET tube. (c) Tissue signal covered by vertical noise bands.

These gaps in the data were interpolated based on surrounding tissue data and adjacent slices superior and inferior, as well as general knowledge of airway anatomy based on CT scans and endoscopies. In situations where large sections of axial images were missing data, we have developed two methods to assist in manual data interpolation by keeping contours more consistent between images.

The first method, called the “dot method,” allows the user to keep the estimated tissue contours consistent between axial images (figure 9) by adding guide dots in areas of missing segments. By using the “multiple slice edit” tool, the same dots were copied throughout multiple axial images containing missing tissue information. Slight variances in tissue position were also accounted for by repositioning some of the dots as the user scanned through the slices. These dots were used as a reference to guide the interpolation in order to achieve higher consistency between slices.

Figure 9. “Dot method” for manual interpolation. (a) Guide dots are placed at areas of missing data and copied throughout multiple slices. (b) Manual segmentation aided by guide dots. (c) Dots are erased after contouring is completed.

The second method, called the “sagittal line method,” involves viewing the data in a sagittal orientation to estimate missing tissue information. Contours were drawn in a different mask throughout several sagittal slices lacking tissue signal. Often it was easier to draw in these connections when viewed in the sagittal plane because this orientation better shows continuous borders between the walls above and below the missing data (figure 10). After several gaps were filled in when viewed in the sagittal orientation, the orientation was switched back to axial. The sagittal estimations in a different mask appear as a different color in the axial slices (figure 10b), which provided a rough guideline to interpolate tissue contours throughout multiple axial slices.

Figure 10. “Sagittal line” method for estimating missing tissue information. (a) Sagittal image with missing tissue data. (b) Connections drawn with a new mask (yellow) to interpolate tissue contour. (c) Resulting connections are shown in the axial view to guide further segmentation.

At multiple intervals throughout the manual interpolation process, 3D representations of the contour mask were created to check the progress of the airway shape and consistency. Mimics provides a tool to create custom quality 3D objects. Parameters for making these 3D models (5 iterations of smoothing at a smoothing factor of 0.9) were chosen based on previous studies of upper airway reconstruction in Mimics¹² and adjusted to account for roughness of OCT tissue information and small inconsistencies resulting from manual interpolation. The resulting 3D model had occasional holes due to large spaces between axial slice contours. These holes were covered with the “wrap” function based on the selected parameters (smallest detail of 0.2 mm and gap closing distance of 1 mm). Wrapping adds an extra layer of thickness to the airway and as a result distorts the dimensions of the contours. The listed parameters were chosen to be the smallest value that would minimize this additional thickness while covering up the majority of holes between slices. Any remaining holes due to drastic changes in between axial slices were filled in during an additional step.

3.4 Filling in Holes

To fill in remaining holes after the “wrap” function was applied the contours were exported and processed outside of Mimics. The axial images were exported as black and white (binary) images of only the drawn contours (no OCT data was included). To export in Mimics, the contour mask was first changed to white, and the contrast view of the data was altered until the background was completely black. This allowed the exported axial images to only show the white contours.

Holes in the axial images were filled using a MATLAB algorithm. This program creates an overlay of adjacent images, determines the differences between the contours, and fills in pockets that were larger than a specified gap closing distance (figure 11). Also, the program only fills in small holes and ensures that the inner surface of the contours remains hollow.

Figure 11. MATLAB process to fill in holes in adjacent contour images. (a,b) Adjacent contour images where remaining holes are found in the wrapped 3D model. (c) Holes in image filled using a MATLAB algorithm that overlays adjacent images and fills in pockets larger than a specified gap closing distance.

4. BENDING

4.1 Obtaining Sagittal Images

Since images are acquired in a linear pullback, the resulting models are upright and vertical, and as a result do not accurately reflect the natural curvature of the airway. To better simulate this curve, the models were further processed in a bending algorithm and interface written in Visual Basic (Microsoft, Redmond, WA).

This bending algorithm can only accommodate images in the sagittal orientation. Thus the hole-filled axial contour images were reimported into Mimics, not only to check for any remaining unfilled holes, but to re-export the stack as sagittal slices. Because the reimported images now only contain a black background and a white contour, a new mask and 3D object can be easily segmented and created using the threshold function. The custom 3D object was wrapped (smallest detail of 0.2 mm and gap closing distance of 1 mm) and checked for any remaining holes that the MATLAB program did not pick up. Any remaining holes could be identified by toggling between two slices where the hole was located and filled in manually using the “edit mask” tool. When there were no more holes, the airway contours were exported in the sagittal orientation.

4.2 Anatomical Bending

The bends used to curve the data were derived from CT scans from three different pediatric patients. For this study, CT scans from normal cases were used. A focus in our future research is to obtain magnetic tracking data for more individualized bending, which could replace using CT derived curves during the bending process. Bend data, from magnetic tracking or CT scans, are saved as a text file containing x and y coordinates of a curve that spreads from the piriform sinus to the tip of the nose. Some points are removed from this curve to limit the ends to only the piriform sinus and the choana.

The adjusted sagittal images were imported into the bending program along with a bend curve text file. The bending program determines the x and y positions of the points along the curve and calculates the rotation and shift between the curve points. Based on the position and curve rotation found, the program then fits axial cross sections of the sagittal image stack at angles normal to the curve along interpolated curve points. This generates a new image stack, now curved to bend data. Sagittal images of this stack were exported for post bend processing. The bending process is illustrated in figure 12.

Figure 12. Bending sagittal image stacks using a Visual Basic algorithm. (a) Stack of unbent sagittal images. (b) Curve plot generated from pediatric CT scans or magnetic tracking system. (c) Resulting stack of sagittal images bent by fitting it to the curve plot.

5. POST BEND PROCESSING

5.1 3D Reconstruction of Bent Airway

Sagittal slices of bent airway contours were imported into Mimics at resolutions $70.4\text{ }\mu\text{m/pixel}$ in the x, y, and z directions. This number was based on the previously used resolutions in the x and y planes of the upright stack. A mask was created in order to threshold the white contours in the images in order to create a 3D object. A custom quality 3D object, with the same previous parameters, was created from this mask to generate a 3D model of the bent airway. The model was then wrapped using the same wrap parameters (smallest detail 0.2 mm, gap closing distance 1 mm). The object was also smoothed at a smoothing factor of 0.9 with 5 iterations. This time, the “compensate shrinkage” option was checked in order to minimize the loss of detail that resulted from smoothing.

5.2 Isolating Inner Surface

Our CFD analysis requires that airway STL files contain only a thin, hollow surface. Because these 3D models contain a thickness, and therefore an inner and an outer wall, one of the walls must be isolated in order to create a thin, hollow STL file. The reason for choosing to isolate the inner wall, rather than the outer wall, is because the inner wall better represents the contoured airway volume.

A new mask (as shown in green) was created from the smoothed, wrapped 3D object of the bent airway (Figure 13a) in order to edit the object and separate the inner and outer surfaces. This second mask contained the wrapped contours of the airway.

The next step was to create a third mask, designated as “world,” that selected for everything throughout the slices, including the tissue contours and the empty space outside and inside (Figure 13b). In “Boolean” operations, which allowed for different combinations of two segmentation masks (subtraction, union or intersection), the mask containing the wrapped contour (green) was subtracted from the “world” mask (red). The resulting fourth mask (blue) now contained a negative profile of the contours (Figure 13c).

A “region grow” function was used to separate the inner surface from the remaining outer parts of the mask. This function created a new mask solely based on the regions in the mask that remained connected to each other throughout the entire stack. The “region grow” function was applied to the inner region of the airway to isolate just this inner surface. However, this function would not work if the inner surface was still connected to the outer regions at the top and bottom ends of the airway (Figure 13c). As a result, these two ends needed to be separated. In the sagittal orientation, the mask was edited throughout all the sagittal slices and areas at the ends were deleted from the mask using the “multiple slice edit” function. This removed the connections between the inner region and the outer region (Figure 13d). “Region grow” was applied after this step to produce the yellow colored mask as shown in figures 13e and f.

Figure 13. Isolation of inner airway surface. (a) Segmentation mask (green) created from smoothed, wrapped 3D object of bent airway. (b) “World” mask (red) containing all contours and empty space. (c) Resulting mask (blue) is a negative profile of the contours. It is created from a Boolean operation of the world mask (red) minus the contour mask (green). (d) Removing connections between the inner airway surface and the outer region. (e) “Region grow” function to isolate inner airway surface and generate a new mask (yellow). (f) Resulting mask of the inner airway surface.

A custom quality 3D object (figure 14) was generated from the newly region grown mask with the same previous parameters (smoothing factor 0.9 at 5 iterations, compensate shrinkage unchecked). 3D models created from Mimics consist of a mesh that was formed from thousands of individually connected triangles. Triangle reduction was applied to the 3D model in order to reduce the resolution of the mesh for easier and faster post-processing. The triangle reduction parameters were set at default parameters (advanced edge mode, 0.05 mm tolerance, 15 degree edge angles, and 10 iterations). The resulting 3D model was exported as an STL file for further processing outside of Mimics.

Figure 14. Inner surface 3D model generation. (a) 3d object created from mask of inner surface. (b) Application of triangle reduction and smoothing to generate model (STL) fit for further processing.

5.3 STL Processing

For our CFD analysis and airflow simulations, the solid model must be made hollow by opening up the two ends. Flat cuts at each end, perpendicular to the direction of the airway curvature, were made at the proximal and distal ends of the airway model.

To create the final STL, the solid model was first imported to NetFabb Studio (NetFabb, Parsberg, Germany), a 3D printing and modeling software. The “cut” tool in NetFabb Studio was used to make flat cuts resulting in a smooth surface at both ends that could easily be removed (Figure 15a, b). Along with this step, any excess slices were also removed to ensure that the two ends were appropriately positioned at the piriform sinus and the choana. The STL models were imported into 3-Matic (Materialise, Leuven, Belgium), an extension of Mimics used to edit STL models, in order to select out the flat ends on both sides for removal. During this step, triangles in the mesh found along this surface were selected and deleted using the “triangles on plane” marking tool, resulting in a hollow airway model (Figure 15c). The final models were exported as an STL file and could be used for CFD analysis.

Figure 15. STL processing to create hollow airways for CFD analysis and airflow simulations. (a) Proximal and distal ends of the solid model were cut perpendicular to the direction of airway curvature. (b) The cut regions removed from the model to generate smooth surfaces. (c) Triangles along the cut surfaces were selected and removed, resulting in a hollow airway.

6. CONCLUSION

We have developed a novel technique to create 3D reconstructions of the upper airway using OCT images from pre- and post-operative pediatric cases. These 3D models provide insight into its structure and shape, and can help identify regions of obstruction. Furthermore, these reconstructions can be exported as STL files that can be processed for further CFD simulations and airflow calculations. We outline herein the steps necessary to generate functional STL airway reconstructions from the raw OCT images.

Developing the tools and methods for 3D OCT reconstruction is an ongoing process. We are presently limited to the use of manual interpolation as a method for tissue segmentation because of many factors causing deterioration of signal quality. Current work is being done to develop automation software that will minimize or even eliminate the need for manual human input. In addition, the workflow and techniques used are constantly being optimized for easier and faster user control. One new development is the transition from Mimics, the gold standard for medical image segmentation, to other open source software such as 3D Slicer (Harvard University, Cambridge, MA) and Amira. By constantly improving techniques for reconstruction, we hope to provide a better understanding of the potentials of using LR-OCT to image the upper airway.

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