

Organ Surface Reconstruction using B-Splines and Hu Moments

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Abstract: The following article presents a combination of image processing and computer graphics methods which form an algorithm for 3D surface reconstruction of inner organs imaged using Computed Tomography. The presented method uses k-means clustering and Hu moments to filter desired contours from a large number detected in CT frames. Least-squares B-spline fitting is used to approximate the filtered contours and finally a B-spline surface is used to approximate the surface of the organ. The algorithm has been tested on several datasets, requires almost no human attention and creates high-quality surfaces in a versatile format that can be used in further applications.

Keywords: medical imaging; computed tomography; B-splines; Hu moments; surface reconstruction

1 Introduction

Currently available software packages provide intuitive ways for navigating through vast amounts of data obtained in Computed Tomography examinations. Image enhancement tools, measuring aids, even video-like visualisation of 3D+t scans, so called *cine* scans, are available either freely [6], [7], or in software bundled with radiologic equipment.

Thanks to the wide adoption of the DICOM standard image data obtained using virtually any medical device can be processed and used. Available software packages offer basic methods for volume rendering of the scanned data, they do not however provide easy methods of creating and exporting reusable 3D models – a substrate for many further computer graphics and simulation applications, such as those proposed in [14], [15]. Creating methods for 3D reconstruction from CT scans therefore remains an area of interest of many groups involved in medical simulation or visualisation. The following paper is a result of an attempt of such kind.

1.1 Related Work

The final objective – organ surface approximation can be achieved only after a significant amount of data processing. Organs have to be identified in the CT images, their boundaries have to be detected and segmented. Consequently – the obtained contours have to be enhanced and filtered due to a large amount of noise that has to be expected. A brief description of many methods used for these goals can be found in surveys like [2], [11]. The extensive work in [11], however referring mostly to the Magnetic Resonance modality, lists eight classes of methods used in organ segmentation i.e. based on thresholding, region growing, classifiers, clustering, Markov random field models, artificial neural networks, deformable models and atlas-guided approaches. Many of the algorithms currently used are using a blend of the mentioned methods in order to create robust solutions for organ segmentation, it appears, however, that the selection of robust and effective methods for segmenting organs from CT scans is still rather small. The ultimate reason for that may be that it is a rather daunting task and even skilled radiologists performing manual segmentation often disagree in determining boundaries of more complicated organs [5] especially in cases where structures under segmentation do not largely differ in image intensities from background. The method that has been used for segmentation in this paper is a blend of thresholding and clustering approaches.

Cross-sections obtained after segmenting organ boundaries can eventually be used to form a skeleton for surface reconstruction, which itself is not trivial and a number of obstacles have to be overcome. An extensive overview of one of the most common methods of surface approximation – based on B-splines, as well as a complete theory of B-splines and Bezier curves is given in [3]. However different approaches are available, [9], [10]. Especially interesting applications of surface reconstruction algorithms to CT data are described in [1] and [2], which have inspired the work described in this paper.

This paper is organized as follows: first – a description of our approach to contour detection and organ boundary segmentation is given, second – the necessary information on surface approximation is outlined, finally – conclusions and discussion of results close the article.

2 Contour Selection

The following chapters will cover the process of constructing a 3D model of the surface of a human lung, based on a set of planar images – slices from a Computed Tomography examination. The dataset used in this paper consists of 1559 images taken during a whole-body CT scan from which only 230 images covering the chest and upper abdomen have been selected for this analysis.

The process of contour selection is a very important step in every surface reconstruction algorithm. It is crucial that each contour (cross-section) is selected carefully and the noise is minimised as it will strongly affect the resulting surface. It is even more important if the product has to be of high fidelity, as in medical imaging. A number of manual, semi-automatic and fully automatic methods have been proposed [2]. This paper shows a different approach.

2.1 Contour Detection and Filtering

Every CT slice is examined, enhanced and contours are detected using the Canny edge detector. The threshold parameter for the edge detector has been empirically set to 0.4. A simple set of morphological operations (i.e. dilation and thinning of the binary image) and filtering small contours is performed in order to filter out unwanted noise – small contours representing sliced blood vessels and bronchi. The filtering effect is visible in second and third columns of images in Figures 1, 2 and 3).

2.2 Clustering

Contour detection creates an even larger dataset and an even greater demand for an automatic method of filtering out noise – in this case undesired contours. For the sake of this paper we will consider an example data set where we have chosen the left lung as the Region Of Interest, however the described methods are applicable to other organs as well.

The contour detection and filtering step creates a set of 1594 contours that need to be examined, majority of which are contours of the chest, right lung, stomach, aorta, etc. The left lung can be manually selected in 215 images. Due to diversity in shape and location of the contours in the image these contours can be filtered using simple machine learning tools, like k-means clustering. In order to account for the shape of contour an n-dimensional vector has been constructed, composed of the X,Y coordinates of the centroid of the contour and a varying number of Hu moments [8].

The clustering step is performed after detecting and pre-filtering the contours. Hu moments and centroid are calculated for each contour and after normalisation are used for k-means clustering. The obtained clusters are later used for classifying examined contours, based on Euclidean distance from the appropriate cluster representing the organ of interest (in this case – the left lung).

All combinations of feature vectors based on the contour centroid and its Hu moments have been tested. The best results were obtained using the 2nd Hu moment along with the centroid coordinates.

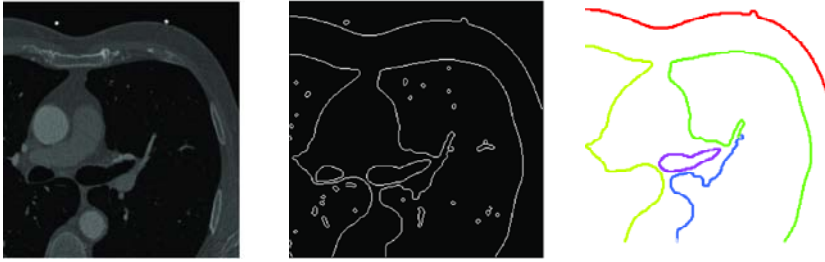


Figure 1

Example images from the first dataset, original image, edges detected, contours detected



Figure 2

Examples from the second dataset, original image, edges detected, contours detected



Figure 3

Further examples from the second dataset, original image, edges detected, contours detected

2.3 Contour Classification

The n -dimensional cluster centroids produced during k -means learning are further used to segment only the desired contours. The conducted experiments show satisfactory response even when using 3-dimensional vectors (composed of the 2nd Hu moment and the XY coordinates of the contour's gravity center).

The experiment was conducted using a labelled set of 1594 contours, 215 of which have been labelled as LeftLung, others were labelled as False.

In the case of the best feature combination it was possible to detect the contours labelled as LeftLung with 98,13% sensitivity (i.e. 4 out of 215 contours were not detected) and with 98,87% specificity (18 contours were incorrectly detected). It is worth noting, that using the 2nd Hu moment alone with X and Y coordinates of the contour's gravity center generated the best results. Using such a 3 dimensional vector substantially reduces the number of calculations performed and produces a faster and more responsive application.



Figure 4

Examples of correctly classified contours of left lung



Figure 5

Examples of false positives classified as contours of left lung

3 B-Spline Surface Approximation

After segmenting the desired contours the approximation part of the algorithm takes over and a least-squares B-spline fitting of each contour is performed. Extensive information on B-splines and NURBS is given in [3], [4], interesting points on application of these methods can be found in [1], [2], [13].

The contour points obtained in previous steps of the algorithm were used to fit a cubic B-spline to each segmented cross-section contour. B-splines are a special case of splines, a generalization of Bezier curves, constructed with orthonormal basis of functions recursively defined as

$$N_{i,0}(u) = \begin{cases} 1 & \text{if } u_i \leq u < u_{i+1} \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

$$N_{i,j}(u) = \frac{u - u_i}{u_{i+j} - u_i} N_{i,j-1}(u) + \frac{u_{i+j+1} - u}{u_{i+j+1} - u_{i+1}} N_{i+1,j-1}(u). \quad (2)$$

The B-spline formula is given by

$$Q_k = C(u_k) = \sum_{i=0}^n P_i N_{i,p}(u_k), u \in [0,1], \quad (3)$$

where P is the control point vector, N are the basis functions and u are the parameters (knots – the spline joining points). The choice of the knot-vector, or the parameterization, affects the shape of the curve and can decide if the final shape will contain loops or wiggle (generally unwanted). The most commonly used, according to [3] is the chord-length parameterization, which gives good results even for non-uniformly distributed curve points.

$$u_0 = 0, \quad u_n = 1$$

$$u_k = u_{k-1} + \frac{|Q_k - Q_{k-1}|}{d}, \quad k = 1, \dots, n-1 \quad (4)$$

where

$$d = \sum_{k=1}^n |Q_k - Q_{k-1}|$$

The problem considered in the described application is the opposite - the curve points (points forming the organ contour), Q_k , are given and the control points, P , need to be calculated. After writing N and C in matrix form:

$$C = N \cdot P, \quad (5)$$

the equation can be solved for P using least-squares – by multiplying by the transpose of N

$$P = (N^T \cdot N)^{-1} \cdot N^T \cdot C. \quad (6)$$

The resulting P matrix contains control point vectors for each considered cross section.

In order to produce a smooth surface all approximated cross-section splines have to be made compatible - they need to have an equal degree (3 in this case) and must be defined on the same knot vector. The common knot vector can be successfully obtained in a similar fashion as in [1] – by averaging the consequent knot vectors of all cross-sections.

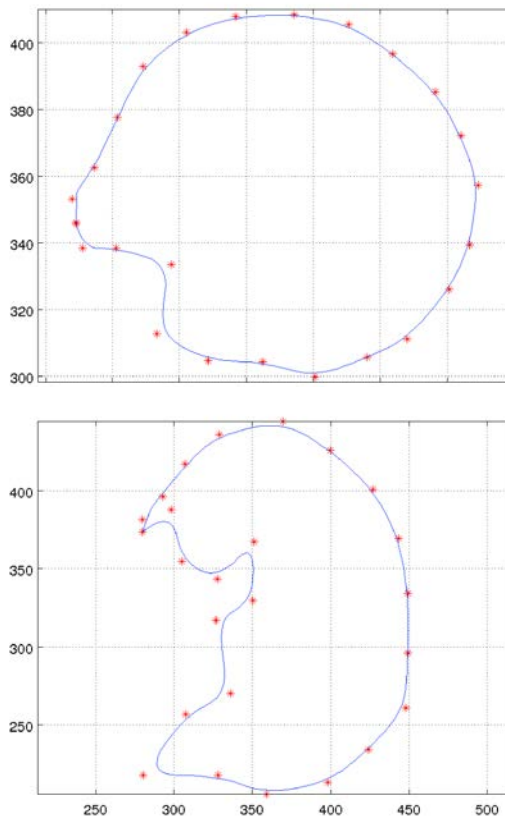


Figure 6

Examples of cross-section contours approximated with B-splines – top image - top part of left lung, bottom image – middle part of left lung, control points marked in red

Control points of all the cross-section curves (which are illustrated in Figure 6) are then taken column after column and a second family of curves is fitted to approximate these columns of control points. This way a second family of B-spline curves is obtained. The two sets of control point vectors form a control net of a tensor surface which can finally be plotted. The control net and 2 knot vectors (one for each family of curves) are enough to completely define the surface. Example of a fragment of the surface of a left lung presented in Figures 7 and 8 has been constructed using 75 3D points. Figures 9 and 10 present a detailed view of a lung fragment showing impressions of ribs in the lung surface.

Satisfying results were obtained when cross-section contours were approximated using 15 control points and a B-spline of degree 3. Curves of higher orders generally demand a higher number of control points and produce curves that are prone to loops and wiggles.

It should be stated, that for this work there was no need for curve alignment and thus the surface presented in Figure 9 and 10 appears twisted. This fact doesn't currently imply any observable problems, other than a slightly unpleasant visual effect and therefore appears to be neglectable.

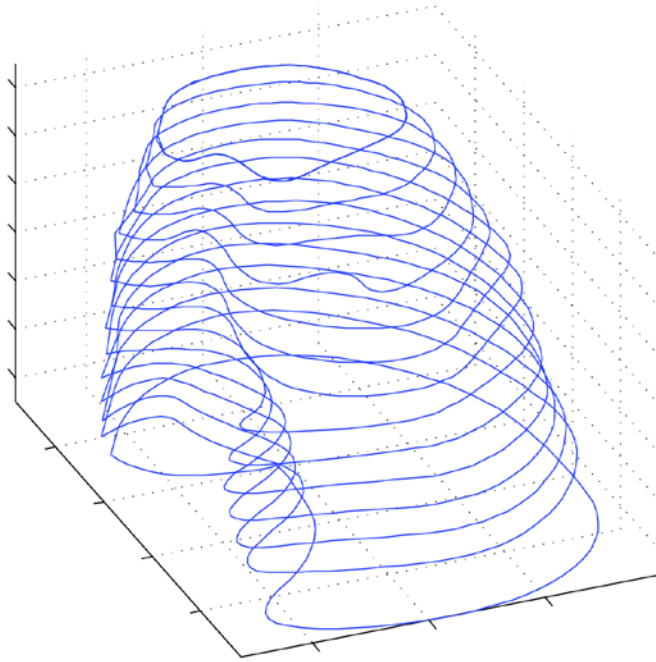


Figure 7

Subsequent cross-sections used for surface approximation

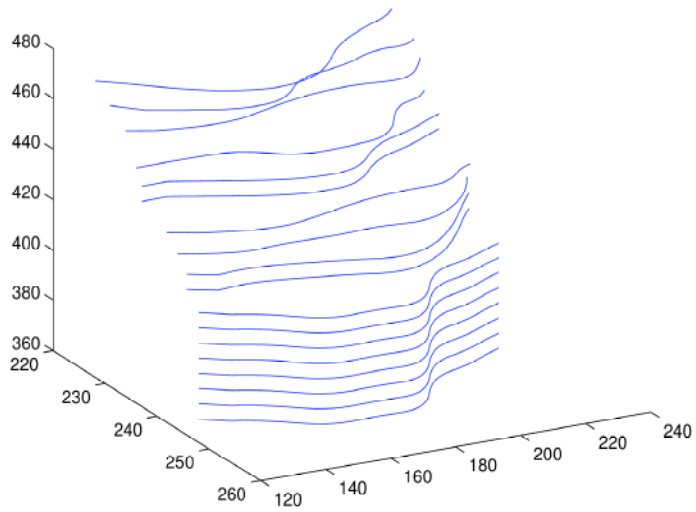


Figure 8
Cross section fragments used to reconstruct lung surface

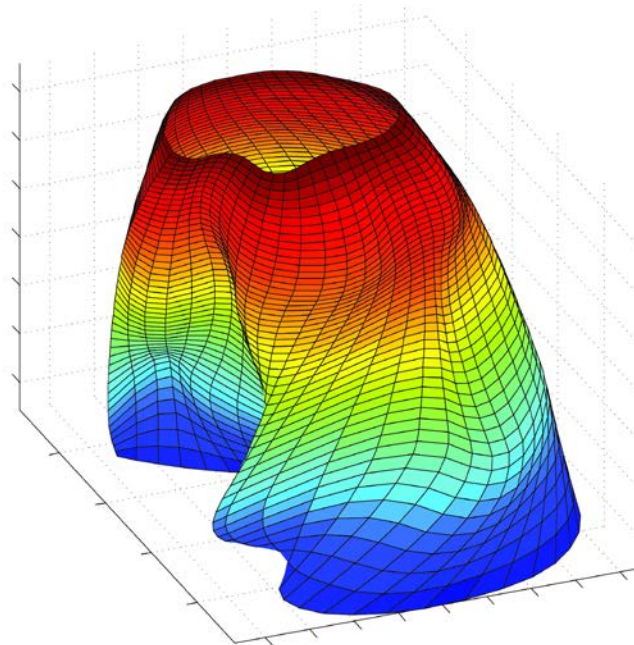


Figure 9
Rendered surface of the left lung

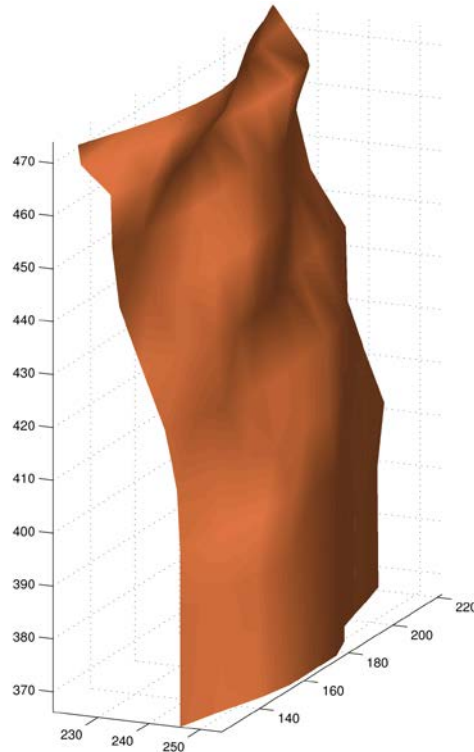


Figure 10

Lung surface rendered from cross sections – costal impressions visible

Conclusions

The combination of methods described in this paper forms a robust tool for processing Computed Tomography data and creating 3D models of inner organs, importantly – the process requires almost no human attention.

Application of a k-means classifier based on Hu moments performs well in the task of segmenting the desired contours out of CT slices – even a 3 dimensional vector of features provides nearly 98% sensitivity and 99% specificity in the test cases.

A least-squares approximation of organ surface using B-splines can be performed and the number of data used to describe the surface can be significantly reduced. Thanks to the interesting mathematical and computational properties of B-splines (i.e. convex hull property, compactness, etc.) further applications of the obtained results are possible.

Future work should consider contour alignment in order to achieve more pleasing visual effects. Alternatively using T-splines for surface reconstruction should be evaluated in order to determine possible benefits of that form of splines [12].

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