TECHNICAL REPORT

An optimized process flow for rapid segmentation of cortical bones of the craniofacial skeleton using the level-set method

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Accurate representation of skeletal structures is essential for quantifying structural integrity, for developing accurate models, for improving patient-specific implant design and in image-guided surgery applications. The complex morphology of thin cortical structures of the craniofacial skeleton (CFS) represents a significant challenge with respect to accurate bony segmentation. This technical study presents optimized processing steps to segment the three-dimensional (3D) geometry of thin cortical bone structures from CT images. In this procedure, anisotropic filtering and a connected components scheme were utilized to isolate and enhance the internal boundaries between craniofacial cortical and trabecular bone. Subsequently, the shell-like nature of cortical bone was exploited using boundary-tracking level-set methods with optimized parameters determined from large-scale sensitivity analysis. The process was applied to clinical CT images acquired from two cadaveric CFSs. The accuracy of the automated segmentations was determined based on their volumetric concurrencies with visually optimized manual segmentations, without statistical appraisal. The full CFSs demonstrated volumetric concurrencies of 0.904 and 0.719; accuracy increased to concurrencies of 0.936 and 0.846 when considering only the maxillary region. The highly automated approach presented here is able to segment the cortical shell and trabecular boundaries of the CFS in clinical CT images. The results indicate that initial scan resolution and cortical–trabecular bone contrast may impact performance. Future application of these steps to larger data sets will enable the determination of the method's sensitivity to differences in image quality and CFS morphology.

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Introduction

Accurate segmentation of skeletal structures, including delineation between the thin cortical shell and trabecular bone, is important in quantifying structural integrity in the craniofacial skeleton (CFS). Subject-specific musculoskeletal modelling applications that attempt to predict functional loading (such as the finite element

method), as well as those used in image-guided surgery, require accurate reconstruction of skeletal geometry.^{1–4} The development of patient-specific implants using imaging data and rapid prototyping are also reliant on accurate image segmentation.³ CT can provide insight into the internal structure of the CFS, with spatial accuracy approaching the sub-millimetre range. However, thin cortical bone structures in the CFS can be difficult to segment owing to partial volume averaging of voxels, leading to loss of continuity in bony structures.^{2,4,5} This is compounded by the abundance of high curvature bone and the intricate and complex geometry

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of the CFS. As such, manual segmentation of thin cortical bone in the CFS can be extremely time-consuming and limit the reliability of quantitative measures derived from them.

Computational processing of medical image data to reduce human intervention and increase repeatability of segmentations is a rapidly growing field that has seen many new algorithms developed for rudimentary segmentation tasks. However, issues that hinder human-directed segmentation (such as limited image resolution, blurring, high curvature and discontinuities) make simple methods such as thresholding unreliable for segmentation of the CFS, and in particular its cortical–trabecular boundary.³ Computer methods that utilize geometrical feature information, such as the level-set method, which is a numerical technique for tracking interfaces and shapes, can facilitate boundary tracking of curved features common in the CFS and along its cortical–trabecular boundary.^{2,6–9} The purpose of this paper is to present a series of largely automated processing steps that enable segmentation of thin cortical bone structures in the CFS based on clinical CT data.

Methods

Algorithm description

The multistep image-processing algorithm of this study is primarily based on connected components thresholding and the level-set method.⁷ The algorithm facilitates segmentation of the external skeletal boundaries of the CFS and delineation of the internal cortical trabecular boundaries. The algorithms are implemented within the commercial image analysis software platform AmiraDev v. 3.0 (Visage Imaging GmbH, Berlin, Germany) and incorporate open source code available through the Insight Segmentation and Registration Toolkit (ITK v. 3.0; Kitware, Inc., Clifton Park, NY). ITK is an open source system from the National Library of Medicine that provides an extensive suite of software tools for image analysis. A schematic of the algorithm is presented in Figure 1.

The algorithm begins with the resampling of clinical CT imaging data to an isotropic resolution matching the in-plane resolution of the scan using a Lanczos filtering kernel (AmiraDev v. 3.0). An anisotropic filter (ITK::CurvatureAnisotropicDiffusionFilter)⁷ is then applied for 10 iterations to smooth the image in order to reduce noise and homogenize (even out) trabecular bone regions while preserving the sharpness of the external cortical boundary. A connected components scheme (ITK::ConnectedComponents)⁷ is then applied with a user-defined seed voxel to identify all connected voxels within the defined threshold range for bone (150–3200 HU).⁴ This results in a segmentation of the external boundaries of the CFS (including both cortical and trabecular bone; Figure 2). Manual user intervention

can be applied at this stage to fill any holes not captured by the segmentation.

A level-set-based method (ITK::GeodesicActiveContourLevelSetImageFilter)⁷ is then employed to segment the interface between the thin cortical shell and underlying trabecular bone. This class of method was chosen because it is best suited to track finely evolving surfaces. The offset distance from the external cortical bone surface to the cortical–trabecular boundary is variable. As such, the external cortical segmentation provides the initial position of the evolving boundary. The evolution (movement) of the boundary from the external cortical bone surface to the cortical–trabecular interface is then locally controlled by a speed image (as described below), and further constrained by curvature weighting parameters.

The gradient of the CT image is used to construct a speed image where the evolving boundary will stop ($= 0$) at the cortical–trabecular boundary. A speed image is the mapping of the gradient magnitude of the original image such that regions with high contrast will have low speeds while homogeneous regions will have high speeds. The gradient of the external cortical surface is stronger than the mid-range gradient across the cortical–trabecular boundary. As such, a band pass filter was constructed using two sigmoid filters that assigned a high speed to both low-gradient homogeneous regions and the high-gradient external cortical surface, and low speeds to the mid-range-gradient magnitudes of the cortical–trabecular boundary. The sigmoid transformation normalizes the gradient magnitudes to a range of 0–1 around a specified location. The speed image was based upon a Gaussian smoothed gradient magnitude image of the CT scan (kernel size from 0.035–0.05 sigma). For the speed image, one sigmoid was constructed at a gradient magnitude of 3000 HU with a relaxation of -750 HU (gradient < 3000 , $HU \approx 1$) and the second at a magnitude of 6000 HU with a relaxation of 1000 HU (gradient > 6000 , $HU \approx 1$).

Data acquisition

To demonstrate proof of concept the process was applied to clinical CT scans of two cadaveric heads with all soft tissues intact. CT images of a preserved CFS (10% buffered formalin) was acquired at a slice thickness of 0.6 mm with an in-plane resolution of 0.488 mm (CFS1) on a GE LightSpeed Plus (General Electric, Fairfield, CT). A CT scan of a second cadaveric CFS (non-preserved, previously frozen), was acquired at a slightly lower resolution, with a slice thickness of 0.8 mm and an in-plane resolution of 0.523 mm (CFS2) on a Philips Brilliance Big Bore (Philips, Amsterdam, Netherlands). The scans were acquired at 120 kVp with an exposure of 215 mAs.

Performance optimization and evaluation

Parametric studies were conducted to examine the curve evolution parameters (propagation, curvature and

Figure 1 Algorithm flow chart. A CT scan is manipulated through various filtering schemes in order to obtain segmentations of the cortical and trabecular bone of the craniofacial skeleton. CFS, craniofacial skeleton

advection) for identifying coarse parametric ranges suitable for further refinement. The three parameters control the relative influence of the different terms of the curve evolution equation. Optimization of the level-set segmentation was performed using automated analyses (+1000) that varied the control parameters and evaluated the outcome against manually user-defined segmentations of the cortical-trabecular boundary

using a volumetric concurrency (VC) metric.¹⁰ Manual segmentation of these CT data sets was conducted on a slice-by-slice basis on the isotropic data sets to yield visually optimized reference segmentations of the external morphology of the CFS and the internal cortical-trabecular boundaries. (Note: owing to the extremely time-consuming and tedious process of manual segmentation, inter- and intraoperator repeatability evaluations

Figure 2 Segmentation of the craniofacial skeleton in a clinical CT image slice using (a) thresholding and (b) anisotropic filter smoothing and connected components thresholding. Note a lower intensity threshold of 150 HU was used in both segmentations. Neither the thresholding technique nor the proposed algorithm can create a continuous segmentation of the thin sinus bones; however, the algorithm substantially reduces islands in the nasal sinuses

were not carried out—the reference was based on visual optimization of the manually segmented images.) VC was defined as the average value of the ratios of the volume of the intersection region between the automated and manual segmentations and individual volumes.

Results

The automated level-set segmentation technique was applied to the CT images and yielded segmentations of the external bony boundaries and cortical trabecular boundaries of the CFS. Representative slices of the outcome of the automated segmentation against the manual segmentations are shown in [Figure 3](#).

In the facial regions, volumetric concurrencies of 0.904 and 0.719 were achieved for the two specimens, CFS1 and CFS2, respectively. For the maxilla, volumetric concurrencies were 0.936 and 0.846. The maxilla was considered separately because it was qualitatively the best-segmented structure for both specimens using the optimized level-set parameters. The best-fit scaling parameters for the two specimens were consistent for propagation (1) and curvature (1.5), but differed for advection (1 and 0.5, respectively).

Discussion

The level-set segmentation scheme developed in this study was able to provide a high-quality segmentation of the cortical–trabecular boundary of the human CFS. The sigmoid band-pass filter established high speed in the high-gradient regions of the external cortical bone

and the homogeneous internal regions, isolating the mid-range gradients of the cortical–trabecular boundary. Although the segmentation algorithm achieved high overall concurrencies, the approximation of the boundary was poorer for the regions of the zygoma and orbits. The differences between the manually and automatically defined boundaries are in the order of 1 voxel in these regions; this equates to a thickness difference of approximately 0.5 mm.

The poorer agreement in areas representing the zygomas and orbits suggests that globally defined parameters may be insufficient to segment the cortical bone of the entire CFS. Owing to the number of trials of the algorithm conducted (1000+), the concurrency metric was chosen using a goodness-of-fit parameter rather than evaluating the fit in separate regions of the CFS. Different regions exhibit varied ranges with respect to curvature change from the external cortical surface to the trabecular bone boundary owing to variation in thickness. As such, different curvature weighting may be required for regions where changes in curvature of the evolving boundary depend on the local structure.

The effectiveness of the level-set algorithm is limited by the resolution of the CT scan data. In both cases the voxel size was set at the maximum achievable on the given scanner (CFS1 = 0.488 mm, CFS2 = 0.523 mm). The two scans differ by approximately 7% in each dimension for an overall difference of approximately 22.5% in the volume of each voxel. The more limited performance on the lower-resolution CFS2 CT data set suggests that the algorithm is sensitive to voxel size and may also be impacted by reduced signal-to-noise ratios. Alternatively, new image-processing algorithms that

Figure 3 Algorithm-based segmentation (black contour) and manual segmentation of CT images from two craniofacial skeleton (CFS) CT data sets. White is cortical bone and light grey is trabecular bone based on the manual segmentations. (a) CFS1 maxilla, (b) CFS1 zygomas, (c) CFS1 orbits, (d) CFS2 maxilla, (e) CFS2 zygomas and (f) CFS2 orbits. Note that the resolution of CFS1 ($0.488 \times 0.488 \times 0.6 \text{ mm}^3$) is significantly better than that of CFS2 ($0.523 \times 0.523 \times 0.8 \text{ mm}^3$)

reduce the loss of both geometric and intensity information because of blurring may improve the performance of this algorithm, even on lower-resolution data sets.¹¹

Insufficient contrast at the cortical–trabecular interface was observed for CFS2, which may be related to morphological variation, in addition to resolution. The differences between the two specimens existed mainly in the zygomatic region, where CFS1 had more mass and greater contrast between the trabecular and cortical bone. CFS2 was much thinner in this region, with the trabecular centrum of the zygomatic arch indiscernible from the cortical bone, resulting in low gradients.

Although some regions of the skeleton are more difficult to segment using the automated technique, overall a level-set-based approach presents a good method for several reasons. The methods as implemented in ITK are best for small changes to an existing segmentation, as required for the thin cortical bone of the CFS. The level-set method implicitly allows the evolving contour representing the boundary to merge and split, while maintaining bulk connectivity and smoothness. The convergence and divergence of regions (from a single

cortical shell to trabecular bone sandwiched between two thin shells of cortical bone) is important in areas of the external cortical segmentation, such as the thin sinus bone, and regions of the temporalis where there is no trabecular bone evident.

The segmentation of the cortical–trabecular interface is important to radiological assessment and quantification of the CFS, and a highly automated method is required to make the segmentation process repeatable and eliminate/reduce the laborious process of manual segmentation. The impetus for developing a method of accurate cortical–cancellous segmentation arises from the clinical need to better quantify the strain patterns in the oral–maxillofacial skeleton, and in particular in areas of thin bone such as the maxilla. The accuracy of strain measurements from radiographically derived finite element models of the complex structure of the facial skeleton is reliant on robust segmentation. Finite element analysis can then be used for the development of better-designed, longer-lasting implants and technologies for oral and maxillofacial reconstruction and rehabilitation. The level-set segmentation process shows

better correlation with the manual segmentation in the maxillary region, suggesting a multiregion approach may ultimately be required to attain optimal segmentation of the cortical bone in the CFS as a whole. Future work may add additional image-processing steps focused on specifically segmenting the extremely thin sinus and orbital bones of the CFS,¹² and evaluate the sensitivity of

the algorithm to differences in image quality and CFS morphology.

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