Anatomical Region Segmentation for Objective Surgical Skill Assessment with Operating Room Motion Data

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Abstract

Background Most existing objective surgical motion analysis schemes are limited to structured surgical tasks or recognition of motion patterns for certain categories of surgeries. Analyzing instrument motion data with respect to anatomical structures can break the limit, and an anatomical region segmentation algorithm is required for the analysis.

Methods An atlas was generated by manually segmenting the skull base into nine regions, including left/right anterior/posterior ethmoid sinuses, frontal sinus, left and right maxillary sinuses, nasal airway, and sphenoid sinus. These regions were selected based on anatomical and surgical significance in skull base and sinus surgery. Six features, including left and right eye center, nasofrontal beak, anterior tip of nasal spine, posterior edge of hard palate at midline, and clival body at foramen magnum, were used for alignment. The B-spline deformable registration was adapted to fine tune the registration, and bony boundaries were automatically extracted for final precision improvement. The resultant deformation field was applied to the atlas, and the motion data were clustered according to the deformed atlas.

Results Eight maxillofacial computed tomography scans were used in experiments. One was manually segmented as the atlas. The others were segmented by the proposed method. Motion data were clustered into nine groups for every dataset and outliers were filtered.

Conclusions The proposed algorithm improved the efficiency of motion data clustering and requires limited human interaction in the process. The anatomical region segmentations effectively filtered out the portion of motion data that are out of surgery sites and grouped them according to anatomical similarities.

Keywords

- anatomical region
- atlas-based segmentation
- motion analysis
- objective skill assessment
- operating room data
- skull base
- sinus surgery

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Introduction

Surgical skill assessment leads to deeper understandings of the relationships between instrument movements, motion patterns, and surgical outcomes.^{1–3} It guides trainees for skill improvement, assists surgeons by identifying high-risk motions, and potentially delivers improved surgical outcomes to patients.^{1–7}

In classical skill assessment models, “expert” surgeons review recorded videos of other surgeons and rate their performance against a rubric.^{2–8} More recent research has enabled objective skill assessment through recording surgical motions, primarily in the laboratory. For example, techniques such as objective structured assessment of technical skills (OSATS)^{3,9,10} are considered the standard for skills assessment and have been utilized in many specialties. An OSATS specific to endoscopic sinus surgery has been described and validated.² This assessment tool defined a surgical skill list and global rating scale for endoscopic sinus surgery and was validated in a cadaver model.⁹

Surgical motion database skill assessment is advantageous over video review because it contains the actual instrument motion path and is purely quantitative and does not require expert grader time. It has been shown that surgical motion datasets in abdominal surgery can differentiate novice and experienced surgeons, based on total task time, instrument path length, and smoothness.^{11,12} To date though, these studies have only evaluated discrete surgical tasks, such as suturing, grasping and cutting in controlled environments (e.g., animal model or simulator). A major challenge has been analyzing instrument motion in the context of a complete operation. If the problem is abstracted as an ordinary classification or regression problem, as long as proper features can be identified, it is realistic to extend skill evaluation to full operations in the operating room (OR) with classical machine learning algorithms, or popular deep learning algorithms.^{2,13–19} For example, during septoplasty, sweeping motions of the surgical instrument illustrates a difference between expert and novice performance.¹⁸ This and related work uses features of the motion, such as stroke curvature consistency, stroke duration consistency, and coverage rate, to automatically and objectively evaluate skill.^{18,19}

Driven by the desire of evaluating surgical skills with general and complete operating room surgeries, we proposed a new objective, automatic surgical skill assessment scheme for sinus and skull base surgery, using OR data collected by commercial surgical navigation systems.^{20,21} Although we preliminarily verified the hypothesis that, with motion data clustered by anatomical regions, not only the classical metrics, such as motion economy, can differentiate novice from expert, but also the statistical properties, such as mean and variance of velocity and acceleration, can indicate skill levels in endoscopic skull base and sinus surgeries.²¹ However, the analysis was bottlenecked by the difficulty of anatomical region segmentation. In this work, we propose and implement an atlas-based anatomical region segmentation method for endoscopic skull base and sinus surgery to perform objective motion analysis on large data-

sets. This work is novel in that preoperative scans are segmented into anatomical regions instead of anatomical structures, according to the anatomical and surgical significance of tissues in skull base and sinus surgeries. As a result, segmentation facility and precision are both improved. These anatomical regions serve as the “surgical map,” which is critical to both human and robotic surgery planning.

Method

This work utilizes the unique characteristics of skull base anatomy that tissues and anatomical regions are confined by rigid bone. Therefore, the surgical procedure does not change the anatomical regions. The proposed method contains six steps, as explained below in order.

Atlas Generation

Nine regions were manually segmented for a computed tomography (CT) scan, including left/right anterior/posterior ethmoid sinuses, frontal sinus, left and right maxillary sinuses, nasal airway, and sphenoid sinus. These regions were selected for both anatomical importance and surgical significance for skull base and sinus surgeries. These regions are critical for motion analysis as motion data will be clustered based on these regions. The regions do not impact the atlas-based segmentation process because unaltered CT scans were used for registration. In the experiments, the atlas was manually segmented by otolaryngology surgeons using a convenient tool ITK-SNAP (National Institute of Biomedical Imaging and BioEngineering [NIBIB]),²² and the precision is visually verified by otolaryngology surgeons. As compared with the other segmentation verification problem, the anatomical regions segmentation verification is easier because the regions are defined by bony boundaries, and the segmentation of those structures is reliable.²³ ▶Fig. 1a–c visualized the sagittal, the coronal, and the axial view of the segmented atlas, correspondingly, and ▶Fig. 1d showed the color codes for regions. In the figure, white color indicated the bony boundaries.

Feature Selection and Affine Registration

The preoperative scans have differences in orientation, scale, position, and most importantly, different anatomical structures. To limit the search range of alignment and speed up the registration, features were used to align scans with affine transformations.

Six landmarks were used in the proposed method, including left eye center, right eye center, nasofrontal beak, anterior tip of nasal spine, posterior edge hard palate, and clival body at foramen magnum, as shown in ▶Fig. 2. These landmarks were selected because the later four landmarks defined the boundary of skull base area and the first two indicate the width of a scan; also because these features are stable and potentially can be automatically detected. For each dataset, the landmarks were manually selected once using three-dimensional slicer (landmark registration model).²⁴ This was the only step in the proposed method which required user input.

The affine transformation is used for feature-based registration. An affine transformation is any transformation

Fig. 1 Anatomical region atlas for motion analysis. (a–c) The sagittal, the coronal, and the axial view of the segmented atlas, correspondingly, and (d) shows the legend. White color indicates the bony boundaries.

Fig. 2 Landmarks for affine registration. The six landmarks used for affine registration are indicated by red stars, including left eye center, right eye center, nasal frontal beak, anterior nasal spine, posterior edge hard palate, and clival body at the foramen magnum.

that preserves collinearity and ratios of distances including translation, scaling, rotation, and shear.²⁵ Mathematically, if X and Y are affine spaces, then an affine transformation has the form $x \mapsto Mx + b$, where in X , b is a vector in Y , and M is a linear transformation, which subjects to the additivity ($f(x + y) = f(x) + f(y)$) and homogeneity of degree 1 ($f(ax) = af(x)$).

B-Spline Deformable Registration

The landmark-based affine registration cannot address the fine difference in anatomical structures between individuals, thus B-spline (basis spline) deformable registration was adopted.²⁶ Mathematically, the cubic B-spline adapted here is defined as:

$$f(x, y, z) = \sum_{i,j,k} c_{ijk} B^{(u_x)}(x - iu_x) B^{(u_y)}(y - ju_y) B^{(u_z)}(z - ku_z),$$

where n_x, n_y, n_z are the number of splines and u_x, u_y , and u_z are the knot spacing in the x, y , and z directions, respectively. In the

proposed method, the ITK²⁷ library was adapted. In both this step and the previous step, the atlas served as moving image, and the scans for segmentation were the fixed images.

Anatomical Region Generation

The previous two steps aligned the atlas with the targeted scans, through an affine and a B-spline transformation. As the atlas served as the moving image, once the two transformations were applied to the atlas, we achieved the anatomical region segmentations for the targeted scans.

Bone Extraction and Registration Correction

Bone boundaries are important clues for localization and identification of skull base and sinus surgeries. They also served as boundaries of skull base region segmentation. If symmetry is assumed in the coronal and axial directions, we use a simple scheme to automatically detect the upper and the lower threshold of intensity values and seed position, which are the three important parameters for region growing segmentation algorithm. In the scheme, the intensity value along the central line (red line in **Fig. 3a**) passes bony structures, and the intensity values are roughly symmetric,

Fig. 3 The automatic bone intensity and speed detection for bone extraction. The intensity values along the central line (red line in [a]) are shown in (b). Local maxima suppression is used to detect the upper and the lower thresholds and the corresponding location for automatic bone extraction.

Fig. 4 Atlas-based anatomical regions segmentation result. The top row is a magnified triplanar view showing one segmented result. The second row shows the sagittal view of the other six segmented computed tomography scans, and the third and the fourth rows show the corresponding coronal and axial views respectively.

as shown in ► **Fig. 3b**. Through local maximum suppression on intensity and slope,^{28,29} we can easily detect the upper and the lower thresholds and the corresponding location for the region grow algorithm.²⁷

The detected bony boundaries form a new boundary which can be used to correct region segmentation achieved in the previous step. Overwriting the bony boundaries on the top of region segmentation also served as an indicator for segmentation precision, as shown in the Results section.

Motion Data Clustering

Motion data were divided into clusters according to the relative position between instrument tip and segmented regions, as mathematically explained below.

$$\begin{cases} X_{idx} = (X - Origin_x) / Spacing_x \\ Y_{idx} = (Y - Origin_y) / Spacing_y \\ Z_{idx} = (Z - Origin_z) / Spacing_z \end{cases},$$

where X , Y , and Z are the coordinates of motion data, X_{idx} , Y_{idx} , Z_{idx} are the coordinates of the motion data in the CT image space, $Origin_x$, $Origin_y$, $Origin_z$ are the origin of the CT scan in the physical space, and $Spacing_x$, $Spacing_y$, $Spacing_z$ are the spacing of the CT scan in the physical space. Therefore, the value of atlas matrix at $(X_{idx}, Y_{idx}, Z_{idx})$ is the region category of the motion data point.

Results

Registration Result

Preoperative CT scans from eight different patients who underwent endoscopic skull base and sinus surgery were used to verify the proposed method. Data collection was approved by the University of Washington Institutional Review Board (# 52114). Surgical instrument motion was passively recorded using a Stryker iNtellect cranial navigation system (Kalamazoo, Michigan, United States), and endoscopic endonasal approaches were performed by an experienced skull base surgeon (K.S.M.). CT scans were anonymized before analysis.

Fig. 5 Motion clustering based on anatomical regions. The images on the left show the motion data clustered according to anatomical regions segmented by the proposed method; the images on the right show the motion data colored according to the sequence in time (rainbow color indicate the sequence of motion in time).

Table 1 Motion data clustering result

Total	Left anterior ethmoid	Right anterior ethmoid	Left anterior ethmoid	Left anterior ethmoid	Frontal sinus	Left maxillary sinus	Right maxillary sinus	Nasal airway	Sphenoid
74,810	133	600	807	583	40	126	196	1,135	1,105

Note: The table shows the total number of collected data points versus the total number of the motion data points in each anatomical region. The region-based clustering filters out irrelevant motions and groups them according to anatomical similarity.

One of the eight datasets was used as the atlas (►Fig. 1). The other seven were segmented according to the proposed method (►Fig. 4). The top row in ►Fig. 4 shows a magnified view of the seven segmented results. The second row shows the sagittal view of the other six segmented CT scans, and the third and fourth rows are the corresponding coronal and axial views. Although the anatomical structures of each patient are different because the adoption of landmarks, the affine transformation, and the B-spline transformation, the desired anatomical regions are accurately segmented.

Motion Data Clustering Result

Motion data were clustered by the anatomical regions generated by the proposed method (►Fig. 5). The left column shows the motion data clustered according to the anatomical regions, and the right column depicts the motion data colored according to the sequence in time. It is clear that, by utilizing anatomical regions, motion data are grouped together according to anatomical similarity, and irrelevant data such as trajectory out of surgical site are naturally filtered out, as shown in ►Table 1.

The proposed method was implemented in C++ for motion data analysis, and the screenshot of the developed software is shown in ►Fig. 6.

Discussion and Conclusion

Motion data are a rich source of information on the performance of surgeries. It is critical to analyze this motion data

relative to key anatomic regions because it offers many advantages. In this study, the paranasal sinuses were defined semiautomatically. The instrument motion within each region can now be analyzed independently, which narrows the range of surgical tasks that are performed within each region. This leads to stronger correlations between movement characteristics and surgeon skill. For example, in the anterior ethmoid region, instruments will open ethmoid cells, but also pass through to open cells superiorly in the frontal region. Instruments will also progress through these anterior ethmoid cells into the posterior ethmoid and sphenoid regions. In the sphenoid region, the motion signature would differ as instruments work mostly at the anterior aspect of the space rather than throughout, and motion in the lateral regions will be curtailed by the presence of the optic nerves and internal carotid arteries. In the future, we believe that real-time feedback will be provided to the trainee (or expert surgeon) based on the known region-specific characteristic motions obtained empirically.

To our knowledge, this is the first study that explicitly studies OR motion data with respect to segmented anatomical regions. Because this had not been performed previously, we developed a rapid method for segmenting CT scans into clinically significant anatomical regions instead of explicit tissues.

This work presents a key component of the novel paradigm mentioned earlier for anatomical structure-based skill assessment in sinus and skull base surgery. This assessment is based on actual OR data and applies to virtually all skull

Fig. 6 Screenshot of software developed for motion data analysis.

base and sinus surgeries. Compared with our previous work,^{21,22} which clustered motion data into three categories through manually defining planes, this new method is more precise with nine regions, less time consuming, and less susceptible to subjective bias. Analyzing large-scale OR motion data are now possible. While the method is still not fully automatic (human interactions are needed for feature selection) it is practical for analyzing hundreds of datasets. We are currently developing a fully automatic segmentation algorithm which will be used in future studies.

As more knowledge is gained about surgical motion relative to critical anatomic landmarks, further refinement and definition of the regions of anatomic segmentation are likely to take place. The system presented in this article is flexible and allows manipulation of these parameters as desired.

Conflict of Interest

None.

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