3D Livewire Based Segmentation and Modeling of Soft Palate

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Abstract

Obstructive Sleep Apnea (OSA) is a common disorder among North Americans and a major topic in health care nowadays. Though the exact cause of this disease is unclear, it is understood as partial or complete obstruction of airway due to collapsing of soft palate while sleeping. Our work is aimed at creating a reference model for soft palate; medical specialists can use a dynamic version of this model to study the origin and possible treatments for OSA or other swallowing disorders. This article deals with the design and implementation of a complete workflow/scheme for segmentation and modeling of soft palate using MR (Magnetic Resonance) images. The segmentation process relies on a semi-automatic technique called 3D Livewire. This method performs user-guided segmentation in order to balance automation and human intervention. It requires the use to draw contours in any two orthogonal directions of 3D medical data and can automatically create seeds in the third direction. The contours or cross-section curves thus extracted are in turn used to reconstruct the surface of the soft palate, which produces a smooth 3D model. The proposed workflow has shown encouraging results. The basic soft palate model created can be improved further to study its behavior and can be used to reproduce sleep apnea phenomenon in future.

1. Introduction

Obstructive Sleep Apnea is caused by collapsing of soft tissue surrounding the airway while sleeping. In most cases, the sight of obstruction is the soft palate. OSA has serious impact in patient's life resulting into excessive daytime sleepiness and hypertension [1]. Soft palate also plays an important role in swallowing by retracting and elevating simultaneously. We believe, segmentation and modeling of this part of human body will eventually help medical specialists to study the origin and design possible treatment or surgical plans for disorders like OSA and Dysphagia (difficulty in swallowing). A 2D finite element model of the soft palate has already been developed by Berry et al. [2] for better understanding of velar control. Chouly et al. [3] have also developed another finite element model of soft palate in order to reproduce hypopnea phenomenon (partial obstruction of airway) numerically. Sagittal radiography has been used in their work to construct the model in agreement with anatomy. These existing models are two dimensional and can not provide proper visualization. A 3D model naturally will have an edge over this kind of models.

Due to immense growth in the field of medical image acquisition techniques, 3D medical data (e.g. MR, CT) has become of common use in clinics and laboratories. These 3D images are usually available in the form of 2D slices. In order to visualize the 3D data properly, automated or semi-automated image analysis is essential. The necessary step prior to visualization (or registration) is 'Segmentation' - the problem of labeling voxels in order to identify a particular anatomical structure [4]. Segmentation is also necessary for localizing and quantifying 3D biological structures. Complexity and variability of the anatomical structures often make segmentation a difficult problem and may require detailed knowledge in anatomy. Existing segmentation techniques include manual, semi-automatic and automatic approaches. Manual techniques require excessive time, user interaction and extensive anatomical knowledge; on the other hand fully automatic ones are prone to error if their parameters are not properly tuned [4]. This indicates that combination of operator knowledge and computer efficiency would be the best way; this is the basic idea behind semi-automatic segmentation techniques. Segmentation methods, which support user interaction, include parametric, explicit [5-8] or level-set based [9-11] energy minimizing models. However, these models are either prone to converge to local minima or user interaction is complicated. For example, in active contour models developed by Yushkevich et al. [12], user initialization is needed for evolving a 3D active contour. Though the interaction is graphical, user knowledge of this algorithm is required for setting up different parameters. Approaches like 'Graph Cuts' [13] also offer some user intervention. It executes globally optimal segmentation using manually specified foreground and background seeds as hard constraints and boundary information as soft constraints. But, graph cuts produce unpredictable segmentation result for weak edges and can vary with the choice of seeds.

2D Livewire [14] is another semi-automatic segmentation technique, which is an image-feature driven method. It finds the minimal path between user specified seeds, thereby reducing the effort and time to manually describe the entire boundary. Image information used in livewire includes image gradient, Laplacian zero-crossing, intensity values etc. [15, 16]. However, curse of dimensionality strikes hard, when considering user interaction for 3D deformable surface or models. Most of the user-steered segmentation techniques cited earlier are limited in 2D [17] and not very effective for extracting 3D image information. A naïve approach to extend 2D segmentation methods to 3D would be to repeat 2D segmentation on each and every slice over the entire volume of MR images. But, obviously that would be inefficient and tedious. Recently, Hamarneh et al. [17] has developed a fast interactive extension of 2D livewire to 3D. Later in [4], Poon et al. showed how this particular method can be modified to handle objects with arbitrarily complex topology that exhibit non-spherical geometry, concavity or protrusions. This method described in [4] requires the user to perform 2D livewire based segmentation in a number of selected slices (preferably sparse and distributed well over the entire volume) and contours are generated automatically in unseen slices. The method is discussed in further detail in section 2.1. It is not difficult to realize, that soft tissues like soft palate do not have a regular geometry and are prone to variation in shape and size. Hence, 3D livewire [4], capable of handling complex structures is our natural choice for segmentation of soft palate. In this article, we present a novel scheme to segment and model soft palate using MR images. After proper preprocessing, images are subjected to 3D livewire based segmentation to extract soft palate geometry. The cross-sectional contours are then used to build a non-parallel curve network to reconstruct the surface.

This paper is organized as follows: section 2 discusses 3D livewire and the surface reconstruction methods, which form the foundation of this work. In section 3, we describe the proposed methodology to create soft palate model in detail, followed by results and discussion in section 4. Finally, section 5 concludes and suggests the future aspects of this work.

2. Background

2.1. 3D Livewire Segmentation

3D livewire is an extension of classical 2D livewire method [14]. Researchers have made several attempts to extend this simple but robust method in 3D. The approach discussed in [19] to extend livewire to 3D have resulted into complex methodologies which require either complicated interaction steps or extensive knowledge in anatomy to segment complex objects. The framework described in [4], is able to handle complex geometry and require the user to perform segmentation on few sparse slices. The user begins the process by segmenting sparsely separated slices on any two orthogonal directions (e.g. sagittal-coronal, sagittal-axial). This part is based on 2D livewire technique [14]; 2D livewire cost function $C(p,q)$ in a particular slice S, for a user-selected seed point $q=(x_1,y_1)$ and neighboring pixel $p=(x_2,y_2)$, is computed using gradient magnitude C_G, gradient direction C_{GD}, canny edge detection [20] C_C, Laplacian of Gaussian C_{LoG} and Euclidean distance C_d as follows [4]:

$$C(p,q) = w_1 C_C(q) + w_2 C_{LoG}(q) + w_3 C_G(q) + C_{GD}(p,q) + C_d(p,q) \tag{1}$$

where, gradient magnitude is given by [4]:

$$C_G(q) = 1 - \frac{1}{\max(G)} \sqrt{\left(\frac{dS(x,y)}{dx}\right)^2 + \left(\frac{dS(x,y)}{dy}\right)^2}\,\Big|_{(x,y)=q} \tag{2}$$

$\max(G)$ represents largest gradient magnitude found in the particular slice. Gradient direction cost is defined as [4]:

$$C_{GD}(p) = \frac{1}{\pi}\arccos\left(\frac{S'(p).S'(q)}{G(p)G(q)}\right) \tag{3}$$

Here, $G(p)$ and $G(q)$ denote the gradient magnitude of pixel p and q, respectively. LoG cost term is computed as follows [4]:

$$C_{LoG}(q) = 1 - (LoG_{\mathrm{ker}\,nel(x,y)}.S)\,|_{(x,y)=q} \tag{4}$$

where, S is the original image and is convoluted with LoG kernel, defined as:

$$LoG_{\mathrm{ker}\,nel(x,y)} = -\frac{1}{\pi\sigma^4}\left(1 - \frac{x^2+y^2}{2\sigma^2}\right)e^{-((x^2+y^2)/2\sigma^2)} \tag{5}$$

$C_d(p,q)$ is proportional to Euclidean distance between p and q. Each cost term is weighted by constant scalar terms w_1 - w_5, which can be tuned to vary segmentation result. A cost map using this cost function is created by determining the minimal path cost from user-specified q and all other pixels in the given slice using Dijkstra's algorithm [21]. This is a graph search algorithm and is used once for each seed point. User selects next seedpoint based on the visible path and the algorithm is repeated. This is evident, that the method can easily bypass the problem of getting stuck into local minima.

3D livewire can automatically generate seedpoints in the third direction using these interactively segmented contours in other two orthogonal directions. These automatically generated points are simply the intersection points of the 2D livewire contours and the unseen orthogonal slices. The intersection points need to be properly ordered before they are used to generate live-wire contours. While traversing along any 2D livewire contour, we cross from one side of the slice to another. This is referred as ‘entering’ and ‘exiting’ slices in [17] by Hamarneh et al. These points are the endpoints of an intersecting line segment. The point ordering algorithm [4] involves the creation of an L-system ‘turtle’ map – a connected graph created by the intersecting line-segments based on turtle graphics [4]. Starting from any arbitrary seedpoint, the turtle moves forward, turns left at intersections and reverses direction as it encounters another seedpoint. The turtle visits the seedpoints sequentially which determines the order. This 3D livewire technique is capable of handling any arbitrary complex topology often encountered in medical image analysis. It is not possible to delve into all the details of 3D livewire technique within the limited scope of this paper. Interested readers can refer to the works of Hamarneh et al. [4, 17].

2.2. Surface Reconstruction

Segmentation of anatomical components allows creation of three dimensional surface models for visualization of patient anatomy. This 3D view definitely has a clear advantage over the 2D cross-sections. Surface models can be created using existing algorithms like marching cubes [22]. In this method, isosurfaces are created by placing cubes connecting voxel centers. It can handle only a limited number of surface topologies though. This kind of approach might be useful, when we already have a clear idea of the geometry of the structure, but not to model soft tissues. Another interesting approach is to construct a complete surface from planar curves that represent cross-sections of the surface. Many solutions exist for connecting curves on parallel cross sections like [18]. We are interested in building a surface for orthogonal contours.

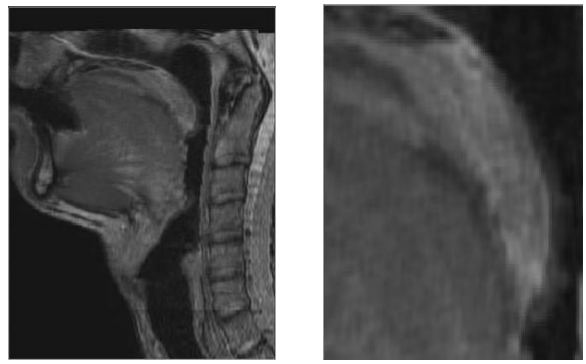


Figure 1: (a) Original image (b) Preprocessed image

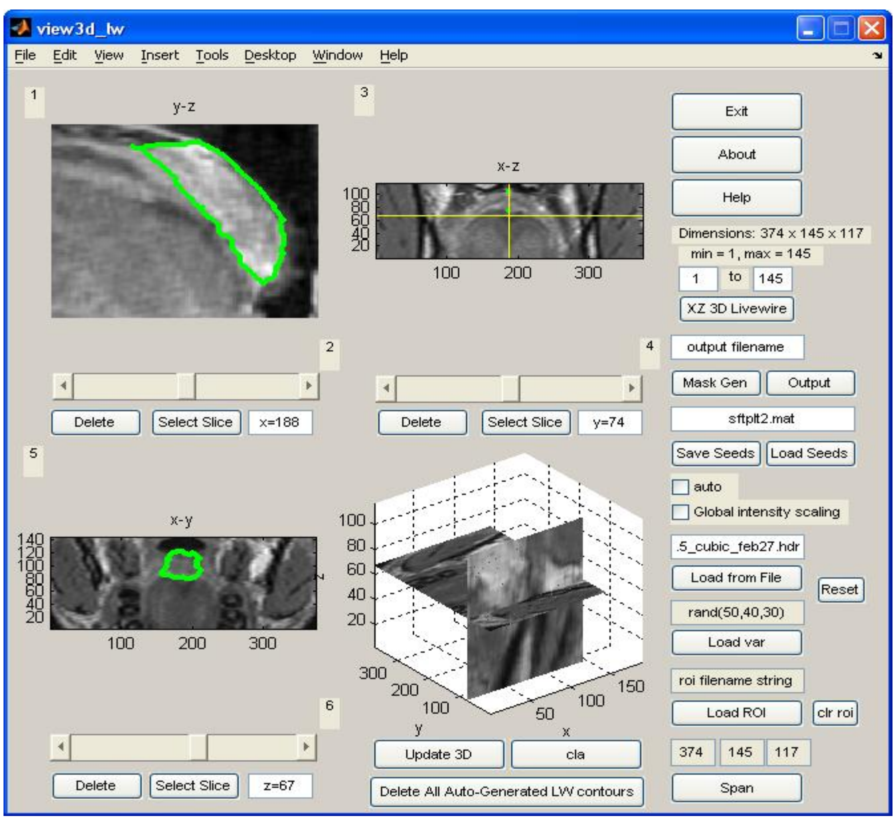


Figure 2: 3D livewire segmentation process of soft palate

A simple but robust surface reconstruction algorithm that uses such curve network has been suggested by Liu et al. [18]. The main idea here is to partition the space into a number of cells by all cross-sectional planes. Then a closed surface network is created with each of the partitioned cell using a projection based approach [23]. Steps include, computing the medial axis of the cell, which is a convex 2D region, partitioning the cell into smaller compartments by projecting the curve networks onto the medial axis, and finally extracting the surface as the boundaries in between. The initial reconstructed surface is often wiggly. Existing techniques like surface diffusion flow [24] have been considered for mesh improvement. This algorithm is simple and robust; it can produce smooth surface from curve networks with any arbitrary topology. However, surface construction is largely dependent on the configuration of the cross-section planes and relative location of the curved network. The reconstructed surface can also result in to disconnected components if the projections of the curve do not overlap on the medial axis between the planes.

3. Proposed Workflow

A workflow has been designed and implemented to perform semi-automatic segmentation and modeling soft palate. We aim at creating a reference model for soft palate, which can then be used to create patient specific models. It begins with preprocessing the raw MR images. Then livewire based segmentation, regularization and surface reconstruction from contours have been performed respectively. Finally, a 3D surface model of soft palate is created. Each of the steps is detailed in following subsections.

3.1. Preprocessing

The very fist step of preprocessing is to crop out the region of interest i.e. soft palate. Working with large images is always computationally expensive and should be avoided whenever possible. We first manually crop out a smaller region containing the soft palate from MR data. MR images often suffer from intensity inhomogeneity. This can be defined as non-anatomic intensity variation in the same tissue over the image domain due to imaging instrumentation [25]. It gives a shading effect to the images. To get rid of any inhomogeneity in intensity, the MR images are passed through non-parametric non-uniform intensity normalization (N3) filter, originally proposed by Sled et al. [26]. N3 method searches for intensity inhomogeneity field to maximize the frequency content of intensity distribution. The method simplifies the multiplicative problem in the log-domain as a deconvolution problem. Say, v_1, v_2 are two independent variables having distribution V_1 and V_2 respectively. It can be shown that the distribution of $(v_1 + v_2)$ is the convolution of V_1 and V_2 [25]. For better segmentation, images have been subjected to cubic interpolation. Original and preprocessed images are shown in figure 1.

3.2. Segmentation and Regularization

Two aspects of the available MR images make segmentation of soft palate a critical task. Firstly, the imaging process; MR is chosen to extract clinically relevant anatomical information about soft palate. But, the anatomical structure of interest often does not have any distinct boundary and is hard to separate from its surroundings. Its weak edges though can be distinguished by human eye, can not be detected by most of the sophisticated segmentation algorithms. Secondly, soft palate constructing the posterior one-third part of the roof of our mouth and is made of soft-tissue, muscle and glands; it has a complex elongated shape, which is very difficult to segment using any completely automatic segmentation technique. A segmentation approach like 3D livewire described in section 2.1, has been found to be most effective as it is interactive and capable of handling any arbitrary geometry. 3D livewire allows the user to select any two orthogonal views to perform semi automatic segmentation. For final segmentation sagittal and axial views have been used as shown in the graphical user interface of 3D livewire in figure 2. Altogether 12 sparsely spaced slices have been segmented, 6 in each direction. All the semiautomatic and automatically generated contours are then used for surface construction.

However, due to low resolution of the available MR images, the segmented contours are noisy. To resolve this issue, we have performed a number of regularization steps. Regularization steps are as follows:

- Creating binary images
- Morphological operations
- Smoothing

By ‘smooth contour’ we mean, that the contours are continuous and differentiable. It is not necessary to consider contours generated for all the slices. On the other hand, this will give rise to more noise in the data. So, we take all the manual contours (for sagittal and axial views) and randomly selected 8 contours in the third direction i.e. coronal direction. Contour points are then used to form a binary image, with the segmented region as foreground (white pixel). Thereafter, simple morphological operations like closing and opening have been performed respectively, to remove irregularities. Closing and opening both tend to smooth contours of an object. Closing operation generally fuses narrow breaks, eliminates small holes or gaps. On the other hand, Opening operation smoothes the contour by breaking narrow isthmuses and eliminating thin protrusions. A morphological filtering consisting of closing followed by opening eliminates local irregularities to a large extent. This is shown in figures 3(a) and (c) for a single slice in sagittal direction.

Snakes [5] are two-dimensional deformable models represented as parameterized functions. Snake algorithm starts from an initialization specified by user (close to the object of interest); this is a first guess at the desired contour. The algorithm then iteratively minimizes the energy of the spline using user imposed constraints and image information to find object boundary. User can use current edge as initialization, which is easy to compute. Then by iterative energy minimization, a smoother contour is produced. The result for a single slice is shown in figure 3(d).

3.3. Surface Reconstruction

Smooth contour points are thus obtained after regularization. These contours can be used to construct a contour network in order to reconstruct the surface. The contours extracted from livewire are arranged in three orthogonal planes, which form a non-parallel cross-section curve network. The algorithm in [18] is capable of handling contours arranged in more than three non-parallel planes as well. All the smoothed contours or a subset of them can be used to build the contour network, as shown in figure 4. As long as, the relative locations of contours are not changed, end result should not vary much. The contours are required to be connected and aligned properly, such that the projections of the curves overlap on the medial axis of the planes. If the curve network fails to achieve such geometry, the reconstructed surface can be disconnected and can even contain holes or gaps. Initial mesh generated using this algorithm can be smoothed by tuning different parameters employing popular existing techniques, as mentioned in section 2.2.

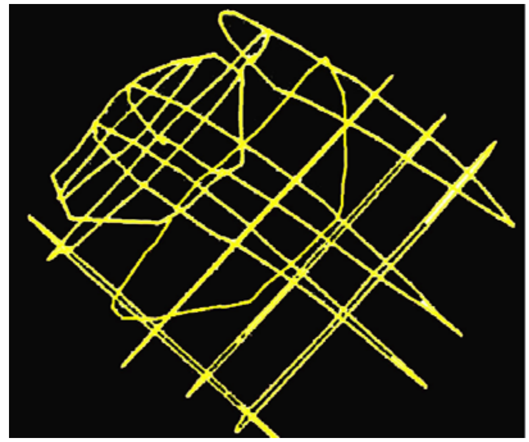
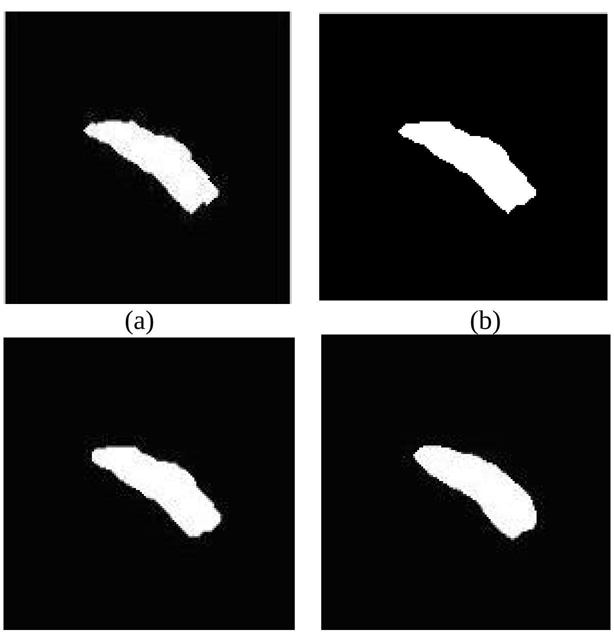


Figure 4: Non-parallel contour curve network created for surface reconstruction; contours arranged in three orthogonal planes



(a) (b) (c) (d)

Figure 3: (a) Binary image from livewire contour (sagittal view) (b) After closing (c) After opening (d) Smoothed contour using snake

4. Results and Discussion

Our suggested workflow has been used on a set of MR images. MR modality has been chosen as it is safer and can provide greater contrast between soft tissues compared to CT. The MR scans we have used were taken using a protrusion appliance. Among different MR scans, PD images show the highest resolution with the most defined contrast gradient. So, PD scans for sagittal, coronal and axial directions have selected. These three

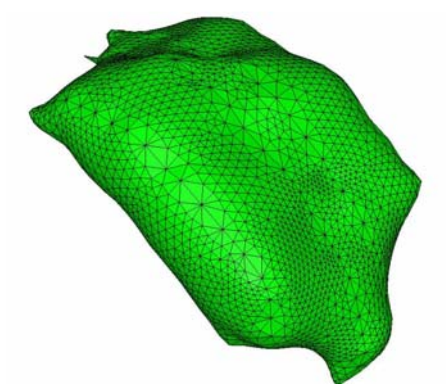


Figure 5: Reconstructed surface mesh using the algorithm of Liu et al. [18]

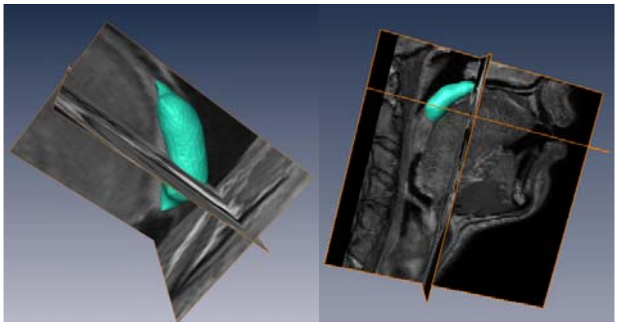


Figure 6: Evaluation of soft palate model positioned in MRI images (sagittal view); left: MR image used for segmentation, right: test image

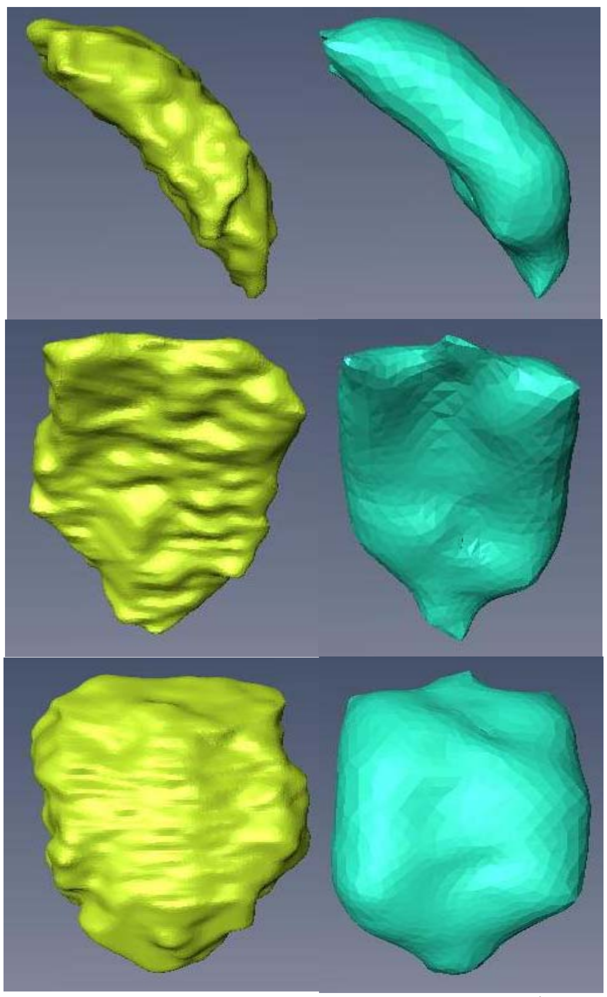


Figure 7: 3D Soft palate model from sagittal (1st row), coronal (2nd row) and axial (3rd row) directions, left column: surface reconstruction with raw segmented data; Right column: surface reconstruction after regularization

scans are registered together employing voxel-intensity based (mutual information) technique with the help of a commercial software called 'Amira 5.2.0'. The merged image size is $x \times y \times z = 281 \times 272 \times 360$. The cropped image is of size $281 \times 109 \times 88$. Cubic interpolation has been performed along y and z direction and dimension is increased by 1.33 times. We have evaluated the resulting soft palate model on a completely different dataset of the same subject collected under different scanning protocols. This has been done by registering the model in the 3D MR image manually. This is shown in figure 4.

Most of the preprocessing, segmentation and regularization have been coded in MATLAB. 7.2.0. N3 correction filter is freely available in ITK platform. So intensity inhomogeneity correction has been done using ITK [27]. For 3D livewire segmentation, two orthogonal directions have to be chosen first to perform user-guided segmentation. Soft palate can be easily identified from sagittal view, but its boundary is not very defined in coronal or axial directions in the given data. After a few trials, it was found that better segmentation results can be achieved while using sagittal and axial directions for user-guided segmentation compared to other combinations. Final segmentation has been done using sagittal and axial views, segmenting 6 slices in each direction. 7-9 distinct clicks (seeds) were required for each contour. The slices for segmentation are carefully chosen, so that they are distributed over the entire volume of the object being segmented. This is a very important aspect of segmentation while using 3D livewire; because unpredictable results can be obtained otherwise. It takes around 15-20 minutes to draw the livewire boundaries in 12 slices. Intersection points in the coronal direction are generated instantly. Drawn contours are deleted and redrawn if there has been any mistake or if unacceptable intersection points are generated in third direction.

Due to noisy or low resolution images, even robust segmentation techniques like 3D livewire can not be fully effective. In such cases, regularization is absolutely necessary. The regularization steps described above have been employed to remove undesired noise along the contours generated as a result of livewire segmentation. For volume rendering, a new algorithm which builds 3D surface from contours has been explored. This algorithm also has inherent smoothing abilities, which lead to even better result. Surface reconstruction has been done using a freely available graphical user interface based on the algorithm of Liu et al. [18]. Much difference between the reconstructed surfaces with and without regularization can be observed. Figure 6 shows the comparative results between surfaces reconstructed with and without regularization. From the models shown in figure 5 and 6 from sagittal, coronal and axial views, it is evident that, the workflow proposed in this article is capable of producing smooth 3D soft palate model, even if the original segmentation is quite noisy. This workflow is likely to be useful for other soft tissue (tongue, for example) segmentation and modeling.

5. Conclusion and Future Work

We have proposed a complete workflow or scheme to build a smooth three dimensional model of soft palate from MR images. The methodologies include preprocessing, semi-automatic livewire based segmentation, post-segmentation regularization and surface reconstruction from non-parallel curve network. The regularization and surface reconstruction makes the process robust against noisy or erroneous segmentation. However, this process would be more efficient in terms of speed and accuracy, if regularization can be performed during segmentation. This possibility can be explored in future work. Also, segmentation method itself can be improved as well. This can be achieved by performing segmentation in sub-pixel resolution to get smooth contours. A possible solution for this could be fitting a 3D quadratic function to the points in the neighborhood of current mouse location point. The accurate minima can then be found by interpolation.

Soft palate is a very important component in human oral, pharyngeal and laryngeal complex. It has major role in physiological activities like swallowing, snoring and is responsible for diseases like OSA or Dysphagia. This work has been done keeping in mind the objective of building a reference model of soft palate, which will eventually be incorporated in a dynamic human upper airway model. For that, an anatomically validated soft palate static model is required in the first place. Anatomical structures vary to a large extent due to subject variation; in order to build a standard model, more data is required. We have validated this model using a different set of MR scans of the same subject taken at a different point of time. But, we need to evaluate the segmented volume on more test data of different subjects, and finally on real patient data, which at this point is unavailable.

Post-processing of the segmented data can indeed produce reasonably smooth 3D volume. Although, another approach could have been to start with a reasonable model, and then morph the segmented data according to the real image to get better result. Future studies can also be directed towards that direction. The basic model built in our first attempt will be improved further, so that it can finally be used to simulate OSA phenomenon, and therefore be helpful in carrying out surgical plans and procedures.

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